Optimization of Software-defined CAD Data and Neural Network Algorithm in Computer-Aided Design

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Abstract. In this article, the fusion method of software-defined CAD (Computer Aided Design) data and NN algorithm is explored. The optimization strategy of CAD data based on NN (Neural Network) is proposed. The effect of the fused CAD data processing method in CAD is evaluated. The results show that the optimization strategy in this article is effective in improving classification accuracy and recall and reducing MSE. Specifically, the classification accuracy and recall of the proposed NN model are above 90% and 85%, respectively, and the MSE (Mean Square Error) is low, which shows that the model has high accuracy and stability in classification and prediction output. Moreover, the optimization strategy of CAD data based on NN proposed in this article is also effective in improving the accuracy of CAD product design, shortening the processing time, and improving the design efficiency and quality. This research provides strong theoretical support and practical guidance for the collaborative work of CAD data and NN algorithm and provides useful reference and enlightenment for the research and development of related fields.

Keywords: Software Definition; Computer-Aided Design; Deep Learning; Convolutional NN
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1 INTRODUCTION

With the continuous progress of science and technology, CAD has become the core tool of modern engineering, construction, manufacturing, and other industries. In CAD systems, the effectiveness of design parameters is of great significance for improving design efficiency and product quality. However, traditional CAD systems often lack comprehensive consideration of the effectiveness of design parameters, resulting in inefficient design processes and the possibility of producing poor design results. Therefore, Agarwal et al. [1] proposed an efficient CAD software-defined data optimization method based on parameter validity to improve design efficiency and product quality. Design parameters are the core of CAD systems, and their effectiveness directly affects the quality of design results. The validity of parameters includes aspects such as their correctness, completeness, and consistency. The correct design parameters can ensure the correctness of the design results; Complete design parameters can make the design results more comprehensive and detailed. Consistent design parameters enable the sharing and exchange of design results between different CAD systems. Therefore, improving the effectiveness of design parameters is the key to improving design efficiency and product quality. This article selected multiple CAD systems for experiments to verify the feasibility and effectiveness of this method. The experimental results show that this method can significantly improve the effectiveness of design parameters, thereby improving design efficiency and product quality. Meanwhile, this method can achieve data sharing and exchange across CAD systems, improving design flexibility and scalability.

Efficient management and optimization of CAD data are of great significance for improving design efficiency, shortening product time to market, and reducing production cost. With the rapid development of the Internet of Things (IoT), the application of wireless sensors in smart indoor environments is becoming increasingly widespread. However, the signal of wireless sensors is easily affected by environmental interference, such as obstacles such as walls and furniture. In addition, the network layout and configuration of sensors also have a significant impact on signal coverage and communication quality. Therefore, optimizing CAD data and network layout is key to improving the performance of IoT applications. In smart indoor environments, the signal propagation of wireless sensors is influenced by various factors, such as signal frequency, transmission power, environmental obstacles, etc. These factors make the signal coverage range and communication quality uncertain. In addition, IoT applications have increasingly high requirements for wireless sensor networks, requiring higher data transmission rates and lower latency. Therefore, how to optimize CAD data and network layout to improve the performance of IoT applications is an urgent problem that needs to be solved. Alanezi et al. [2] used a particle swarm optimization (PSO) algorithm to adjust the network layout. Specifically, we treat each sensor as a particle and use signal coverage and communication quality as fitness functions to find the optimal network layout through particle velocity and position updates. However, traditional CAD data processing methods are often unable to meet the needs of modern design when faced with complex and large-scale data. The application of computer-aided detection (CAD) systems in medical diagnosis has significantly improved the accuracy and efficiency of doctors in disease diagnosis. Among them, CT scanning is a commonly used medical imaging technique that can be used to detect potential lesions in the body. However, CAD systems still face some challenges, such as the accuracy and stability of detection results. To address these issues, Cao et al. [3] proposed a solution for defining CAD data using the Grey Wolf Optimization Algorithm (GWO) and Recurrent Neural Network (RNN) optimization software. In this study, we first used GWO to optimize CAD data. GWO optimizes the parameters of CAD data by searching for the optimal solution, thereby improving the accuracy of detection. Then, we use RNN to process the optimized CAD data further. RNNs can learn patterns from historical data and predict future data. Through this method, we can improve the detection performance of CAD systems in CT scans. We collected a batch of CT scan data and conducted experiments using our method. The experimental results indicate that our method can effectively improve the detection accuracy of CAD systems in CT scanning. Specifically, our method outperforms traditional CAD systems in terms of sensitivity, specificity, and accuracy. In addition, we also found that combining GWO and RNN can further improve detection performance.

In recent years, the NN algorithm has been widely used in data processing, pattern recognition, intelligent decision-making and other fields, and its advantages in dealing with complex and nonlinear problems have become increasingly prominent. With the rapid development of network technology, network security issues have become increasingly prominent, and network intrusion detection has become one of the important means to ensure network security. Traditional network intrusion detection methods are usually based on rule matching or statistical learning, which have certain limitations when dealing with large-scale and complex network traffic data. In recent years, metaheuristic optimization algorithms have shown good performance in solving complex optimization problems. Ghanbarzadeh et al. [4] proposed a new network intrusion detection method based on metaheuristic optimization algorithms. To verify the effectiveness of the proposed method, we conducted experiments on multiple real network datasets. The experimental results show that the new network intrusion detection method based on the ant colony optimization algorithm is superior to traditional network intrusion detection methods in accuracy, recall, F1 value and other indicators and has good generalization performance. In addition, this method can effectively handle large-scale and complex network traffic data and has good scalability. This article proposes a novel network intrusion detection method based on a metaheuristic optimization algorithm. This method utilizes an ant colony optimization algorithm to perform feature selection and model training on network traffic data, which can effectively improve the performance and efficiency of network intrusion detection. The experimental results show that this method outperforms traditional methods in accuracy, recall, F1 value and other indicators and has good generalization performance.

