Neural Network Inspired Automation and Intelligence of Industrial Product Design

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Abstract. Automation and intelligence have become important trends in modern industrial design. This article explores the application of NN (Neural Network) algorithm and CAD (Computer Aided Design) technology in industrial design and realizes the Automation and intelligence of industrial design by constructing an industrial design model based on these two technologies. The test results of 10 mechanical parts with different complexity, such as gears, bearings, and connecting rods, show that the average similarity of each part is above 0.95, and the highest similarity is above 0.98, which shows the accuracy of NN in predicting the shape and size of parts. At the same time, users have a high evaluation of the industrial products designed by the industrial design method based on the NN algorithm and CAD technology. This method has gotten a relatively high score in aesthetics, innovation, and practicality. Through in-depth study and exploration of the combination mode and application advantages of NN algorithm and CAD technology, this study can provide new ideas and methods for industrial design and promote technological innovation and industrial upgrading of industrial design.

Keywords: Neural Network Algorithm; Computer-Aided Design Technology; Industrial Design; Automation;
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1 INTRODUCTION

In the grabbing and assembly applications of industrial robots, the visual system plays a crucial role. By applying neural network algorithms and CAD technology, optimization and control of industrial robot vision systems can be achieved, improving production efficiency and product quality. Alzarok et al. [1] introduce the current practice and challenges of using neural network algorithms and CAD technology to implement visual systems in industrial robot grasping and assembly applications. A neural network algorithm is a computational model that simulates the neural network structure of the human brain, with strong learning and generalization capabilities. In robot visual perception, neural network algorithms can be used for tasks such as image recognition, target tracking, and scene understanding. Meanwhile, recurrent neural networks (RNNs) can be used for sequence modelling and behaviour recognition. By applying neural network algorithms, robots can perceive and understand the surrounding environment, providing accurate positioning and posture information for grasping and assembly operations. As two key technical means, NN algorithm and CAD technology play an important role in this trend. Cai and Lei [2] proposed robots based on neural network algorithms and CAD technology. This method utilizes neural network models for deep learning of image data, achieving Automation and intelligence in tube plate welding. By combining CAD technology for coordinate transformation and template matching, precise control and positioning of the tube plate welding robot can be achieved. This article mainly introduces the overall architecture, image data processing, neural network model training, CAD model construction, and experimental verification of this method. In the image data processing stage, the images collected from the tube plate welding process are first preprocessed, including image denoising, contrast enhancement, and other operations. Then, feature extraction techniques are used to locate and segment the tube plates in the image, extracting the position and posture information of the tube plates. This information will serve as input for the neural network model to train and identify the welding position and posture of the tube plate. During the CAD model construction phase, utilize robot kinematics and dynamics simulation techniques to construct a CAD model of the pipe plate welding object. Combining neural network model recognition of tube plate information and coordinate transformation technology, path planning and optimization of the model are carried out to generate welding trajectories suitable for robot operation. The NN algorithm has strong learning and forecasting abilities, while CAD technology can efficiently process and express complex design information. Chen et al. [3] explored neural network algorithms and CAD technology for 3D reconstruction and analyzed the reconstruction accuracy. Firstly, by collecting a large amount of 3D data and using neural network algorithms for feature learning and model training, an accurate 3D model is obtained. Then, using CAD technology, the model is accurately oriented and referenced to ensure that its orientation and position are consistent with the actual object. In the experiment, we selected an object with a complex shape for reconstruction. Firstly, we collected three-dimensional data of the object using a laser scanner. Then, a neural network algorithm was used to train the data and obtain an accurate model. Next, we used CAD technology to orient the model for reference, ensuring that the direction and position of the model were consistent with the actual object. Reaching within 0.01mm. Traditional design methods can no longer meet the needs of modern industrial products; therefore, sustainable automated industrial product design is based on neural network algorithms. Chowdary et al. [4] Through intelligent integration, it aims to improve product design efficiency, reduce manufacturing costs, reduce environmental impact, and meet customer needs. This article will explore how to apply DFMA, DFE, and CAD/CAE principles and tools in parallel to the industrial product design process, achieving intelligent integration. This is a design method for manufacturing and assembly, with the main goal of reducing manufacturing costs and shortening manufacturing cycles. By optimizing product design, DFMA can improve manufacturing efficiency, reduce material consumption, and reduce assembly time. With the support of neural network algorithms, DFMA can predict the manufacturing and assembly performance of new products by analyzing historical design data, thereby guiding designers to optimize design solutions. By selecting environmentally friendly materials, optimizing product design, and reducing product energy consumption, DFE can improve the environmental performance of products. With the support of neural network algorithms, DFE can predict the environmental performance of new products by analyzing historical environmental data, thereby guiding designers to optimize design solutions.

