Application of Computer Vision and Neural Networks in Feature Extraction and Optimization of Industrial Product Design

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Abstract. Computer-aided design (CAD) technology not only improves production efficiency but also optimizes design schemes through precise mathematical models. A neural network (NN) is a computational model that simulates human brain neurons with strong learning and optimization capabilities. It can automatically adjust network parameters based on input data and achieve various complex tasks. This article combines computer vision with NN, two advanced technologies, and applies them to the industrial design process. This method utilizes computer vision technology to extract features from CAD models, including information on shape, size, colour, texture, and other aspects. In industrial design, designers need to receive timely feedback and results in order to make adjustments and optimizations. This article's algorithm adopts more advanced calculation methods, reducing redundancy and complexity in the calculation process. Compared with traditional manual feature extraction methods, this method can automatically learn useful features from CAD models, avoiding the subjectivity of manual operations. By analyzing and integrating user needs, design solutions can be adjusted and optimized to meet their actual needs and expectations better.

Keywords: Computer Vision; Neural Networks; Industrial Design; CAD; Feature Extraction
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1 INTRODUCTION

In the past decades, the field of industrial design has gradually abandoned the traditional manual drawing and solid model-making methods and turned to CAD technology. Angrish et al. [1] construct an mvcnn model, which accepts images from multiple perspectives as input and learns to extract effective features from these images. The structure of the mvcnn model can include multiple convolution layers, pooling layers, and full connection layers to process multiview image data effectively. Then, it provides a detailed introduction to the implementation process of CAD model shape classification and retrieval. This method is verified through experiments. MVCNN is a multiview neural network (CNN) that can extract and learn feature representations of objects from multiple views. Compared with traditional CNN, MVCNN can better handle objects with complex shapes and structures and can improve the accuracy and stability of feature extraction. In CAD model shape classification and retrieval, MVCNN can be used for feature extraction, classification, and retrieval of models. Using MVCNN to extract multiview features from CAD models. Firstly, divide the CAD model into multiple sub-views and extract features from each sub-view. Then, the features of all sub-views are fused to obtain the final feature representation. The feature extraction method based on MVCNN can effectively learn the feature representation of CAD models, has higher classification accuracy, and has a lower false detection rate compared to traditional methods. Meanwhile, the model retrieval method based on shape similarity has also achieved good results, which can quickly and accurately retrieve models similar to the model to be retrieved. However, with the intensification of market competition and the diversification of customer needs, traditional CAD technology has made it difficult to meet all the needs of modern industrial design. Traditional CAD technology mainly focuses on the geometric shape and size of the model, ignoring other useful information contained in the model, such as design intent and functional industrial visual objects, and defect recognition plays an increasingly important role in the production process. Traditional machine vision methods are usually based on manually designed feature extraction algorithms, but these methods are often limited when dealing with complex industrial scenes. To overcome these limitations, Apostolopoulos and Tzani [2] proposed a method of extracting multilevel features from industrial scenes using deep learning methods to achieve more accurate industrial visual objects and defect recognition. By constructing multi-layer CNN models, we can learn layer-by-layer representations from the original image to advanced semantic information. This layer-by-layer representation can help us capture features at different levels, thereby improving our ability to recognize industrial visual objects and defects. Introducing attention mechanisms can help models focus on more important regions and channels, thereby extracting more representative features. By introducing auxiliary classifiers in the middle layer, we can utilize layer-by-layer supervised learning to optimize the feature extraction process and improve recognition accuracy. By comparing traditional machine vision methods with other deep learning methods, we have demonstrated the superiority of our method in industrial vision object and defect recognition tasks.

Industrial product colour design is one of the important links in the field of industrial design, which has a crucial impact on the appearance, quality and user experience of products. However, traditional industrial product colour design methods mainly rely on the experience and creativity of designers, making it difficult to achieve automation and intelligence. Ding et al. [3]. This method utilizes CNN to learn and extract features from a large amount of industrial product colour data and uses SNN for colour recommendation and combination optimization to achieve automated and intelligent industrial product colour design. This article provides a detailed introduction to the design and implementation process of this method and verifies its feasibility and effectiveness through experiments. We conducted experiments on a publicly available industrial product colour dataset. The experimental results show that the industrial product colour visual design method based on CNN and SNN can effectively recommend and optimize colours, and the generated colour schemes have high accuracy and aesthetics. Meanwhile, this method can also provide personalized recommendations based on user needs and product characteristics, which have high practical value and application prospects. The rapid growth of computer vision and NN has brought new opportunities for industrial design. Computer vision technology can use image processing and machine learning algorithms to extract useful information from images and videos, such as shape, colour, texture and other features. NN, on the other hand, is a computational model that simulates human brain neurons. It has strong learning and optimization abilities and can automatically adjust network parameters according to the input data to realize various complex tasks. Hou et al. [4] explored the application of computer vision and neural networks in the navigation of new industrial product mobile robots with hand-drawn paths. By combining computer vision technology and neural network models, robots can recognize and parse hand-drawn paths, achieving high-precision navigation and movement. This article will provide a detailed introduction to the implementation method, working principle, and experimental verification of the system. In order to meet diverse production needs, researching a new type of industrial product mobile robot that can recognize and analyze hand-drawn paths has important practical significance and application value. This robot is capable of high-precision analysis and recognition of hand-drawn paths through computer vision and neural network technology, achieving autonomous navigation and movement. Input the preprocessed image into a neural network model and use deep learning algorithms to recognize and analyze the hand-drawn path. The trained model can achieve high-precision recognition and analysis of any hand-drawn path. Based on the hand-drawn path information analyzed by the neural network model, utilizing the principles of kinematics and dynamics, trajectory planning and optimization are carried out on the robot to generate navigation trajectories suitable for robot operation. High-precision hand-drawn path recognition and navigation while also having high mobility accuracy and efficiency.