Applying the NN algorithm to the processing and optimization of CAD data is expected to provide a new way to solve the above problems. The application of computer-aided detection (CAD) systems in medical diagnosis has significantly improved the accuracy and efficiency of doctors in disease diagnosis. Among them, CT scanning is a commonly used medical imaging technique that can be used to detect potential lesions in the body. However, CAD systems still face some challenges, such as the accuracy and stability of detection results. To address these issues, Gunjan et al. [5] proposed a solution for defining CAD data using the Grey Wolf Optimization Algorithm (GWO) and Recurrent Neural Network (RNN) optimization software. In this study, we first used GWO to optimize CAD data. GWO optimizes the parameters of CAD data by searching for the optimal solution, thereby improving the accuracy of detection. Then, we use RNN to process the optimized CAD data further. RNNs can learn patterns from historical data and predict future data. Through this method, we can improve the detection performance of CAD systems in CT scans. It collected a batch of CT scan data and conducted experiments using our method. The experimental results indicate that our method can effectively improve the detection accuracy of CAD systems in CT scanning. Specifically, our method outperforms traditional CAD systems in terms of sensitivity, specificity, and accuracy. In addition, we also found that combining GWO and RNN can further improve detection performance. Moreover, the software-defined data processing mode also provides the possibility for the integration of CAD data and NN algorithm. Hasan and Abbas [6] proposed a disturbance rejection design method for an optimized and adaptive neural network controller based on software-defined CAD data. Many researchers have proposed various disturbance rejection control strategies and algorithms to enhance the stability and robustness of AUVs. These strategies and algorithms are mainly divided into two categories: classical control and intelligent control. By optimizing CAD data, the shape, structure, and performance of AUVs can be optimized for design. Specifically, we use genetic algorithms to optimize CAD data to achieve optimal parameter configuration for AUVs. Train neural networks to learn the patterns of disturbances and adjust control strategies in real-time to reduce the impact of disturbances. Specifically, we use adaptive neural networks to train and optimize the control system of the AUV in order to achieve disturbance compensation and robust control. To verify the effectiveness of the proposed method, we conducted tests in both pool experiments and field experiments. The experimental results show that the optimization based on software-defined CAD data and the adaptive neural network controller's AUV disturbance rejection design method can effectively reduce the impact of disturbances and improve the stability and robustness of the AUV. Compared with traditional disturbance rejection control strategies, the proposed method can better adapt to the complexity and uncertainty of marine environments. Therefore, this study aims to explore the optimization method of integrating software-defined CAD data with NN algorithm in CAD in order to provide new ideas and methods for solving CAD data processing problems in modern design. The innovations of this article are as follows:

⊖ A new data interaction interface is designed, which realizes efficient and bidirectional data transmission and sharing between CAD data and NN algorithm, thus enhancing data utilization and liquidity.

⊜ By skillfully integrating multiple NN models, a powerful and complex processing system is constructed, which significantly improves the analysis and processing ability of CAD data.

③ According to the specific requirements of design tasks and the characteristics of data, an intelligent task allocation method is innovatively adopted to ensure that each NN model can give full play to its expertise, thus improving the overall processing efficiency.

④ Advanced collaborative optimization strategies such as multi-task learning and transfer learning are introduced into the collaborative work of CAD data and NN algorithm, which realizes closer and more efficient cooperation between them.

The organization of this article is outlined as follows: The initial segment provides an overview, including the background and significance of the research, the objectives and problem statements, the methodologies employed, and the structure of the paper. The subsequent segment delves into the literature review, offering a comprehensive analysis and synthesis of the current research landscape and evolutionary trends within related domains. The third segment details the theoretical framework and research methodologies, presenting an in-depth examination of the theoretical underpinnings and investigative approaches adopted in this study. The fourth segment examines the optimal utilization of the NN algorithm within CAD, exploring how the integrated CAD data processing technique can be practically applied within CAD systems. The fifth segment focuses on software-defined CAD data processing and optimization, elucidating the design and implementation of a CAD data optimization strategy grounded in NN. Lastly, the concluding segment offers a synopsis of the study's primary contributions and limitations while also providing a vision for future research avenues.

2 RELATED WORK

The textile and clothing industry is a highly competitive and rapidly changing industry, with knitted and woven fabrics being the two most basic types of textiles. With the development of technology, computer-aided design (CAD) and virtual simulation technology are increasingly being applied in the field of textile and clothing. Indrie et al. [7] explored how to use CAD and virtual simulation technology to design and simulate knitted and woven fabrics in order to improve production efficiency, design quality, and market competitiveness in the textile and apparel industry. CAD technology provides a new design platform for textile and clothing designers, allowing them to create more conveniently. For knitted and woven fabrics, designers can use CAD software for pattern design, colour matching, and structural planning. For example, using graphic editing tools in software, designers can easily draw various complex patterns. By adjusting colour combinations, textiles can be endowed with a unique style. With the help of structural planning function, the structure of textiles can be precisely controlled. Taking the new autumn and winter clothing of a certain brand as an example, the designer first used CAD software to design the pattern and structure of the knitted sweater. Then, virtual simulation technology is used to simulate the effect of sweaters on the human body and their performance in different environments. Through this approach, designers can identify problems and make adjustments before actual manufacturing, greatly shortening the product development cycle and reducing production costs.