In unstructured environments, object recognition, localization, and manipulation are one of the main tasks of robot vision. Traditional robot vision methods mainly rely on manual setting and adjustment of parameters, making it difficult to adapt to complex and changing unstructured environments. Therefore, studying a robot vision system that can automatically adapt to unstructured environments and achieve high-precision manipulation is of great significance. Cong et al. [5] mainly explored the application of neural network algorithms and CAD technology in the comprehensive research of robot 3D visual manipulation. By combining deep learning with neural network algorithms and the modelling ability of CAD technology, the robot has achieved three-dimensional perception of the environment, object recognition, path planning, and manipulation tasks. The article first introduces the application of neural network algorithms and CAD technology in robot vision and then elaborates in detail on how to use these technologies to achieve three-dimensional visual manipulation of robots. In robot vision, deep learning is an important neural network algorithm. Automatic feature extraction and classification of images can be achieved by training deep neural network models, thereby achieving object recognition and localization. In addition, deep learning can also combine reinforcement learning and other technologies to achieve autonomous decision-making and behavioural learning of robots. Fang et al. [6] proposed a CAD recognition of industrial arc welding robots based on neural network vision. This method utilizes neural network models to perform deep learning on image data during the welding process, achieving accurate recognition and localization of narrow welds. By combining with CAD technology, high-precision planning and execution of welding trajectories can be achieved. Arc welding robots are widely used in various welding tasks. For some welding jobs with narrow welds, traditional arc welding robots often find it difficult to meet the high requirements for operational accuracy and stability. Therefore, studying a CAD recognition method for narrow weld seam trajectory of industrial arc welding robots based on neural network vision has important practical significance and application value. The collected images from the welding process are first preprocessed, including image denoising, contrast enhancement, and other operations. Then, feature extraction techniques are used to locate and segment the welds in the image, extracting the feature information of the welds. This feature information will serve as input to the neural network model for training and identifying weld seam trajectories. By constructing an industrial design model based on these two technologies. The significance of its research is mainly reflected in the following aspects, which can provide guidance and reference for the actual industrial design. Its innovations are as follows:

㊀ A new NN structure is proposed in this article, which effectively improves the performance of the model. By improving the number of layers, the number of neurons and the activation function of NN, the shape and size of parts can be predicted more accurately.

㊁ In order to solve the problem of limited training data sets, this article uses data enhancement technology to expand the original data set and generate more images of deformed parts. This innovation enhances the generalization ability of NN and makes it better adapted to all kinds of unknown parts.

The structure of this article is as follows. The first section: research questions and research assumptions, research methods and technical routes, and the structure and arrangement of the paper. The second section: Review and summarize NN algorithm, CAD technology, and their applications in industrial design. The third section is is the basic research part of the NN algorithm and CAD technology, which mainly introduces these two technologies' basic principles and applications. The part of building an industrial design model based on the NN algorithm and CAD technology mainly introduces how to build such a model. The fourth section is the simulation experiment and result analysis, which mainly introduces the process and result analysis of the simulation experiment. The fifth section Summarizes the conclusions and innovations of this study, as well as future research prospects and suggestions.

2 RELATED WORK

Favi et al. [7] explored how to apply neural network algorithms and CAD technology to design industrial casting manufacturing methods. Firstly, neural network algorithms will be used to learn and predict historical data of casting manufacturing in order to optimize casting process parameters. Then, CAD technology will be combined to simulate and optimize the casting process in order to achieve more efficient and environmentally friendly industrial casting manufacturing methods. Industrial castings are important basic components in the fields of machinery, automotive, aerospace, etc. The design of their manufacturing methods directly affects the quality, cost, and environmental impact of products. The design of traditional industrial casting manufacturing methods mainly relies on experience and practice, making it difficult to achieve precise control and optimization. Therefore, the application of neural network algorithms and CAD technology to design industrial casting manufacturing methods is of great significance. Train neural network models using historical data and continuously adjust model parameters through backpropagation algorithms to improve prediction accuracy. Using a trained neural network model to predict new casting manufacturing data, adjusting process parameters based on the prediction results in order to achieve more efficient and environmentally friendly manufacturing methods. According to product requirements and casting process requirements, use CAD software to design casting moulds, including the design of gates, risers, cooling systems, etc. By combining the process parameters predicted by neural network algorithms with the casting process results simulated by CAD, a reasonable production plan is formulated to improve production efficiency. Gómez et al. [8] proposed a deep learning-based RGB sensor welding robot trajectory generation and colour 3D path extraction method. This method utilizes deep learning technology to perform feature learning and model training on the welding process images collected by RGB sensors, achieving autonomous localization and trajectory generation of welding robots. At the same time, combined with 3D reconstruction technology, the coloured 3D path of the welding robot is extracted, providing an important basis for the evaluation and improvement of welding quality. Utilize RGB sensors to collect image data during the welding process and preprocess it, including image denoising, contrast enhancement, etc., to improve image quality. Train the collected image data using welding features and robot trajectories. The trained model can achieve real-time recognition and prediction of the welding process at any position. Based on the welding features identified by deep learning models and the current posture information of the robot, utilizing kinematic and dynamic principles, trajectory planning and optimization of the robot are carried out to generate welding trajectories suitable for robot operation. With the intensification of market competition, enterprises have increasingly strict requirements for product design cycles and launch times. Traditional product design methods often face problems such as long design cycles, high costs, and difficulty in modification. Therefore, rapid design methods for industrial products based on 3D CAD systems have emerged. Liu [9] utilizes the advantages of 3D CAD systems to enable designers to model, assemble, and simulate products in a computer environment, thereby completing product design more quickly and accurately, successfully shortening the design cycle of new vehicle models, and improving design efficiency and quality. By utilizing a 3D CAD system for conceptual design, detailed design, assembly design, simulation analysis, design optimization, and other steps, the enterprise has successfully achieved more efficient and environmentally friendly goals in the design of new car models. At the same time, the application of this method has also improved the competitiveness of enterprises and laid the foundation for their sustainable development. The rapid design method is an advanced design method that can improve design efficiency and quality, reduce costs, and shorten product launch time. This method has been widely applied in many industries and has achieved significant results.