Huo et al. [5] use computer vision technology for object recognition and localization; neural networks are used to adaptively adjust impedance control parameters adaptively, achieving precise polishing of complex shaped and material objects by robots. The article first introduces the basic principles of computer vision and neural networks, then elaborates on the implementation process of model-free adaptive impedance control strategy, and finally verifies the feasibility and effectiveness of this method through experiments. Computer vision is a technology that utilizes image sensors to obtain surface information of three-dimensional objects. Through computer vision technology, object recognition, localization, and tracking can be achieved. A neural network is a computational model that simulates the structure of human brain neural networks with strong learning and adaptive capabilities. In autonomous robot polishing, neural networks can be used to adjust impedance control parameters to adapt to changes in different objects and environments. The core idea of a model-free adaptive impedance control strategy is to use computer vision technology to obtain geometric information of the object surface and then use neural networks to learn and predict the obtained information, adaptively adjusting impedance control parameters. Construction equipment generates a large amount of video data during operation. By analyzing these data in real-time, abnormal actions of building equipment can be detected, potential faults can be detected in a timely manner, and safety accidents and economic losses caused by equipment failures can be avoided. Artificial intelligence technology and real-time motion detection methods for building equipment videos based on deep learning have gradually become a research hotspot. Jung et al. [6] proposed a model that can automatically detect and identify abnormal actions during the operation of building equipment through real-time analysis of building equipment videos, providing strong support for fault prediction and preventive maintenance of building equipment. This model directly sends the input video data into 3D-CNN for feature extraction, avoiding the complex feature extraction and classification process in traditional methods. Meanwhile, the model has high real-time performance and can meet the needs of real-time analysis of building equipment videos. Kansal and Mukherjee [7] proposed a method for kinematic analysis of delta robots in visual object capture based on computer vision and neural networks. This method utilizes computer vision technology to recognize and locate target objects. Then, a neural network model is used to analyze the kinematics of the delta robot, achieving precise object capture and handling. This article will provide a detailed introduction to the implementation method, working principle, and experimental verification of the system. Using computer vision technology to recognize and locate target objects. By collecting image information of the target object, performing image processing and feature extraction, precise positioning of the target object is achieved. Construct and train a neural network model using known kinematic data of delta robots. Through training, the model can predict and optimize the motion trajectory of the delta robot based on the position information of the target object. Perform kinematic analysis. Through analysis, achieve precise control of robots and capture and transport target objects. The experimental results achieve accurate object capture and handling while also having high kinematic analysis and execution efficiency. Under experimental conditions, this method achieved good recognition and handling effects on target objects of different types and sizes.

This article aims to explore the application of computer vision and NN in feature extraction and optimization of industrial design CAD models, so as to provide. By using computer vision technology to extract the features of the CAD model, we can get all kinds of useful information contained in the model. Then, the information is input into NN for training, and the design scheme can be automatically adjusted. This method can not only improve production efficiency but can also be customized according to the needs of users.

Through the combined application of computer vision and NN technology, designers can extract CAD model features more efficiently, reduce the time and cost of manual operation, and thus improve the overall production efficiency [6]. By introducing computer vision and NN technology, designers can dig deeper into the potential value of CAD models, thus inspiring more design concepts. Through the accurate extraction of CAD model features, designers can find and correct design defects in the early stage of product development and improve the final product quality. The innovations of this article include:

(1) In this article, computer vision and NN are combined and applied to industrial design. This comprehensive application can not only improve production efficiency but also automatically optimize the design scheme according to the needs of users.

(2) This method uses computer vision technology to extract features of the CAD model, including shape, size, colour, texture, and other information. Compared with the traditional manual extraction method, this method can capture more detailed information.

(3) This article constructs an appropriate NN model and uses the existing data sets for training and optimization so that it has the ability to learn and adjust the design scheme automatically.

This article first introduces the significance of industrial design optimization; then, the related basic theory and algorithm principle are elaborated on in detail; then, the advantages of the feature extraction method of the CAD model based on NN are verified by experiments. Finally, the full text is summarized, and the future research direction is discussed.