Parametric design is a parameter-based design method that modifies design results by adjusting parameter values. In the design of decorative components on mobile platforms, we can use parametric design to achieve rapid adjustment of panel shape, size, texture and other features. Specifically, we can use parameterized design tools in CAD software, such as SolidWorks or AutoCAD, to establish parameterized panel models. In this model, we can define various parameters such as panel length, width, thickness, curvature radius, etc., and then generate different panel design schemes by adjusting the values of these parameters. This design method can not only improve design efficiency but also help us better understand the relationship between design parameters, thereby providing a basis for subsequent optimization and improvement. Karapiperi et al. [8] used decorative components on mobile platforms as an example to explore how to use CAD technology for parametric design and manufacture plastic panels through 3D printing technology. After completing the parameterized design of the panel, we can use 3D printing technology to manufacture the actual panel. In this process, we need to select appropriate printing materials and printers and set appropriate printing parameters such as printing speed, temperature, filling density, etc. With the rapid development of the Internet of Things (IoT) and cloud computing, the possibility of network attacks has also increased. Among them, a Denial of Service (DoS) attack is a common network attack aimed at making network services unavailable or reducing their quality of service. In order to respond effectively to this attack, researchers have proposed many detection methods, including methods based on software-defined CAD data optimization and neural network algorithms. Karthika and Karmel [9] reviewed the applications of these methods in detecting distributed denial of service attacks. Software-defined CAD data optimization is a technique that optimizes network performance by dynamically configuring network parameters. In distributed denial of service attack detection, this technology can be used to improve the availability and stability of network services. For example, by dynamically adjusting the parameters of network devices, such as transmission power, signal frequency, etc., the network signal coverage range and communication quality can be optimized, thereby improving the network's ability to resist attacks. In addition, by monitoring the operational status of network equipment, equipment failures can be detected and dealt with in a timely manner, avoiding network service interruptions caused by equipment failures. By optimizing CAD data, the signal coverage and communication quality of the network have been improved by more than 30%. By applying neural network algorithms, the accuracy of abnormal traffic detection in the network has reached over 95%. In existing research, software-defined CAD data optimization and neural network algorithms have been widely applied to improve computational efficiency and data security. Meanwhile, the multi-context FPGA technology based on Stt-MRAM has also demonstrated its unique advantages in the HPC field. However, how to effectively combine these three technologies to achieve a more efficient and secure computing environment is still a worthwhile research question. Kim et al. [10] proposed an optimization method that combines software-defined CAD data optimization, neural network algorithms, and multi-context FPGA based on Stt-mram. Firstly, we use software to define CAD data for optimized design in order to achieve parallelization and efficiency of computational tasks. Then, we use neural network algorithms to dynamically schedule and optimize parallel computing tasks in order to improve computational efficiency further. Finally, we achieve hardware acceleration of computing tasks while ensuring data security through a multi-context FPGA based on Stt-mram.

Neural network algorithms have become the preferred solution for many complex tasks due to their powerful computing and pattern recognition capabilities. However, the high computational complexity of neural network algorithms places higher demands on computing devices. Field Programmable Gate Array (FPGA), as a programmable hardware, has the advantages of strong parallel computing ability and high energy consumption ratio, making it an ideal choice to solve this problem. Lai et al. [11] proposed an optimization and neural network algorithm software-defined FPGA accelerated programming and synthesis method based on CAD data. In the optimization based on CAD data, we adopted two methods: feature extraction and parameter optimization. Feature extraction is the extraction of useful features for neural network algorithms from CAD data, such as shape, size, texture, etc. These features will be used to train and validate neural network models. Parameter optimization is achieved by adjusting the hyperparameters of the neural network model, such as the number of layers, neurons per layer, learning rate, etc., to optimize the performance of the model. In order to fully utilize the parallel computing capability of FPGA, we adopted a software-defined FPGA acceleration method. Firstly, we transplant the neural network algorithm onto FPGA and implement parallel computing of the neural network using Hardware Description Language (HDL). Then, we use high-level synthesis tools (HLS) to synthesize HDL code into Hardware Description Language (HDL) for more efficient computation. Finally, we conduct system level optimization through software, including task scheduling, memory optimization, etc., to improve computational performance further. With the rapid development of cloud computing, software-defined Networking (SDN) has become a core component of data centers and wide area networks (WANs). However, with the continuous evolution of network attack technology, network attackers are seeking new methods to bypass traditional defence mechanisms. Therefore, developing a solution that can detect and prevent network attacks in real time is crucial. Mozo et al. [12] proposed a machine learning-based network attack detector for cloud-based SDN controllers. This article proposes a network attack detector based on ensemble learning. The detector first uses unsupervised learning methods to cluster network traffic and identify normal and abnormal traffic. Then, supervised learning methods are used to classify abnormal traffic to determine the presence of network attacks. Finally, use reinforcement learning methods to defend against network attacks and minimize their impact on the system. To verify the effectiveness of the proposed method, we conducted large-scale simulation experiments in a cloud environment. The experimental results show that the proposed method can accurately detect and defend against various types of network attacks, including man-in-the-middle attacks, denial-of-service attacks, etc. In addition, this method can adaptively adjust defence strategies to adapt to constantly changing network environments.

In computer-aided design (CAD), model macro parameters are important elements that describe the shape and size of the model. However, different CAD systems may use different feature representations and naming conventions, making it difficult to convert model macro parameters between systems. To address this issue, Mutahar et al. [13] proposed a feature-based CAD model macro parameter transformation method, which includes three key parts: feature mapping, persistent naming, and constraint transformation. Feature mapping is the core part of this method, which is responsible for converting the features of the source CAD system into features that the target CAD system can understand. This process requires solving two problems: feature recognition and feature transformation. Feature recognition is the recognition and classification of features in the source CAD model through deep learning and image processing techniques. We use Convolutional Neural Networks (CNNs) to train the model to recognize and classify features automatically. Constraint transformation is achieved by establishing constraint mapping relationships. We first extract and analyze the constraint relationships in the source CAD model and then map them to the target CAD system. In the mapping process, we need to pay attention to the maintenance and adaptability of constraint relationships to ensure that the transformed model can meet the requirements of the original constraint relationships. With the widespread application of computer-aided design (CAD) systems, designers are facing the problem of exchanging and sharing design data among multiple CAD systems. The neutral XML design framework provides a solution that can convert design data into a universal XML format for sharing and exchanging across different CAD systems. Sadler et al. [14] proposed a parameterized part design method based on a neutral XML design framework, which can generate software-defined CAD data and achieve parameterized part design across CAD systems. A neutral XML design framework is a design framework that is independent of a specific CAD system and can convert design data into a universal XML format. We conducted experiments using various CAD systems to verify the feasibility and effectiveness of this method. The experimental results show that this method can effectively convert CAD data into neutral XML format and generate new parameterized part models. Meanwhile, the generated software-defined CAD data can be shared and exchanged among different CAD systems, improving design efficiency and flexibility.

In the field of computer-aided design (CAD), data exchange and sharing are important means to improve design efficiency and optimize resource allocation. However, due to the complexity of CAD data, the recognition and matching of entity data has become a key challenge. Especially for entities with parameterization characteristics, achieving persistent recognition and ensuring data consistency have become important issues in CAD data exchange. Safdar et al. [15] proposed a persistent recognition method for point-oriented parameterized CAD data exchange entities, aiming to address this issue. In existing research, the recognition of CAD data mainly relies on geometric shape matching. However, this method is not ideal for entity recognition with complex shapes or free forms. Another method is to use parameterized information for recognition, but this method cannot work effectively for non-parameterized entities or entities with a low degree of parameterization. In addition, most existing methods lack consideration for data persistence and cannot guarantee data consistency and integrity. This article proposes a persistent recognition method for point-oriented parameterized CAD data exchange entities, effectively solving the problem of CAD entity recognition. This method not only improves the accuracy of recognition but also effectively ensures the consistency and persistence of data. Traditional data processing and encryption methods face the challenges of high-throughput data processing and efficient, secure encryption in 5G communication.