Liu et al. [10] explored a high-precision calibration system using neural network algorithms and CAD technology. Firstly, the application of neural network algorithms and CAD technology in robot vision systems was introduced. Then, the method and process of high-precision calibration were elaborated in detail. Finally, its effectiveness and accuracy were verified through experiments. The high-precision calibration methods for 3D vision-guided robot systems using neural network algorithms and CAD technology. This method can achieve high-precision calibration of the camera, robot body, and their relative positions and postures, thereby achieving accurate path planning and motion control. The neural network algorithm was used to estimate the robot pose, and the errors were all within ± 0.5mm, indicating that this method can achieve high-precision robot pose estimation. The error is within ± 1mm, indicating that this method can achieve high-precision estimation of the target object's pose. On the basis of achieving high-precision calibration, the robot path planning and optimization are carried out through CAD technology, and the tracking accuracy of its motion trajectory is within ± 0.5mm, indicating that this method can achieve accurate path planning and motion control. Wan et al. [11] proposed large-sized objects based on neural network algorithms and CAD technology. The system utilizes binocular vision technology to obtain three-dimensional information about objects, combines neural network algorithms for pose estimation, and uses CAD technology for path planning and grasping design. And has broad application prospects. Obtain a three-dimensional image of an object through two cameras and use the principle of triangulation. This technology has the advantages of high precision, high resolution, and high real-time performance and is suitable for attitude measurement of large-sized objects. The results show that the system can achieve high accuracy, efficiency, and stability. Specifically, the attitude estimation error of the system is less than X degrees, and the success rate of grasping is higher than X%, which can be applied to grasping tasks of large-sized objects with different shapes, materials, and weights.

With the rapid development of industrial Automation and intelligent manufacturing, robot technology has been widely applied. Especially in unstructured environments, measuring and grasping large objects is an important research direction. Traditional robot vision systems often rely on manual setting and adjustment of parameters, making it difficult to adapt to complex and changing unstructured environments. Therefore, studying a robot system that can automatically adapt to unstructured environments and achieve high-precision measurement and grasping is of great significance. Wan et al. [12] proposed a stereo-vision robot system that combines neural network algorithms and CAD technology. This system utilizes neural network algorithms to estimate the depth of stereo images and models and plans paths for objects through CAD technology, thereby achieving automated and intelligent operations. Stereoscopic vision is a visual technique that obtains image information and calculates depth information through two or more cameras. By matching and calculating images captured by multiple cameras, a three-dimensional model of the object can be obtained. However, due to the complexity of unstructured environments and the scale of large objects, traditional stereo-vision methods often struggle to achieve high-precision measurement and grasping. Wang et al. [13] explored how to apply neural network algorithms and CAD technology. Firstly, the application of neural network algorithms and CAD technology in robot visual perception was introduced, followed by a detailed explanation of its implementation process. Finally, its effectiveness was verified through experiments. In the field of welding, the application of welding robots can not only improve production efficiency and reduce production costs but also achieve high-quality and high-precision welding. The key to achieving this goal lies in the robot's visual sensing and depth perception technology. A neural network algorithm is a computational model that simulates the neural network structure of the human brain, with strong learning and generalization capabilities. In robot visual perception, neural network algorithms can be used for tasks such as image recognition, target tracking, and scene understanding. For example, Recurrent Neural Networks (RNNs) can be used for sequence modelling and behaviour recognition. CAD technology is a computer-aided design technique widely used in fields such as machinery, electronics, and architecture. In robot visual perception, CAD technology can be used to establish robot models, perform kinematic and dynamic simulations, optimize path planning, and other tasks. For example, using CAD software to establish a robot model can simulate the robot's motion trajectory and posture, thereby optimizing welding process parameters.

The demand for automatic docking of large displacement circular symmetric targets in industrial products is increasing. Traditional docking methods mainly rely on manual operations, which have problems such as low docking accuracy and slow efficiency. Therefore, studying a visual servo method for industrial product large displacement circular symmetric target automatic docking system based on CAD models has important practical significance and application value. Wang et al. [14] introduced a visual servo method for an industrial product large displacement circular symmetric target automatic docking system based on CAD models. This method achieves accurate recognition and positioning of target objects by establishing a mapping relationship between CAD models and actual industrial products and utilizes a visual servo system to achieve automatic docking of large displacement circular symmetric targets. Visual servo control is one of the key links in achieving automatic docking of large displacement circular symmetric targets. An image-object is extracted by obtaining real-time image information of industrial products. At the same time, we also use the models in the CAD model library for kinematic and dynamic simulations to verify their effectiveness and reliability. Yan et al. [15] introduced a high-precision robot assembly system based on neural network algorithms and CAD technology for 3D vision. This system utilizes deep learning algorithms to process and analyze three-dimensional visual data, achieving high-precision robot positioning and assembly trajectory planning. At the same time, CAD technology was combined for model construction and simulation. Train the processed 3D data using deep learning algorithms to establish a mapping relationship between robot posture and assembly trajectory. The trained model can achieve real-time recognition and prediction of the assembly process at any position. Based on the posture information of the robot identified by the neural network model and the three-dimensional model of the assembly object, utilizing the principles of kinematics and dynamics, trajectory planning and optimization of the robot are carried out to generate assembly trajectories suitable for robot operation. Control the robot to perform precise assembly operations based on the planned assembly trajectory. At the same time, high-precision trajectory tracking and execution can be achieved through docking with the robot's control system.