2 RELATED WORK

With the rapid development of Industry 4.0 and intelligent manufacturing, digital twin technology has become an important direction for the manufacturing industry. Digital twins provide manufacturers with an unprecedented perspective to observe, analyze, and optimize the performance of production lines by replicating and simulating real production processes in virtual environments. Mincă et al. [8] explored how to apply integrated robot systems and mobile vision sensors to mechatronics production lines and achieve flexible assembly multifunctional technology through digital twins. Digital twin technology utilizes interdisciplinary knowledge, including physics, control theory, computer graphics, etc., to construct detailed models of production lines. By integrating robot systems, production lines can execute various tasks more flexibly and improve production efficiency. Mobile visual sensors provide real-time and accurate data, enabling production lines to self-optimize and improve quality. Consider a specific mechatronics production line that includes multiple robots and mobile vision sensors. These devices are connected through wireless networks and transmit data in real-time to digital twin models. By observing the model, manufacturers can immediately understand the operation status of the production line and solve problems accordingly. For example, if there is a malfunction in the production line or a decrease in product quality, the manufacturer can quickly locate the problem and take measures based on the predictions of the digital twin model. However, computer vision technology can achieve automated and accurate 3D model reconstruction. A neural network is a computational model that simulates the connectivity of human brain neurons with strong learning and adaptive capabilities. In 3D model optimization, neural networks can automatically identify errors and defects in the model by learning a large amount of 3D model data and optimizing it. Specifically, neural networks can analyze and learn the shape, texture, lighting, and other information of 3D models, achieving automatic model repair, smoothing, and optimization functions. Qin and Gruen [9] explored the application of computer vision and neural networks in machine intelligence for the 3D modelling of industrial product photogrammetry. By analyzing a large amount of image data, computer vision technology can achieve automated and accurate 3D model reconstruction, while neural networks can further optimize the model and improve its accuracy. Industrial product photogrammetry and 3D modelling, improving production efficiency and quality.

Industrial product shape modelling is one of the key technologies for achieving automated production, quality control, and intelligent manufacturing. Traditional shape modelling methods are usually based on manually designed feature extraction and pattern recognition algorithms, which are difficult to adapt to complex and variable industrial product shapes. Object detection has also been widely used in the establishment of shape models for industrial products. However, improving the classification accuracy and robustness of CNN to adapt to the complexity and uncertainty of different industrial product shapes remains a challenge. SFS (Sequential Feature Selection) is a feature selection method that can gradually select the best features based on the dependency relationships between features. Rizwan et al. [10] proposed a method that combines SFS with CNN to optimize CNN's hierarchical feature extraction and establish a robust industrial product shape model. Using SFS to optimize CNN's hierarchical feature extraction, gradually extracting and selecting the best features from the bottom to the top, making each layer's features more discriminative and robust. Train and optimize CNN using a large amount of industrial product image data, adjust network parameters and learn. In the industrial production process, workpiece inspection is a key link to ensure product quality. With the continuous development of machine vision and artificial intelligence technology, workpiece detection methods based on computer vision are receiving increasing attention. Shi et al. [11] proposed a computer vision for rapid industrial workpiece detection. This method utilizes SSD models for object detection in images and combines multiple feature fusion techniques to improve detection accuracy and speed. Through experimental verification, this method has achieved good results in industrial rapid workpiece detection. Utilize high-resolution industrial cameras to capture workpiece images and preprocess them to remove noise and improve image quality. Extract multiple features of the image, including colour, shape, texture, etc., and use feature fusion technology to combine these features to improve the accuracy of object detection. Train an SSD model using the annotated workpiece image dataset. This model can achieve efficient object detection of workpieces. The experimental results show that computer vision and neural networks based on multi-feature fusion SSD can achieve efficient object detection of workpieces in industrial rapid workpiece detection methods while having high detection accuracy and speed. Compared to traditional methods, this method can significantly improve detection efficiency and meet the rapid detection needs in industrial production.