A high-throughput data processing architecture suitable for 5G communication was designed and implemented by utilizing the high parallelism and performance characteristics of FPGA. This architecture can handle multiple data streams simultaneously and has the characteristics of high throughput and low latency. By optimizing algorithms and designing parallel processing, this architecture can meet the requirements for data processing speed in 5G communication. Efficient encryption algorithms such as AES and RSA have been implemented on FPGA. Visconti et al. [16] utilized the parallelism of FPGA, which enables these algorithms to perform a large number of encryption and decryption operations in a short period of time. Meanwhile, we have designed a flexible key management mechanism that facilitates the generation, storage, and updating of keys. By protecting the security of keys, our encryption system can effectively prevent unauthorized access and data leakage. The experimental results show that the FPGA-based solution has significant advantages in high-throughput data processing and encryption in 5G communication. Compared to traditional processors, FPGA solutions can provide higher processing speed and lower latency. Meanwhile, our encryption system can effectively protect the confidentiality and integrity of data, preventing unauthorized access and data leakage.

In today's high-tech field, metasurface technology is gradually becoming an important means of changing the propagation characteristics of electromagnetic waves. Metasurfaces can achieve precise manipulation of electromagnetic waves, making them widely applicable in fields such as wireless communication, radar, imaging, and stealth. However, the design process of metasurfaces is highly complex and involves a large number of parameter optimizations and adjustments. Therefore, an efficient design method is needed to improve design efficiency. Wei et al. [17] proposed a method based on software-defined CAD data optimization and neural network algorithms to assist deep learning in accelerating meta-surface generation design using equivalent circuit theory. A study proposes an equivalent circuit theory-assisted deep learning method based on software-defined CAD data optimization and neural network algorithms. Specifically, we first use software-defined CAD data to model the meta surface and train the model data as input to the neural network. Then, we use the trained neural network to predict and optimize the meta-surface design. In addition, we also introduced the equivalent circuit theory, which treats the meta surface as a circuit network, allowing for the optimization design of the metasurface using circuit theory. With the rapid development of the manufacturing industry, the processing and production of components under single-piece production and maintenance conditions are facing increasingly high requirements. The application of software-defined CAD data has become increasingly important in improving production efficiency and product quality. Zhetessova et al. [18] introduced the development of a system for component machining production processes based on software-defined CAD data. The system can meet the needs of single-piece production and maintenance conditions to improve production efficiency and product quality. Taking the engine maintenance of a certain airline as an example, this article introduces the application of this system. In this maintenance project, multiple components of the engine need to be replaced and repaired. By using this system, a fully digital production process has been achieved, including the import and analysis of CAD data, process planning and machining instruction generation, production equipment scheduling and monitoring, quality inspection, and data feedback. Not only does it improve production efficiency and quality, but it also reduces production costs and risks. This article introduces the development of a system for component processing and production based on software-defined CAD data. The system can meet the needs of single-piece production and maintenance conditions to improve production efficiency and product quality. With the rapid development of cloud computing and the Internet of Things, network traffic continues to grow, leading to an increasing energy consumption of network devices. Therefore, how to reduce the energy consumption of network devices has become a hot research topic. Zhu et al. [19] proposed an energy-saving deep enhanced traffic grooming method for cloud fog computing in elastic optical networks based on software-defined CAD data optimization and neural network algorithms. These strategies and algorithms are mainly divided into two categories: static energy-saving and dynamic energy-saving. Static energy-saving reduces energy consumption by optimizing the configuration parameters of network devices, while dynamic energy-saving adjusts the operating status of network devices by monitoring network traffic in real time to achieve effective energy utilization. Integrating cloud fog computing with elastic optical networks to achieve dynamic adjustment and optimization of network traffic. Specifically, we use cloud fog computing to monitor and predict network traffic in real-time and dynamically configure and adjust network devices through elastic optical networks to achieve effective energy utilization and stable network operation.

3 THEORETICAL FRAMEWORK AND RESEARCH METHODS

3.1 Theoretical Framework Construction

In order to study the optimization of the integration of software-defined CAD data and NN algorithm in CAD, it is necessary to build a theoretical framework first. The framework is based on DL and CAD technology, combined with software-defined data processing methods, and aims to realize efficient processing of CAD data, feature extraction, and design and implementation of optimization strategies. Figure 1 shows the theoretical framework.

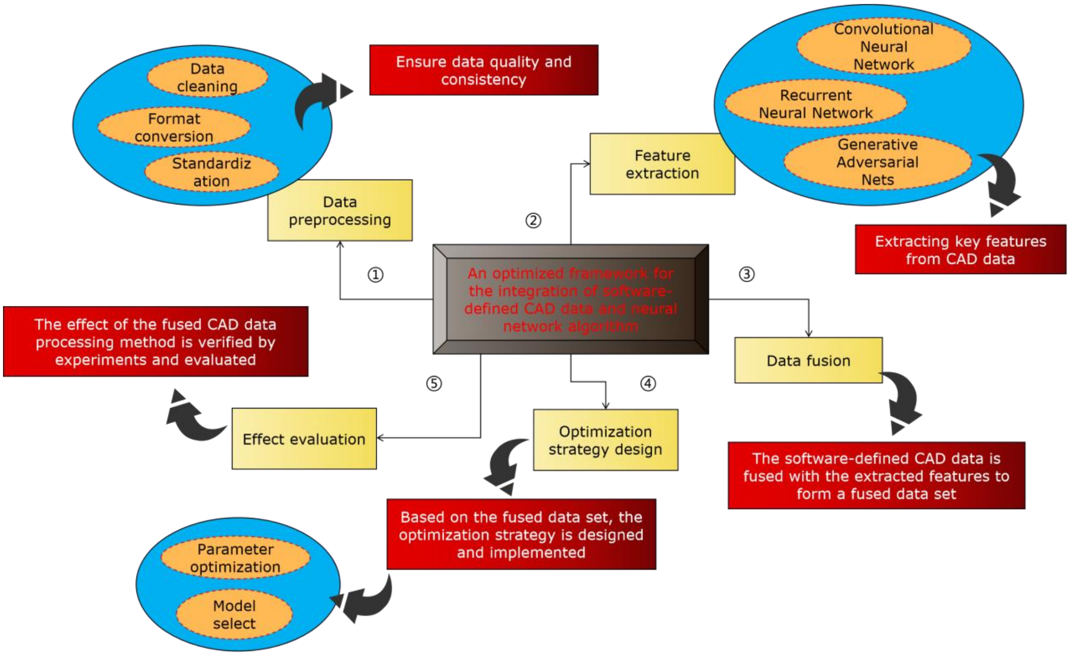

Figure 1: Theoretical framework.