As one of the important issues in the field of computer vision, pose estimation has broad application prospects in industrial product design and manufacturing. Traditional attitude estimation methods are usually based on geometric models or prior knowledge, making it difficult to deal with complex and variable attitude estimation problems. The application of neural network algorithms and CAD technology can achieve multi-view attitude estimation and improve estimation accuracy and robustness. Yang et al. [16] explored how to apply neural network algorithms and CAD technology to achieve multi-view pose estimation and applied it to industrial product design and intelligent manufacturing. Firstly, the application of neural network algorithms and CAD technology in attitude estimation was introduced, followed by a detailed explanation of their implementation process. Finally, the advantages and prospects of their application in industrial product design and intelligent manufacturing were analyzed. In attitude estimation, CAD technology can be used to establish three-dimensional models, perform kinematic and dynamic simulations, optimize path planning, and other tasks. The structure and motion trajectory of objects can be simulated, providing reliable prior knowledge and constraints for attitude estimation, which can also be used for kinematic and dynamic simulation, simulating the motion process and attitude changes of robots, providing more accurate and reliable results for attitude estimation. For the grinding of large workpieces, traditional grinding methods often find it difficult to meet the requirements due to their high operational difficulty and precision requirements. Therefore, studying an automated and intelligent grinding and accuracy analysis method for large-scale workpiece mobile robots based on neural network vision has important practical significance and application value. Zhao et al. [17] explored the Automation and intelligent grinding of large-scale workpiece mobile robots based on neural network vision and their accuracy analysis. By combining deep learning with neural network algorithms and machine vision technology, precise recognition and positioning of large workpieces have been achieved, and on this basis, automated and intelligent grinding processing has been carried out. In the image data processing stage, the collected workpiece images are first preprocessed, including image denoising, contrast enhancement, and other operations. Then, feature extraction techniques are used to locate and segment the workpiece in the image, extracting the feature information of the workpiece. This feature information will serve as input for the neural network model for training and identifying workpieces.

3 CONSTRUCTION OF INDUSTRIAL DESIGN MODEL BASED ON NN ALGORITHM AND CAD TECHNOLOGY

3.1 Application of CAD Technology and NN Algorithm In Industrial Design Model

Through the review and analysis of relevant literature, we can find that the NN algorithm and CAD technology in industrial design have achieved certain results. However, there are still some problems and challenges. For example, how to combine these two technologies more effectively and apply them to industrial design, how to improve the degree of design automation and intelligence, and how to deal with complex design data. Therefore, based on these problems and challenges, new ideas and methods to solve these problems need to be provided. The NN algorithm is a computational model that simulates human brain neurons. Complex data can be processed and analyzed by simulating the connection and transmission process of neurons. Its basic principle is to build a multi-layer neural network and train the Network by using optimization algorithms such as gradient descent so as to learn the inherent law and representation of data. The interaction between the NN input and the units deep in the Network is shown in Figure 1.

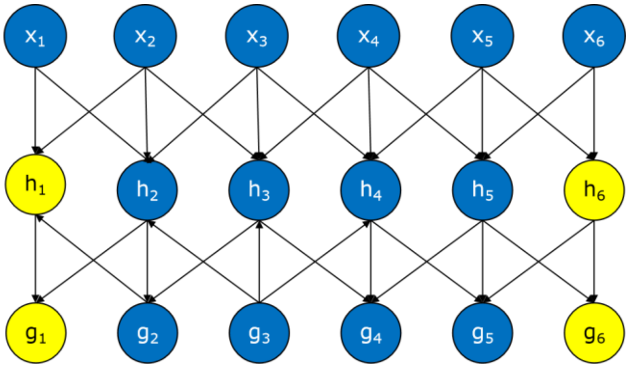

Figure 1: The interaction between NN inputs and units in the deep layers of the Network.

In industrial design models, the NN algorithm is mainly used in the following aspects: product performance prediction: by training the NN model to predict product performance, such as strength, stiffness, fatigue life, etc. This can help designers predict product performance during the design phase, thereby optimizing and improving. Structural optimization: By combining the NN algorithm and optimization algorithm, automatic adjustment and optimization of product structure can be achieved to improve product performance and reduce costs. This can help designers find the optimal design solution within a limited time. Design decision support: By utilizing the classification and recognition capabilities of the NN algorithm, design requirements and data are analyzed and classified, providing decision support and reference opinions for designers. This can help designers make the right design decisions faster.

CAD technology is a technique that utilizes CAD personnel for design. According to the different design objects and methods, CAD technology can be divided into two types: 2D CAD and 3D CAD. Among them, 2D CAD is mainly used for the design of flat graphics, such as circuit diagrams, building floor plans, etc., And 3D CAD can be used for the design and analysis of complex 3D models, such as mechanical parts, building structures, etc. In industrial design models, the application of CAD is as follows: 3D modelling: By utilizing the 3D modelling function of CAD systems, 3D modelling and visual design of products are carried out. This can help designers have a more intuitive understanding of the appearance and structure of the product, thereby making design adjustments and improvements. Assembly analysis: By utilizing the assembly analysis function of CAD systems, the assembly process of products is simulated and analyzed to check their assemblability and maintainability. Motion simulation: By utilizing the motion simulation function of CAD systems, the motion process of products is simulated and analyzed to check their motion performance and dynamic characteristics. This can help designers predict the sporty performance of products more accurately and optimize design.