With the advancement of Industry 4.0, intelligent manufacturing has become mainstream. Machine vision, as one of the key technologies for achieving intelligent manufacturing, is increasingly being applied. Computer vision and neural networks play important roles in the planning and deployment of machine vision artifacts. Silva et al. [12] explored computer vision and neural networks in optimizing visual product workpiece routes in the context of Industry 4.0. By utilizing advanced computer vision technology and neural network algorithms, a detailed analysis of the production process aims to improve production efficiency, reduce costs, optimize resource allocation, and achieve intelligent manufacturing. Utilize computer vision technology to perform real-time image recognition and classification of visual product workpieces on the production line. Automatic recognition and classification can be achieved by extracting the features of the workpiece and matching them with the preset template. Real-time monitoring of visual product workpieces on the production line is achieved by deploying industrial cameras and image processing systems. By analyzing image data, discovering abnormal situations in a timely manner, and taking corresponding measures to ensure a smooth production process, Due to the numerous manual operations involved in the production process of traditional handicrafts, production efficiency is low, and quality is unstable. Therefore, how to achieve automated design and production of oil paper bamboo umbrella. Wu and Zhang [13] proposed a deep learning-based method. This method utilizes deep learning technology to recognize the style of oil paper bamboo umbrella images and achieve intelligent design. By constructing a deep learning model, different styles of oil paper and bamboo umbrella images can be learned and feature extracted to achieve automated style recognition. At the same time, intelligent design algorithms are used to automate the design of new oil-paper bamboo umbrella images, generating oil-paper bamboo umbrellas with similar styles. The experimental can accurately recognize different styles of oil paper bamboo umbrella images and has high recognition accuracy and robustness. At the same time, intelligent design algorithms can be used to design images of oil paper bamboo umbrellas with similar styles automatically, and the design results have been recognized by professionals.

Yao et al. [14] proposed a multi-visual feature point product cloud model processing. This method utilizes hierarchical neural networks to learn multi-visual feature point product cloud models and automatically recognize processing features. By combining multiple visual feature points and cloud models, this method can more accurately describe and recognize complex machining features, improve production efficiency, and reduce costs. In multi-visual feature point product cloud model processing feature recognition, hierarchical neural networks can be used to learn multi-visual feature points in the cloud model and automatically recognize processing features. By combining multiple visual feature points and cloud models, this method can more accurately describe and recognize complex machining features. It also has higher accuracy and lower false detection rates compared to traditional methods. Meanwhile, this method can also be customized and optimized according to actual production needs, providing new ideas and methods for industrial automation production. Feature recognition in industrial product processing has become increasingly important. Traditional feature recognition methods are usually based on manual feature extraction and recognition, which is not only time-consuming and laborious but also prone to errors. Therefore, Yeo et al. [15] proposed an industrial product processing feature recognition method based on deep visual neural networks, which can automatically extract and recognize processing features, improve production efficiency, and reduce costs. CNN can automatically extract and learn useful features from images or videos. In industrial product processing feature recognition, deep vision neural networks can be used to automatically extract and recognize processing features, such as surface roughness, shape error, etc. By training a deep neural network model, it can be equipped with the ability to recognize various processing features and support close integration with 3D CAD systems. The experimental results show that the industrial product processing various processing features and the close integration with 3D CAD systems can achieve automated measurement and processing.

Two-wheeled industrial robots are a common mobile robot platform with high flexibility and autonomy, suitable for autonomous navigation in various complex environments. As one of the important sensors, IMU (Inertial Measurement Unit) can perceive the posture and motion status of industrial robots in real time, providing important support for precise control and environmental perception of industrial robots. However, traditional IMU data processing methods often suffer from error accumulation and attitude drift, making positioning and environmental mapping difficult. Therefore, Zhai et al. [16] proposed a new industrial robot positioning and mapping stereo IMU system based on precise attitude parameterization. In order to achieve high-precision robot positioning and environment mapping, the system adopts an accurate attitude parameterization method. This method converts IMU data into accurate attitude information through quaternions and uses the Kalman filtering algorithm to fuse and filter the data, further improving the accuracy of attitude measurement. High-precision robot positioning and environment mapping while also having high robustness and real-time performance. Under experimental conditions, the system achieved good perception and adaptability to different types of environments, with the continuous development of various fields. How to quickly and accurately retrieve the required model in a massive 3D CAD model has become an important issue. Zhang et al. [17] The traditional 3D CAD model retrieval methods are mainly based on geometric shape similarity measures, such as Euclidean distance, cosine similarity, etc. These methods ignore the visual information of the 3D model and cannot fully utilize the semantic information of the model. In recent years, deep learning technology has achieved significant results. Use deep residual networks to extract features from each view. Deep residual networks have good robustness and learning ability and can extract effective features from views. Merge the features extracted from each view to obtain a global feature vector. This feature vector contains the appearance, structure, and semantic information of the 3D model.

The generalization ability of NN models used in existing research may be limited when dealing with industrial design problems of different types and complexities, leading to unstable optimization results. Some studies have not fully considered the actual needs and preferences of users when using

NN to optimize design schemes, resulting in a certain deviation between the optimized scheme and user expectations. This article adopts a new type of NN model, which improves the generalization ability of the model in dealing with industrial design problems of different types and complexities by introducing techniques such as regularization and data augmentation. Moreover, this method fully considers the actual needs of users and introduces a user feedback mechanism to make the design scheme more in line with user expectations.