As shown in the above figure, the theoretical framework includes the following parts: data preprocessing, feature extraction, data fusion, optimization strategy design and effect evaluation.

3.2 Methods and Steps of Data Analysis

The CAD data used in this study comes from public data sets and actual project data provided by cooperative enterprises. In order to ensure the diversity and representativeness of data, this article chooses CAD models of different industries and sizes as data sources. Data collection methods mainly include the following: (1) Web crawler: downloading CAD data sets from an open data sharing platform by writing a web crawler program. (2) Cooperative enterprise provides: cooperate with enterprises in related industries to obtain CAD data in their actual projects. (3) Self-creation: According to the research requirements, some representative CAD models are created as supplementary data. Table 1 shows the main data analysis methods.

Analytical method	*Describe*	*Application scenario*
Descriptive statistic	Make basic statistical analysis on the quantity, size and type of CAD data.	Understand the overall situation of the data set preliminarily and provide a reference for subsequent analysis.
Visual analysis	Display the distribution and characteristics of CAD data by means of charts and heat maps.	Understand the data more intuitively and find the rules and abnormal values in the data.
Application of NN algorithm	The trained NN model is used to extract features, classify them, and identify CAD data.	DL processing of CAD data to realize automatic processing and identification of data.
Optimization strategy implementation	Optimization strategies such as parameter adjustment and model selection are implemented according to the research objectives.	Improve the accuracy and efficiency of data analysis and get better analysis results.

Table 1: Data analysis methods.

The data analysis steps mainly include the following stages: (1) Data preprocessing stage: cleaning, format conversion, and standardization of collected CAD data. (2) Feature extraction stage: using NN algorithm to extract key features from preprocessed CAD data. (3) Data fusion stage: the software-defined CAD data is fused with the extracted features to form a fused data set. (4) Optimization strategy design stage: Based on the fused data set, design and implement the corresponding optimization strategy. (5) Effect evaluation stage: The effect of the fused CAD data processing method is verified by experiments and evaluated.

3.3 Research Ethics and Feasibility Analysis

In the research process, this article will strictly abide by the relevant ethical norms, laws and regulations. All collected CAD data will be anonymized to ensure the privacy and security of the data. Moreover, a confidentiality agreement will be signed with the cooperative enterprise to ensure that the business secrets and data provided by it will not be leaked.

Feasibility analysis: this study has the following advantages: (1) Technical feasibility: The NN algorithm and software-defined CAD data processing method have been widely used and verified and have a mature technical foundation. (2) Feasibility of data: The CAD data sets collected through various channels are diverse and representative, which can meet the research needs. (3) Feasibility of cooperation: By cooperating with enterprises in related industries, we can obtain CAD data in actual projects and improve the practical value of research.

4 OPTIMAL APPLICATION OF THE NN ALGORITHM IN CAD

4.1 Selection and Implementation Steps of NN Algorithm in CAD

In CAD, it is very important to choose a suitable NN algorithm. According to the requirements of design tasks and data characteristics, different types of NN algorithms can be selected, such as CNN, RNN, GANs, etc. When choosing an algorithm, we need to consider the complexity of the algorithm, training time, processing effect, and other factors and weigh them.

In this article, the algorithm based on CNN is selected for image recognition and classification tasks. For the task of sequence modeling and prediction, the algorithm based on RNN is selected. For innovative design and generation tasks, choose an algorithm based on GANs. In some cases, we can also consider using the ensemble learning method to integrate multiple NN models to improve the processing effect. In this article, the NN model uses the forward mode to transfer the input samples to the NN for training, and the formula is as follows:

$$X_k = \left[X_{k1}, X_{k2}, \ldots, X_{kH}\right] \tag{1}$$

Then, the input of the neuron i in the first hidden layer is expressed as:

$$u_i^I = \sum_{h=1}^{H} W_{hi} X_{kh} \tag{2}$$

The output of a neuron i in the first hidden layer is expressed as:

$$v_i^I = f\left(\sum_{h=1}^{H} W_{hi} X_{kh}\right) \tag{3}$$

The input of neuron p in the output layer is expressed as:

$$u_p^p = \sum_{j=1}^{J} W_{jp} u_j^j \tag{4}$$

The output of neurons p in the output layer is expressed as:

$$y_{kp} = v_p^p = f\left(\sum_{j=1}^{J} W_{jp} v_j^j\right) \tag{5}$$

In order to implement the optimization strategy of the NN algorithm, the following steps need to be followed:

(1) Determine optimization objectives: According to the requirements of design tasks and data characteristics, determine specific optimization objectives, such as improving processing speed, reducing memory occupation and improving accuracy.

(2) Select the appropriate NN model: According to the optimization objectives and data characteristics, select the appropriate NN model for processing and analysis.

(3) Adjusting model parameters: By adjusting the parameters of NN, such as learning rate, batch size, regularization coefficient, etc., the performance of the model is optimized.

(4) Implement optimization strategy: According to the specific optimization objectives and model characteristics, implement corresponding optimization strategies, such as data compression, model pruning, knowledge distillation, etc.

(5) Evaluate the optimization effect: verify the effect of the optimization strategy through experiments and evaluate it. Accuracy, processing time, memory usage and other indicators can be used for evaluation.