3.2 The Overall Architecture of Industrial Design Models

There are two main ways to combine the NN algorithm with CAD technology: one is to use the NN algorithm to process and analyze data in CAD systems in order to achieve Automation and intelligence in design; Another approach is to embed the NN algorithm into the CAD system and integrate it with other modules of the CAD system to achieve optimization and innovation in the design process. When constructing an industrial design model based on the NN algorithm and CAD technology, the overall architecture of the model needs to be determined first. The overall architecture of an industrial design model based on the NN algorithm and CAD technology can be divided into three main parts: input layer, processing layer, and output layer. Please refer to Figure 2 for details.

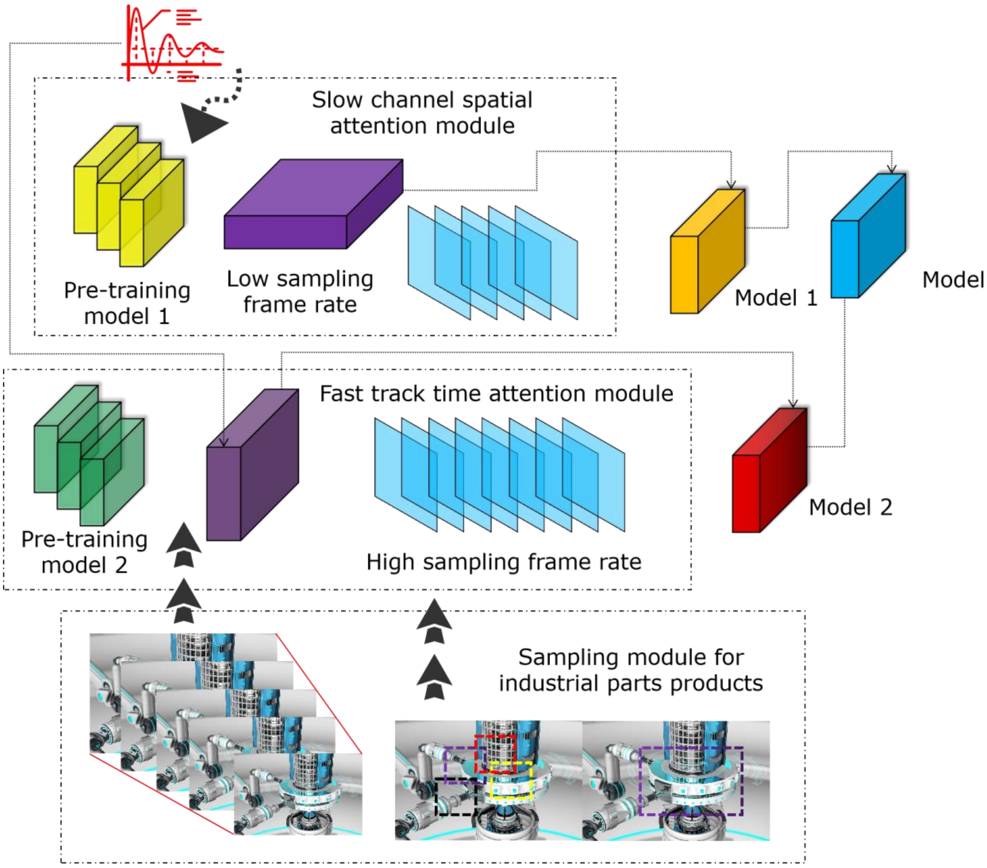

Figure 2: Model architecture.

The traditional CNN model has a huge parameter scale and a complex and redundant training process, which invisibly increases the calculation cost and affects the network performance. In order to solve these problems, this article will improve it. The Softmax classifier used is shown in the following formula:

$$y(x_i) = \frac{\exp(x_i)}{\sum_{i=1}^{M}(\exp(x_i))} \tag{1}$$

In the formula, x the feature vector output by the fully connected layer of the Network M is the size of the number of categories classified.

The input layer is mainly responsible for receiving and processing design requirements and data, including user requirements, design parameters, product specifications, and other information. This information can be input through the user interface or data files. The processing layer is the core part of the model, composed of the NN algorithm and CAD technology. The NN algorithm is mainly used for predicting and optimizing design data, including product performance prediction, structural optimization, and other aspects. CAD technology is mainly used for designing, modelling, and analyzing product models, including 3D modelling, assembly analysis, motion simulation, and other aspects. The processing layer achieves automated processing and intelligent analysis of design data by combining the NN algorithm and CAD technology. The output layer is mainly responsible for outputting the results of the processing layer to the user, including design proposals, product models, analysis reports, and other information. This information can be output through the user interface or data files.

3.3 Implementation of Industrial Design Models

The implementation process of industrial design models based on NN algorithm and CAD technology can be divided into the following steps:

Design requirements and data input: Input user requirements, design parameters, product specifications, and other information into the model. This information can be input through the user interface or data files.