3 APPLICATION OF COMPUTER VISION AND NN IN INDUSTRIAL DESIGN

3.1 The Role of Computer Vision

Computer vision is a technology that simulates the human visual system and can automatically extract information from images or videos. In the process of CAD model design, designers usually need to manually extract various features of the model, such as edges, corners, contours, etc. This process is very time-consuming and error-prone. Computer vision technology can automatically extract these features from CAD models and filter and classify them as needed. Computer vision technology can automatically detect product defects by analyzing and processing product images and can classify and locate defects. Designers need to classify and identify products based on their different characteristics in order to facilitate subsequent design and optimization. Computer vision technology can automatically recognize different products by learning and training product images and can classify and archive products based on their features.

3.2 Application of Neural Network (NN)

NN is an algorithm model that simulates the operation of the human nervous system. In product design, designers need to jump rope design solutions based on user needs and market trends. NN can automatically adjust design parameters and schemes by learning and training existing design schemes, making the design schemes more in line with user needs and market trends. NN can establish a mapping relationship between product features and performance by learning from existing data and can evaluate performance based on new product features. NN can also learn from user browsing and purchasing records, establish associations between users and products and services, and make intelligent recommendations based on user preferences and needs.

3.3 The combination of Computer Vision and NN

The combination of computer vision and NN can further improve the performance of industrial design. Specifically, computer vision technology can be used for feature extraction in CAD models, and the extracted features can be input into NN for optimization. This combination approach can fully leverage the respective advantages of computer vision and NN to achieve more efficient and intelligent industrial design.

4 FEATURE EXTRACTION OF CAD MODELS BASED ON NN

With the rapid growth of computer technology, CAD models have become an indispensable part of industrial design. However, traditional CAD model feature extraction methods mainly rely on manual operations, which are inefficient and prone to errors. To address this issue, this section will explore a feature extraction method for CAD models based on NN.

4.1 Construction and Training of NN

In order to extract effective features from CAD models, it is necessary to construct a suitable NN model. This NN model should have strong learning and optimization capabilities and be able to extract useful features automatically based on the input CAD model. When constructing an NN model, it is necessary to consider key factors such as network structure, activation function, loss function, and optimization algorithm. This article adopts Deep Convolutional Neural Network (DCNN) as the basic network structure and extracts the features of CAD models through multi-layer convolution and pooling operations (as shown in Figure 1).

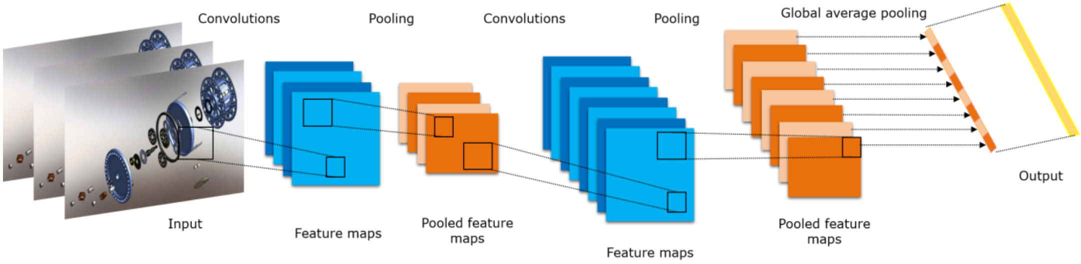

Figure 1: DCNN model of CAD feature extraction.

$$Y_i^k = f(X_i^k) \tag{1}$$

$$X_i^k = \sum_{j=1}^{n+1} W_{ij} Y_j^{k-1} \tag{2}$$

Generally, f it is an asymmetric Sigmoid function:

$$f(x_i^k) = \frac{1}{1+\exp(-X_i^k)} \tag{3}$$

$$e = \frac{1}{2}\sum_i (Y_i^m - Y_i)^2 \tag{4}$$

When training NN, a large amount of CAD model data is required. These data should include various product categories and shapes to facilitate network learning of a wider and more useful range of features. Moreover, it is needed to preprocess and enhance the data to improve the network's generalization ability. Through continuous iterative training and optimization, a DCNN model that can automatically extract CAD model features can be obtained.

4.2 Application of NN in Industrial Design Optimization

After training the NN model, apply it to industrial design optimization. This information can be used for product design, manufacturing, and testing. In the product design stage, use the features extracted by NN for product classification and recognition in order to facilitate designers in making subsequent adjustments. During the product manufacturing phase, use NN to detect product defects and make timely improvements. During the product testing phase, use NN for automatic testing to improve product testing efficiency.

In order to enhance the generalization ability of NN, image data is enhanced to increase data diversity. Use the trained DCNN (DCNN) to extract features from CAD model images. This process can be understood as NN learning a large number of image samples to understand and extract key information from the images. After extracting features in NN, some post-processing operations are needed to better understand and use these features. The extracted and processed features can be applied to various industrial design optimization tasks. At this stage, it is necessary to further utilize features based on specific task requirements.

$$p(X_k | Z_k) \approx \sum_{i=1}^{N} w_k^i \delta(X_k - X_k^i) \tag{5}$$

$$E(f(x)) = \int f(x) p(X_k | Z_k) dx = \sum_{i=1}^{N} w_k^i f(x_k^i) \tag{6}$$

The attention mechanism of the human visual system can help humans dynamically capture discriminative information in the scene rather than directly receive and process information from the entire scene because the human visual nerve can only perform limited processing on the images in the scene. Under the influence of attention mechanisms, humans mainly focus on certain important parts and ignore areas with less information. The core idea of visual attention in the DL field is to explore the necessary correlations within existing data and highlight key features from them. Spatial attention helps NN select appropriate target spatial regions for scale transformation. Through different spatial transformation methods, the information in the image is transformed from the original space to another space, simplifying the classification process and improving classification performance, as shown in Figure 2.