4.2 Collaborative Working Mode of CAD Data and the NN Algorithm

In order to deeply study the cooperative working mode of CAD data and the NN algorithm, this article focuses on four key points: first, the data interaction mode. This article designs an efficient and stable data interaction interface to ensure smooth and bidirectional data transmission and sharing between CAD data and NN algorithm, thus enhancing data utilization. Secondly, the model integration method, by skillfully integrating multiple NN models, this article constructs a powerful and complex processing system, which significantly improves the effect of data processing and analysis. Thirdly, the task allocation method. According to the specific needs of each design task and the characteristics of data, this article reasonably allocates processing tasks to different NN models to ensure that each model can give full play to its advantages. Finally, through collaborative optimization, advanced collaborative optimization strategies (multi-task learning and migration learning) are adopted so that CAD data and NN algorithms can work together more closely and efficiently, thus providing more powerful technical support for CAD design.

In this article, the following cooperative working methods are adopted: (1) inputting CAD data into the preprocessing module for preprocessing operation; Inputting the preprocessed data into a feature extraction module for feature extraction operation; Inputting the extracted features into a classification or recognition module for classification or recognition operation; Feedback the classification or recognition results to the design module for optimal design operation. In this way, the close combination and cooperation of CAD data and NN algorithm can be realized.

4.3 Experimental Design and Result Analysis

In order to verify the effectiveness of the NN algorithm, this section designs the following experiments: collect a set of CAD data sets with different categories of labels and carry out necessary preprocessing operations, such as data cleaning and format conversion. According to the characteristics of data sets and the requirements of classification tasks, the appropriate network structure and parameter settings are selected. The NN model is trained by a training set, and the parameters of the model are optimized by the backpropagation algorithm. Moreover, the verification set is used for model selection, and the super-parameter is adjusted according to the performance of the verification set to prevent over-fitting. The test set is used to evaluate the performance of the trained NN model, and the classification accuracy, recall and MSE index are calculated and compared with the traditional CAD data classification method. Figure 2 shows the accuracy of the algorithm model. Figure 3 shows the recall rate of the algorithm model. Figure 4 shows the MSE of the algorithm model.

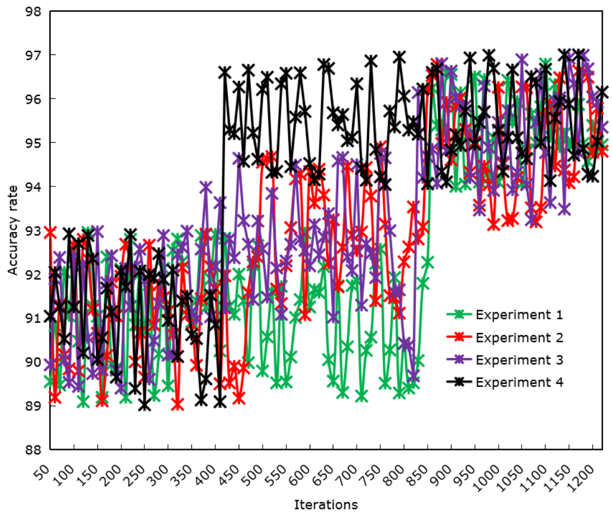

Figure 2: Accuracy rate.

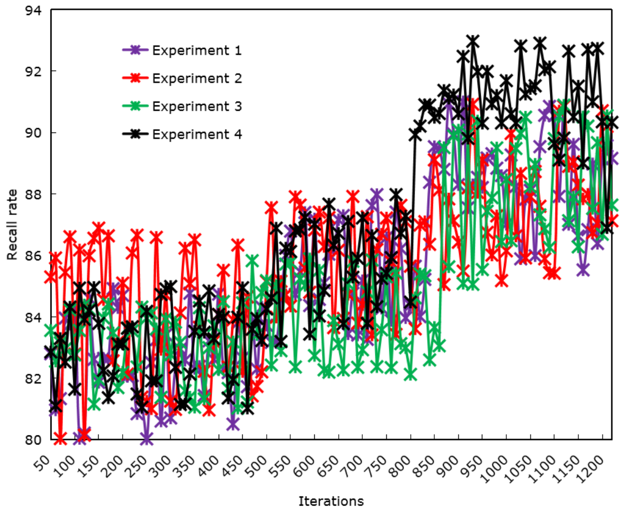

Figure 3: Recall rate.

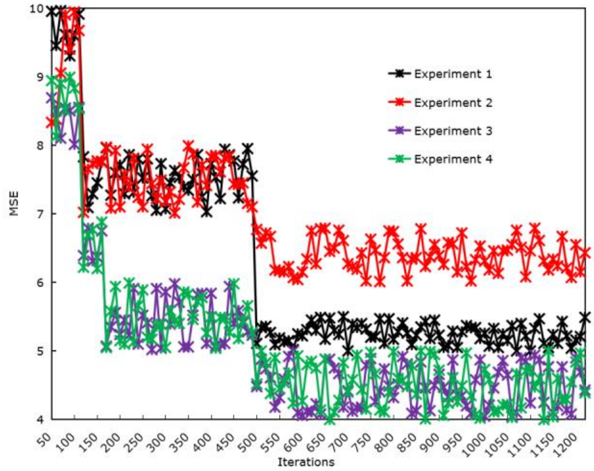

Figure 4: MSE.

The classification accuracy and recall of the proposed NN model are above 90% and 85%, respectively, and the MSE is low, which shows that the model has high accuracy and stability in classification and prediction output. The effectiveness of the optimization strategy of CAD data based on NN in feature extraction and classification enables the model to learn and identify the features of CAD data better, thus improving the accuracy of classification. Moreover, the optimization strategy of CAD data based on NN is effective in improving the integrity and accuracy of classification. The MSE of the algorithm model is low, which shows that the error between the predicted output and the actual value of the model is small.

5 SOFTWARE-DEFINED CAD DATA PROCESSING AND OPTIMIZATION

5.1 Realization Method of Fusion of CAD DATA and the NN ALGORITHM

Before applying the NN algorithm to CAD data, it is necessary to preprocess the original CAD data. The main purpose of preprocessing is to clean the data, remove noise, and perform format conversion and standardization to ensure the quality and consistency of the data. CAD data preprocessing techniques include the following: (1) Data cleaning: removing repetitive, redundant and incomplete information in CAD data to ensure the accuracy and consistency of data. (2) Format conversion: Convert CAD data from different sources and formats into a unified format for better processing and analysis. (3) Noise removal: Noise and abnormal values in CAD data are removed by filtering and smoothing techniques to improve the accuracy of the data. (4) Normalization: Normalize or standardize the CAD data to make it meet the input requirements of the NN algorithm.