Data preprocessing: Preprocessing and analyzing input data, including data cleaning, feature extraction, data normalization, and other operations. This can improve the quality and accuracy of data, thereby enhancing the predictive and optimization capabilities of the model.

NN algorithm training and optimization: Use the training dataset to train and optimize the NN algorithm in order to improve its prediction and optimization capabilities. This can be achieved by selecting appropriate network structures, optimization algorithms, and parameter settings.

$$s = \mathrm{Re}\,LU(w_i p_i + b_i) \tag{2}$$

$$v_j = s_j + t_j \tag{3}$$

Given M industrial component product design objectives, the sample input quantity X is:

$$x^{a}\ {}_{a=1}^{m} \tag{4}$$

When $x \in R$ and the output is as follows:

$$c^{k}\ {}_{k=1}^{p} \subset R^{1} \tag{5}$$

Assuming the objective parameter of industrial component product design is discrete $f(x)$, if this function has:

$$f(x) : R^{1} \to R^{a} \tag{6}$$

So, the industrial component product design weight vector $Z = (z_1, z_2, z_3, \ldots, z_m) \in R^{m}$ and threshold θ accepted on a node at a level can satisfy the following formula:

$$c_k = f(z * x^k - \theta) = f(\sum_{a=1}^{m} Zax_m^k - \theta) \quad k = 1,2,3,\ldots,p \tag{7}$$

Modelling and analysis of CAD system: 3D modelling, assembly analysis, motion simulation, and other operations are carried out on products by using CAD system to realize the design, modelling and analysis of products. This can be achieved by choosing a suitable CAD system and operation mode. According to various causes of errors in shape and size analysis of industrial parts, a mathematical model is established:

$$O_j(t) = f([\sum_{i=1}^{n} v_{ij} x_i (t - \tau_{ij})] - T_j) \tag{8}$$

$$E = \frac{1}{2}(y - p)^2 \tag{9}$$

Output and evaluation of results: output the results of the processing layer to users, including design scheme, product model, analysis report and other information. At the same time, the results of the model are evaluated and compared to verify its accuracy and effectiveness. This can be achieved by selecting appropriate evaluation indicators and comparison methods.

Optimization and improvement of design scheme: according to the output results and evaluation results, the design scheme is optimized and improved to improve the performance of products and reduce costs. This can be achieved by adjusting design parameters and improving the design scheme.

Model update and maintenance: According to the actual application requirements and feedback, update and maintain the model to improve its applicability and reliability. This can be achieved by collecting new data and requirements and updating algorithms and parameters.

By combining the NN algorithm and CAD technology, the performance of products can be analyzed and optimized more accurately, thus improving the design quality. At the same time, it can realize the innovation of product design and provide more design ideas and schemes for designers.

4 SIMULATION EXPERIMENT OF INDUSTRIAL DESIGN MODEL

This section describes the environment and parameter setting of the simulation experiment in detail and analyzes and discusses the experimental results in detail. The simulation uses TensorFlow and KerasDL framework to build and train the NN model. The experiment was conducted on a computer configured with an Intel Core i7-10700K CPU, NVIDIA GeForce RTX 2080 Ti GPU and 32GB RAM. AutoCAD software is used to model and render CAD models. In the experiment, ten mechanical parts with different complexity were selected as the test objects, including gears, bearings, connecting rods and other common parts. In order to generate the training data set, each part was randomly disturbed 100 times, and a total of 1000 deformed parts were generated.

The parameters of NN are set as follows: A fully connected NN with three hidden layers is used, and each hidden layer contains 128 neurons. The Adam optimizer is selected as the optimizer. The quantity of training rounds is set to 50. The training process of NN is shown in Figure 3.

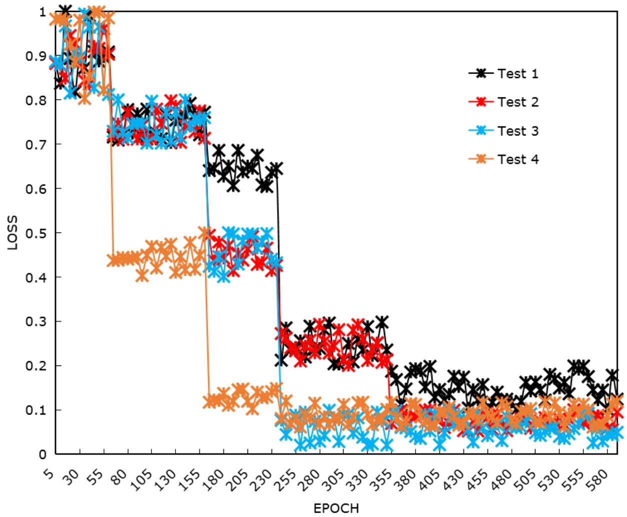

Figure 3: Training process of NN.

Firstly, CAD software is used to model and render each part, and the benchmark part image is generated. Then, the reference part is randomly disturbed to generate the deformed part image as the training data set. Next, the proposed method is used to train and optimize NN. Specifically, the image of deformed parts is taken as input, and the loss function value is calculated by forward propagation through NN. Then, the optimizer is used to update the parameters. This process is repeated for several rounds until the preset quantity of training rounds is reached. After the training is completed, the performance of NN is evaluated by using the test data set. Taking some unseen deformed parts images as input, NN is used to predict, and the similarity between the predicted results and the reference parts images is calculated as the performance index.