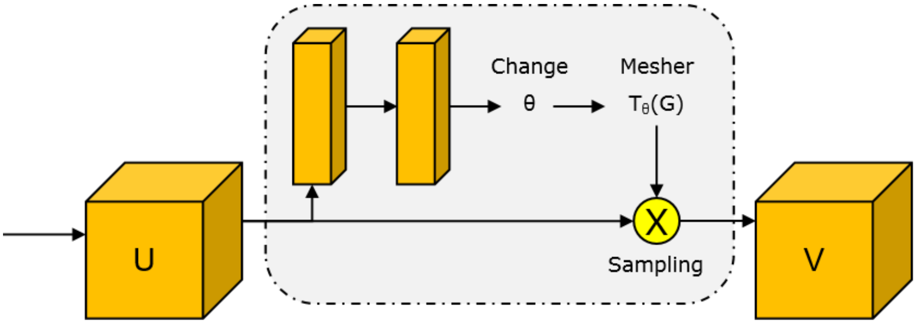

Figure 2: Spatial attention mechanism.

Self-attention refers to the ability to learn the relationship between a pixel and all other pixel positions, representing the degree of prominence to other positions at the position of that pixel, that is, capturing the relationship between the distances of each local pixel in the image. The most significant advantage of the self-attention mechanism is that it can utilize the features of all positions to help generate a specific detail in the image, thereby highlighting the effective features of that position. As shown in Figure 3, the input features are directly passed through a 1 × 1 convolutional layer, which is used to extract the features of each pixel. During the training process, the parameters of the convolutional layer are initialized to 0. In the initial stage of training, the network mainly relies on the features of neighbouring pixels and then gradually increases the weight of its dependence on distant regions to better model the relationships between different regions of the image.

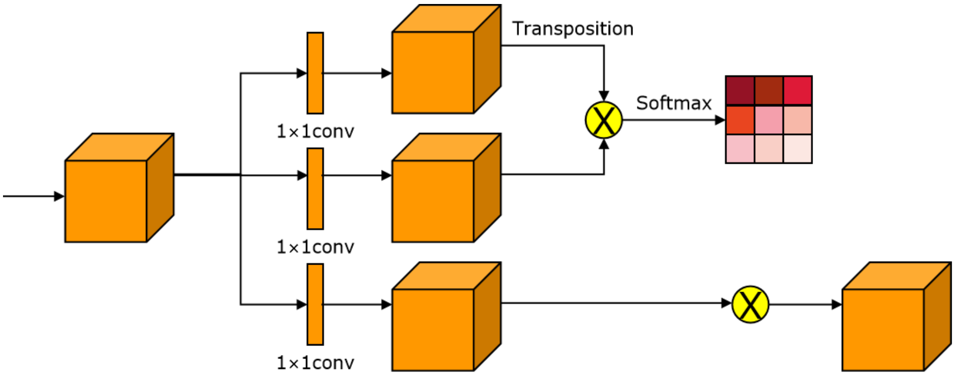

Figure 3: Self-attention mechanism.

Image processing constitutes a pivotal subject within art and design research, with visual communication design playing a vital role in art and design. This field of design primarily involves artistic creations that utilize visual symbols, employing essential elements like text, graphics, and colour to convey diverse information in an artistic manner. To mitigate noise, the image function can be subjected to convolution with a smoothing function, such as the Gaussian smoothing function, which is expressed as:

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}\exp(\frac{x^2+y^2}{2\sigma^2}) \tag{7}$$

$$\left|V^*(p')\right|(1-g^*(p))<\sum\nolimits_{p\in U(p)}(1-g^*(p)) \tag{8}$$

$$\phi(p)=\begin{cases}1, & p\in M\\ 0, & p\notin M\end{cases} \tag{9}$$

During histogram calculation, statistics are obtained by assigning threshold values to gray-scale pixels:

$$p(a_i)=\begin{cases}\dfrac{p}{h} & h_i>p\\ \dfrac{h_i}{h} & h_i<p\end{cases} \tag{10}$$

5 IMPROVEMENT BASED ON USER NEEDS

Meeting user needs is crucial in industrial design. Therefore, improving based on user needs is an important step in feature extraction and optimization of CAD models. This section will explore how to improve based on user needs. In order to fully understand the needs of users, the design team needs to have in-depth communication and interaction with them. Moreover, market trends and competitors can be analyzed to understand the overall needs of users for the product and industry development trends. After collecting a large amount of user demand information, it is necessary to organize and analyze these requirements. This process needs to consider the priority and weight of user needs in order to facilitate subsequent design adjustments and optimizations.