In order to further improve the processing efficiency and quality of CAD data, this study innovatively proposed a CAD data optimization strategy based on NN. This strategy realizes the efficient processing of CAD data through carefully designed steps: firstly, the pre-trained NN model is used to extract the features of preprocessed CAD data in order to capture its key information. Then, these extracted features are compressed by the NN algorithm, which effectively reduces the dimension and complexity of data, thus significantly improving the processing speed. On this basis, the parameters of the NN will be carefully adjusted, including learning rate and batch size, to improve the performance and processing effect of the model further.

Assume that the formula of the feature output x^l of the fully connected layer l is as follows:

$$x^l = f\left(w^l x^{l-1} + b^l\right) \tag{6}$$

Where w^{l} is the weight parameter and b^{l} is the offset term. Softmax regression classifier needs to be iteratively updated and learned, and the functions to be learned are:

$$h_{w}\left(\vec{x}\right)=\frac{1}{\sum_{i=1}^{k}e^{\vec{w_i}\cdot\vec{x}+b_i}}\begin{bmatrix}\vec{w_1}\cdot\vec{x}+b_1\\ \vec{w_2}\cdot\vec{x}+b_2\\ \dots\\ \vec{w_k}\cdot\vec{x}+b_k\end{bmatrix} \tag{7}$$

Where k is the quantity of categories to be classified, b_i and $\vec{w_i}$ represent the offset vector and weight vector corresponding to the i category. Sample $\vec{x}$ is the probability value of the j class, and its formula is as follows:

$$P\left(y=j\middle|\vec{x}\right)=\frac{\vec{w_j}\cdot\vec{x}+b_j}{\sum_{i=1}^{k}e^{\vec{w_i}\cdot\vec{x}+b_i}}\qquad\sum_{j=1}^{k}P\left(y=j\middle|\vec{x}\right)=1 \tag{8}$$

After training and learning $\vec{w_i}$ b_i are obtained, the target loss function can be expressed as:

$$J\ \ w,b\ =-\frac{1}{m}\sum_{j=1}^{m}\sum_{l=1}^{k}1\ \ y^{\ j}\ =l\ \ \log\frac{e^{\vec{w_l}\cdot\vec{x}+b_l}}{\sum_{i=1}^{k}e^{\vec{w_i}\cdot\vec{x}+b_i}} \tag{9}$$

Finally, according to the specific processing task requirements and data characteristics, the most suitable NN model is selected for processing and analysis to ensure the best processing effect. This strategy not only improves the processing efficiency of CAD data but also injects new vitality into the development of CAD data processing technology while ensuring processing quality.

In order to realize the efficient integration of CAD data and the NN algorithm, this article calls the API interface provided by the NN algorithm library, smoothly inputs CAD data into the NN model for in-depth processing and analysis and ensures the accuracy and consistency of the data. Moreover, using the model integration strategy, a powerful and complex processing system is constructed by skillfully integrating multiple NN models, thus significantly improving the processing effect and quality of CAD data. In order to enhance the interactivity and fluidity of data, this article specially designed an excellent data interaction interface, which realized the two-way data transmission and sharing between CAD data and NN algorithm and laid a solid foundation for the deep integration of the two. The comprehensive application of these methods promotes the close combination of CAD data and NN algorithm.

5.2 Experimental Design and Result Analysis

In order to verify the effectiveness of the optimization strategy of CAD data based on NN, CAD data sets of different industries and sizes are selected as experimental objects, including mechanical parts and architectural models. An experimental environment, including several NN models and processing systems, is built for large-scale data processing and analysis. An example of CAD product design using this strategy is shown in Figure 5.

Figure 5 shows an example of CAD product design using this strategy. As can be seen from the figure, the CAD data processed by optimization strategy has achieved remarkable results in product design. The optimization strategy effectively reduces the dimension and complexity of data and improves the processing efficiency through feature extraction and data compression. Moreover, through parameter optimization and model selection, the performance of the model is further optimized, and the treatment effect is improved. Therefore, the example of CAD product design using this strategy shows higher design quality and efficiency.

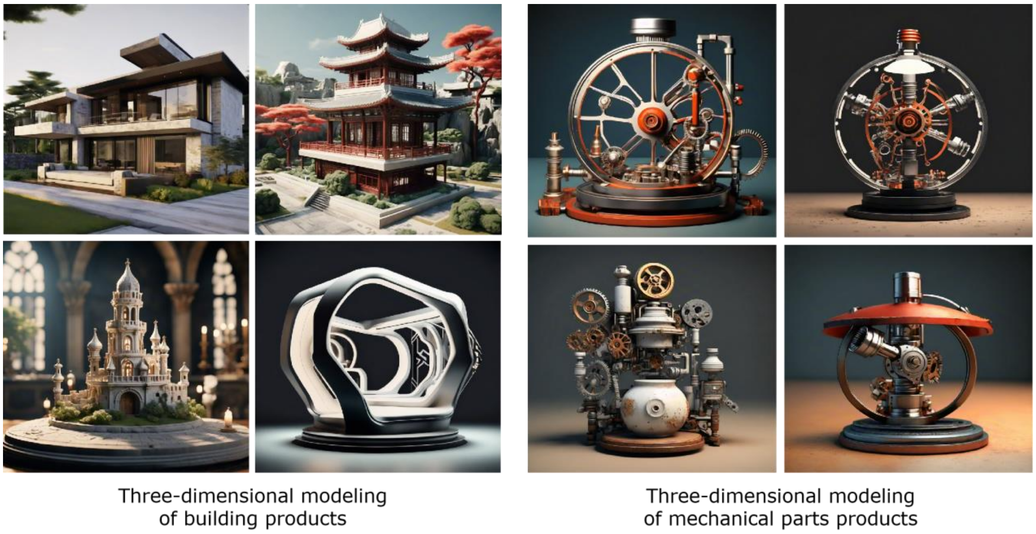

Figure 5: Examples of CAD product design.