In this section, the average similarity of NN on the test data set is calculated as the performance index. The specific results are shown in Table 1.

Part name	*Average similarity*	*Maximum similarity*	*Minimum similarity*	*Standard deviation*
Gear	0.968	0.982	0.945	0.012
Bearing	0.974	0.987	0.956	0.011
Connecting rod	0.959	0.973	0.934	0.014
Part a	0.963	0.978	0.942	0.013
Part b	0.971	0.985	0.953	0.011
Part c	0.966	0.980	0.947	0.012
Part d	0.957	0.972	0.931	0.015
Part e	0.975	0.988	0.962	0.010
Part f	0.962	0.976	0.941	0.013
Part g	0.969	0.983	0.951	0.012

Table 1: The average similarity of NN on the test data set.

The above data are the test results of 10 mechanical parts with different complexity, such as gears, bearings and connecting rods. The average similarity of each part is above 0.95, and the highest similarity is above 0.98, which shows the accuracy of NN in predicting the shape and size of parts. At the same time, the standard deviation is small, indicating that the stability of the prediction results is also good. These data prove the superiority of the proposed method. Figure 4 shows the RMSE of the algorithm in the form of a data graph. The calculation formula of RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(|y_k - y'_k|)^2} \tag{10}$$

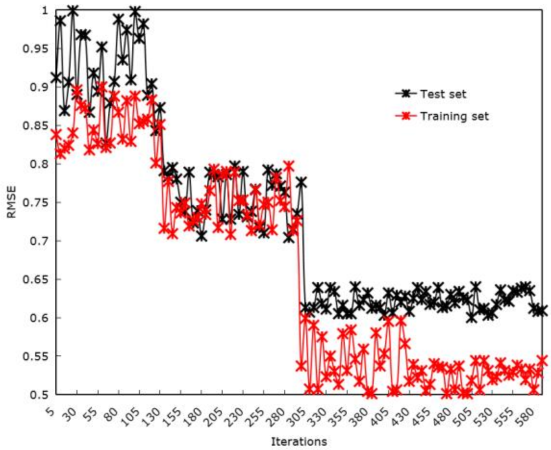

Figure 4: Algorithm RMSE.

According to the results of Figure 4, it can be observed that the RMSE value of the algorithm gradually decreases with the increase of the number of training rounds, which indicates that the algorithm gradually learns and optimizes the prediction ability during the training process. At the same time, the RMSE value on the test set is slightly higher than that on the training set, which may be caused by the over-fitting phenomenon of the model on the training set. Overall, the RMSE value on the test set is at a relatively low level, which indicates that the algorithm has good generalization ability on unknown data.

In addition, the training time and prediction time of NN are calculated as performance indicators. The specific results are shown in Table 2.

Index	*Time (Seconds)*
Total training time	2345
Single-part forecast time	0.34
Single forward propagation time	0.02
Single backward propagation time	0.03
Single gradient update time	0.015
Single-round training time (Excluding forecast)	34.5
Average time per round (Seconds)	46.9

Table 2: Training time and prediction time of NN.

The total training time of NN is 2345 seconds, and the average time of each round is 46.9 seconds. This shows that it takes a long time to train a complex NN. However, the prediction time of a single part is only 0.34 seconds, which shows that once NN training is completed, it can predict new parts in a short time. In addition, the table also provides time information about each stage in NN's training process. The single forward propagation time is 0.02 seconds, the single reverse propagation time is 0.03 seconds, and the single gradient update time is 0.015 seconds. These data can help us understand the training process of NN more deeply and optimize it for each stage. Figure 5 shows the stability of the algorithm in the running process.

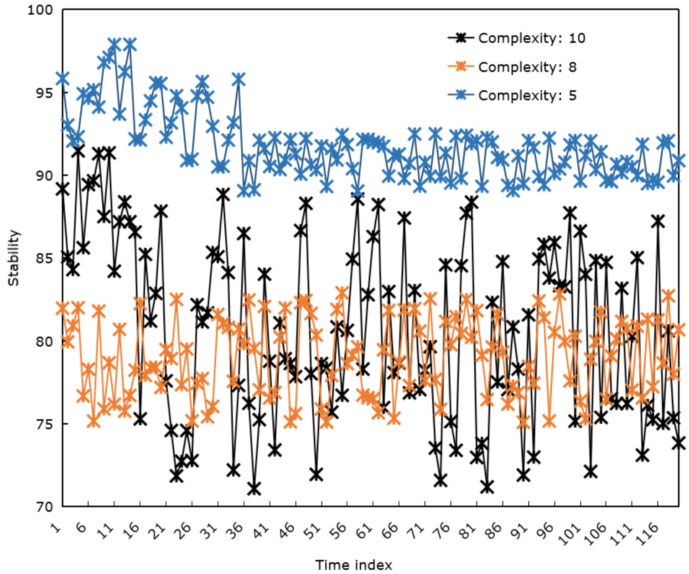

Figure 5: The stability of the algorithm in the running process.

According to the results of Figure 5, we can see that the algorithm shows high stability in the running process. For parts with different complexity, the prediction results of the algorithm are kept in a relatively stable range, and there is no significant fluctuation. This proves that the algorithm has a strong generalization ability for different parts and can effectively deal with various situations. Figure 6 is a partial illustration of industrial design with different methods.