After collecting data, it is necessary to perform data preprocessing work, including data cleaning, word segmentation, removing stop words, part-of-speech tagging, and other operations. These operations can help us better understand the language and behaviour of users and transform them into formats that algorithms can handle. Next, useful features need to be extracted from the preprocessed data. In order to better understand the mining results, visualization tools can be used to display and analyze the results. These tools can help us have a more intuitive understanding of user needs and behaviour patterns. The weight of each intermediate node word in the interest-spanning tree is:

$$Node(p_i)\cdot w_j=\sum\nolimits_{i=1}^{k}w_i \tag{11}$$

The freshness of each intermediate node word is:

$$Node(p_j)\cdot x_j=\sum\nolimits_{i=1}^{k}(\frac{w_i x_i}{w_j}) \tag{12}$$

Among them w_j are the weight of the intermediate node p_j, x_j the freshness of entries of the intermediate node p_j, k the quantity of children of a node p_j, w_i the weight of children's interesting entries p_i, and x_i the freshness of children's interesting entries p_i.

Adjusting the design plan according to user needs is the core aspect of improvement. After understanding the specific needs of users, the design team needs to adjust and improve the original design scheme based on these needs. This includes modifications and optimizations to the shape, size, colour, structure, and other aspects of the product. In this process, the NN-based CAD model feature extraction method mentioned earlier can be used to extract corresponding features according to user needs and apply them to the adjustment of design schemes.

For the lifting tree model, assuming there is a K tree, the predicted result is:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{13}$$

Its objective function is defined as:

$$ob_j = \sum_{i=1}^{m} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{14}$$

$$P_{u,i} = \bar{R}_u + \frac{\sum_{u_k \in U} sim(u, u_k) \times (R_{u_{k,i}} - \bar{R}_{u_k})}{\sum_{u_k \in U} (\left| sim(u, u_k) \right|)} \tag{15}$$

To ensure that the improved design solution meets the actual needs and usage habits of users, the design team also needs to communicate and provide feedback to users repeatedly. By creating prototypes or samples, users can have a practical experience with improved design solutions, collect feedback and suggestions from users, and facilitate further design adjustments.

6 RESULT ANALYSIS AND DISCUSSION

In the ImageNet, COCO, and Pascal VOC datasets, there are only 60-100 images per category. In order to avoid overfitting or underfitting caused by the quality and richness of data samples in the network, this article adopts methods such as flipping, rotation, translation, and scaling for data preprocessing (as shown in Figure 4). In the study, each training image was flipped horizontally or vertically with a 50% probability, allowing the network to observe the image's mirror image during training. Moreover, each image will be slightly rotated around the center of the image, ensuring that each image can be rotated counterclockwise by 10 degrees. In addition, translation and scaling methods were adopted to make the network more robust to slight movements and subtle features in the image. These operations include moving each image 5 pixels to the left or right, then 3 pixels up or down, and scaling the image to 90%. By enhancing the dataset, the training set for each dataset can be expanded five times, allowing the network to learn more diverse and rich image details, thereby improving its representation ability.

Figure 4: Data enhancement examples of training sets in three standard data sets.

Figure 5 shows the change in feature extraction accuracy before adding overfitting measures. As the quantity of iterations increases, the accuracy shows a fluctuating upward trend, but the overall upward speed is slower.

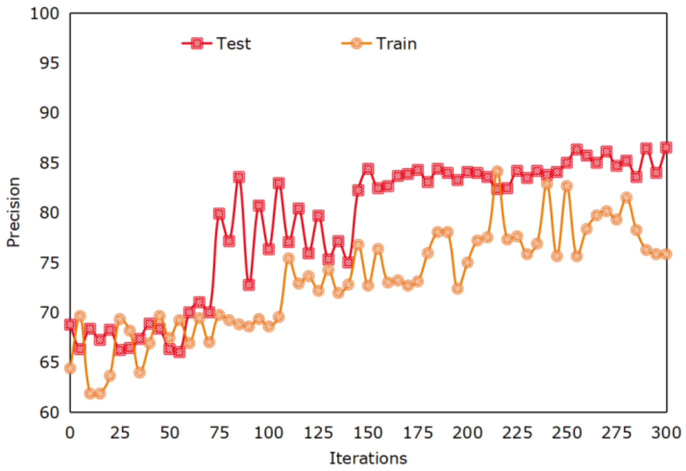

Figure 5: Changes in accuracy before fitting measures are added.