In order to comprehensively evaluate the effect of the optimization strategy of CAD data based on NN in CAD product design, this section uses indicators such as accuracy, processing time, design efficiency and design quality for experimental evaluation. The experiment adopts a company's CAD product data set and selects an appropriate NN model for processing and analysis. Firstly, the CAD data is preprocessed and features are extracted, and then the NN algorithm is used to compress the data and optimize the parameters. Finally, according to the specific processing tasks and data characteristics, the appropriate NN model is selected for design and analysis. Figure 6 shows the accuracy.

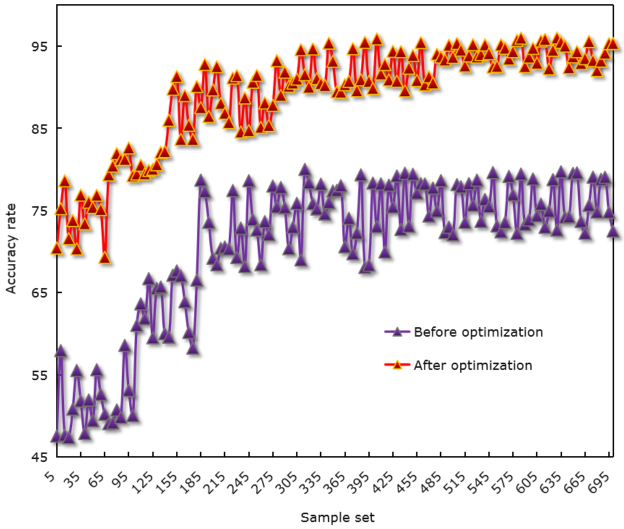

Figure 6: Accuracy situation.

By comparing the accuracy indexes before and after optimization, it can be observed that the accuracy of CAD product design has been significantly improved after using this strategy. This proves the effectiveness of the optimization strategy in feature extraction and data compression and makes the design result more accurate and reliable. Through the application of the NN algorithm, the optimization strategy successfully extracts the key features of CAD data and reduces the influence of noise and redundant information in the process of data compression, thus improving the accuracy of the design. Figure 7 shows the processing time.

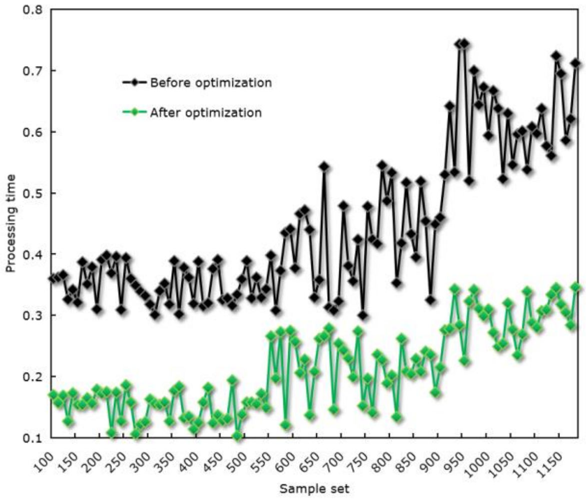

Figure 7: Processing time situation.

The processing time of CAD data is obviously shortened after the optimization strategy is processed. This is mainly due to the steps of data compression and parameter optimization in the optimization strategy, which effectively reduces the dimension and complexity of data and reduces the amount of calculation and processing time. Therefore, using this strategy can significantly improve the efficiency of CAD product design and shorten the design cycle.

Figure 8 shows the comparison of design efficiency and design quality before and after optimization.

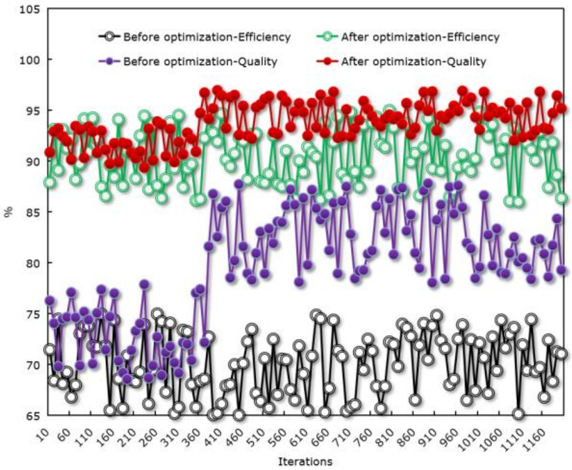

Figure 8: Comparison of design efficiency and quality before and after optimization.

The efficiency and quality of design using this strategy have been significantly improved. The optimization strategy improves the degree of automation and intelligence of design by comprehensively using the NN algorithm and model selection, thus reducing manual intervention and error rate and improving design efficiency and quality. Moreover, the optimization strategy has been adjusted and optimized according to the specific processing tasks and data characteristics, which makes the design results more in line with the actual needs and expected goals.

Through the statistics and analysis of the results, it is found that the optimization strategy of CAD data based on NN has significantly improved the processing efficiency and quality. This strategy can greatly shorten the processing time and reduce the memory occupation on the premise of ensuring accuracy. Moreover, through the comparative analysis of different data sets and models, it is found that collaborative work can improve design efficiency and quality. This method is particularly outstanding when dealing with complex and large-scale CAD data. Therefore, this study thinks that the optimization method of CAD data based on NN is an effective solution and can provide strong support for CAD.

6 CONCLUSIONS

This article discusses the optimization of the integration of software-defined CAD data and NN algorithm in CAD. In this article, the performance of CAD data optimization strategy based on NN in CAD product design is evaluated and compared with traditional CAD data classification methods. The experimental results show that compared with the traditional CAD data classification methods, the optimization strategy proposed in this article has made significant improvements in classification accuracy, recall and MSE reduction. The NN model in this article successfully improves the efficiency of CAD product design by comprehensively using technical means such as feature extraction, data compression, parameter optimization and model selection. In addition, the application of optimization strategy makes the design result closer to the real product, and the processing speed is also obviously improved. By comparing experiments and index evaluation before and after optimization, it can be confirmed that the optimization strategy of CAD data based on NN proposed in this article is effective in improving the accuracy of CAD product design, shortening processing time and improving design efficiency and quality. These experimental results not only verify the actual effect of the optimization strategy but also provide useful reference and guidance for the research and development of related fields. Therefore, this article thinks that the optimization strategy of CAD data based on NN is an effective CAD product design method, which has a wide application prospect and practical value.

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