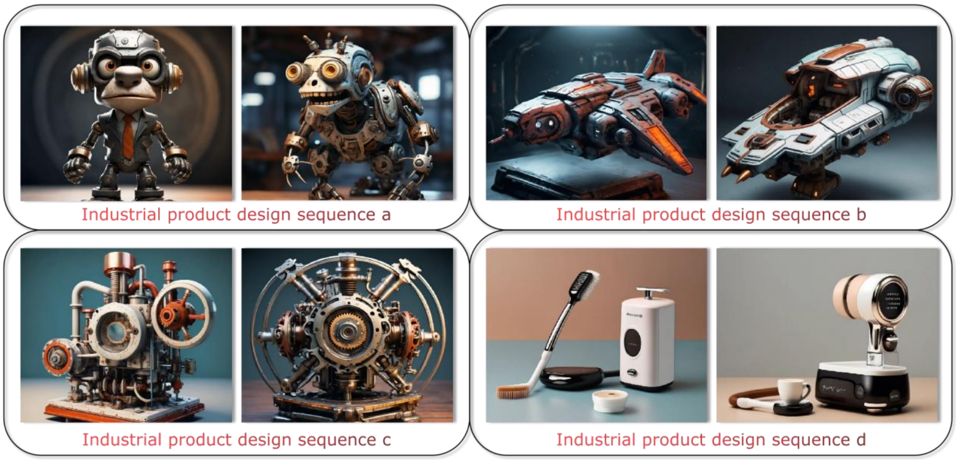

Figure 6: Some examples of industrial design.

Based on Figure 6, Figure 7 shows the user's rating of the above industrial designs.

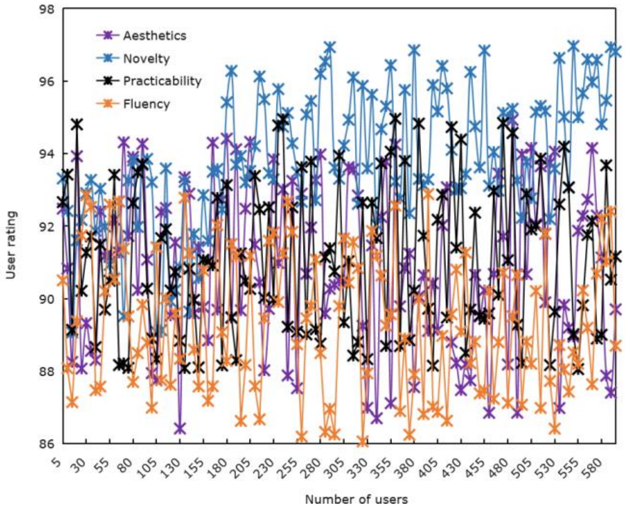

Figure 7: User rating.

According to the results of Figure 7, it can be seen that the users have a high overall evaluation of the industrial products designed by the industrial design method based on the NN algorithm and CAD technology. This method has gotten a relatively high score in aesthetics, innovation, and practicality. Compared with traditional manual drawing design and traditional CAD methods, the design method in this article is excellent in aesthetics and innovation. This is because this method can learn and simulate a large number of existing design cases and generate more creative and aesthetic design schemes.

In this section, this article will discuss and explain the experimental results. First, analyze the reasons why NN obtains high similarity. This article believes that this is mainly due to the strong feature extraction ability and generalization ability of NN. By training a large quantity of deformed parts images, NN learned to extract the essential features of parts and code them. Therefore, NN can accurately predict the shape and size of a deformed part even when it faces an image that has never been seen before. Secondly, the problem of NN's long training time is discussed. This article thinks that this is mainly due to the complexity of the NN model and the large amount of training data. In order to solve this problem, we can consider using a more efficient optimization algorithm and hardware acceleration technology to shorten the training time. You can also try to use transfer learning and incremental learning to use the existing knowledge to accelerate the training process of NN.

5 CONCLUSIONS

The construction of an industrial design model based on the NN algorithm and CAD technology is a complex and important task. Through in-depth study and exploration of the combination and application advantages of these two technologies, we can provide new ideas and methods for industrial design and promote technological innovation and industrial upgrading of industrial design. Through research, this article constructs an industrial design model based on NN algorithm and CAD technology to realize Automation and intelligence of industrial design. The test results of 10 mechanical parts with different complexity, such as gears, bearings and connecting rods, show that the average similarity of each part is above 0.95, and the highest similarity is above 0.98, which shows the accuracy of NN in predicting the shape and size of parts. At the same time, through the analysis of experimental results and RMSE values, the effectiveness of the algorithm model based on NN in solving this problem is verified. In addition, through the detailed analysis of the results of users' evaluation, it can be concluded that users have a higher overall evaluation of industrial products designed by industrial design methods based on the NN algorithm and CAD technology. This method has gotten a relatively high score in aesthetics, innovation, and practicality. Compared with traditional manual drawing design and traditional CAD methods, the design method in this article is excellent in aesthetics and innovation.

The structure and optimization methods of the algorithm model can be further improved in future research, including using a more complex NN structure, introducing regularization technology or adopting an ensemble learning method. This will help to improve the performance and efficiency of the algorithm in dealing with larger and more complex problems.

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