During the training process of NN, the update of weights is random, which may cause fluctuations in accuracy after each iteration. In addition, the complexity of the dataset may also lead to fluctuations in accuracy. If the dataset contains a lot of noise and outliers, or if the feature differences between different categories are small, the training process of NN may be more difficult. If the complexity of the NN model is insufficient, that is, the network structure is too simple, or the quantity of parameters is too small, the network may not be able to fully learn the complex features in the data. If the training data is insufficient, i.e. the dataset size is small, or the data distribution is uneven, the network may not be able to fully learn the distribution pattern of the data, resulting in a slow increase in accuracy. The accuracy change after processing is shown in Figure 6. Compared with the accuracy change curve before adding overfitting measures, the accuracy of the model has significantly improved.

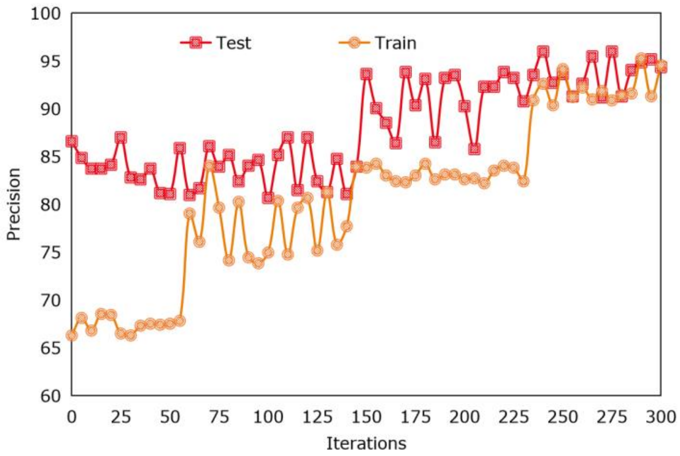

Figure 6: Changes in accuracy after adding over-fitting measures.

Overfitting is one of the common problems in NN training, which can lead to the model performing well on training data but poorly on test data. Secondly, the accuracy change curve after processing is more stable and has smaller fluctuations. This is because adding overfitting measures effectively controls the complexity of the model, thereby reducing the impact of randomness on accuracy during the training process. The accuracy change curve after processing still maintains an upward trend in the later stages of iteration, indicating that there is still room for further optimization of the model. This may be due to the complexity of the dataset itself; even if overfitting measures are added, the model requires more iterations to learn the complex features in the data fully.

In industrial design, feature detection is an important step that requires processing and analyzing a large amount of data. If the feature detection time is too long, it will seriously affect the progress of the entire design process. Figure 7 shows the comparison of feature detection times for different algorithms, and the response time of our algorithm is much lower than that of traditional algorithms.

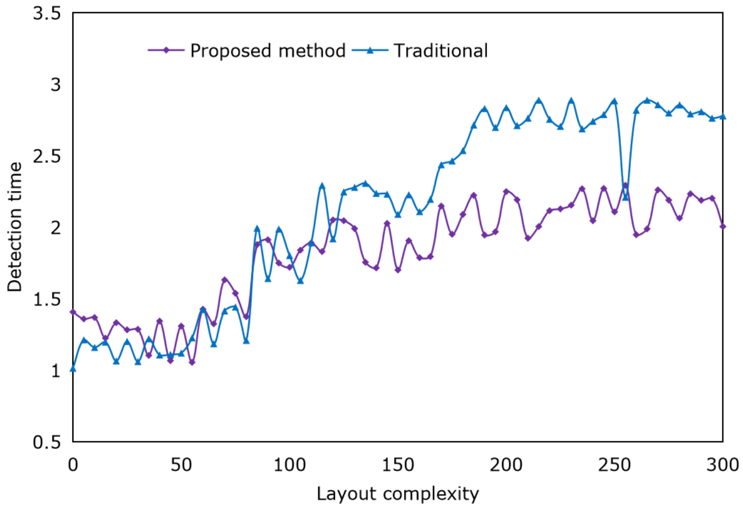

Figure 7: Feature detection time of different algorithms.

In industrial design, designers need to get feedback and results in time so as to facilitate adjustment and optimization. If the feature detection time is too long, designers need to wait a long time to get the results, which will affect their efficiency. The algorithm in this article adopts more advanced calculation methods, which reduces the redundancy and complexity in the calculation process.

7 CONCLUSION

This article combines computer vision with NN, two advanced technologies, and applies them to the industrial design process. By combining computer vision and NN technology, designers can more efficiently extract CAD model features, reduce the time cost of manual operations, and thus improve overall production efficiency. This method can automatically learn useful features from CAD models, improving the efficiency and automation of feature extraction. By analyzing and integrating user needs, design solutions can be adjusted and optimized to better meet their actual needs and expectations. This can not only improve the user experience and satisfaction of the product but also enhance its market competitiveness. Rapid response and real-time feedback can enable designers to make more efficient adjustments and optimizations, improving design flexibility. These results provide useful references for subsequent algorithm research and application, as well as new ideas for improving the level of industrial design. In future research, more advanced NN models and algorithms can be further explored, and their applications in other fields can be expanded.

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