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Design of Multimedia Interactive System for Mechanical Model Based on Deep Neural Network

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Abstract. In this study, we employ Deep Neural Network (DNN) technology to manipulate Computer-Aided Design (CAD) models and create a comprehensive interactive system enriched with multimedia components. Initially, we present an overview of the system's architectural design, encompassing the data, business logic, presentation, and integration/interface layers. Subsequently, we delve into the crucial aspects, including the multimedia interaction module, user interface design, interactive logic, system integration, and testing methodologies. Experimental simulations are conducted to validate the system's functionality and performance. The experimental results show that the system is excellent in aesthetics, ease of use, and rationality of interactive logic. At the same time, the system performs well in processing speed, accuracy, and user experience. It can not only process CAD models efficiently but also provide rich multimedia interactive functions, bringing a convenient operation experience to users. It also provides useful support for the technical progress and application expansion in related fields.

Keywords: Deep Neural Network; Mechanical CAD Model; Multimedia; Interactive System
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1 INTRODUCTION

As computer technology advances swiftly, the utilization of mechanical CAD models has become increasingly prevalent in industrial design, manufacturing, and educational settings. Traditional shape retrieval methods often rely on manually designed features and complex matching algorithms, making it difficult to handle large-scale, high-dimensional 3D data. To address this issue, Bickel et al. [1] proposed a novel shape retrieval method for 3D mechanical components based on object projection, pre-trained deep learning models, and autoencoders. The core idea of this method is to project 3D mechanical components into objects, convert them into 2D image representations, and then use pre-trained deep learning models for feature extraction and encoding. In the shape retrieval stage, we use the encoded features for similarity matching. By calculating the feature encoding similarity between the query component and the components in the database, we can find candidate components with similar shapes to the query component. This method not only improves the accuracy and efficiency of retrieval but also can process large-scale 3D mechanical component datasets. While conventional mechanical CAD models excel in geometric information display, they exhibit limitations in multimedia interaction. In the digital age, innovation in marketing methods is becoming the key to enhancing the competitiveness of enterprises. Mechanical CAD model multimedia interactive augmented reality marketing, as a technology-based positioning customer experience method, is gradually emerging. It can not only provide customers with an immersive interactive experience but also accurately locate customer needs and achieve maximum marketing effectiveness. Multimedia interaction achieves information transmission and user participation through various media forms such as audio, video, and images. Chylinski et al. [2] combined mechanical CAD models with multimedia to enhance customer awareness and interest in the product. Through AR technology, customers can preview and experience the appearance, functions, and operation of products in actual environments, thereby gaining a more intuitive understanding of the characteristics and advantages of the products. Customized mechanical CAD model display solutions based on the industry characteristics and application scenarios of the client. Using AR technology to simulate the effectiveness of products in actual use, helping customers better understand and evaluate the products. Fortunately, the emergence of DNN technology in recent years has presented a novel approach to enhance multimedia interaction. In the field of 3D model learning, the introduction of VR technology provides learners with an immersive and interactive learning environment. Huang and Lee [3] effectively utilized deep neural network technology in this environment to improve the usability of interactive learning for 3D models. By training deep neural network models, automatic classification, feature extraction, and recognition of 3D models have been achieved. This will help learners quickly locate the required models in VR environments and improve learning efficiency. At the same time, deep neural networks can also be used to finely process the surface details, textures, lighting, and other attributes of the model, making the presentation of the model in virtual environments more realistic and vivid. Provide personalized 3D model learning resources based on the interests and needs of learners. Classify and annotate models using deep neural networks to recommend suitable models and learning paths for learners.

Jiang et al. [4] proposed a multimedia interaction feature vector derivation method based on Convolutional Neural Networks (CNN). This method extracts feature vectors with rich information from patent images by training convolutional neural network models, providing effective data support for multimedia interaction systems. When using convolutional neural networks to derive multimedia interaction feature vectors for patent images, it is necessary to first construct a suitable network model. The model should have sufficient depth to capture the complex features of the image, while also considering the requirements of computing resources and real-time performance. By selecting appropriate network architecture, activation functions, and optimization algorithms, an efficient and accurate convolutional neural network model can be trained. Through multiple iterations and optimizations, we can obtain a well-trained convolutional neural network model that can accurately derive multimedia interaction feature vectors from patent images. These neurons receive input signals, process them based on their internal states and weights, and generate output signals accordingly. In VR environments, the design of user interaction interfaces directly affects the quality of user experience and usability. Kharoub et al. [5] designed an efficient, intuitive, and user-friendly immersive VR 3D user interaction interface based on deep neural networks. Deep neural networks have powerful feature extraction and pattern recognition capabilities, which can automatically learn and optimize the design parameters of user interaction interfaces. In VR environments, deep neural networks can be used to analyze user interaction behavior and identify user intentions and needs, thereby providing users with a more personalized and intelligent interaction experience. By training deep neural network models, precise recognition of user gestures can be achieved. When users make specific gestures in a VR environment, deep neural networks can quickly recognize and convert them into corresponding operation instructions, thereby achieving control over virtual objects. This gesture recognition-based interaction method not only improves the convenience of operation but also enhances the user's immersion. Neural network learns and stores knowledge by adjusting the connection weights between neurons, so as to realize the tasks of pattern recognition and classification of input data. Deep learning is a branch of neural networks, that aims to build a deeper and more complex neural network structure to deal with large-scale high-dimensional data. The progression of deep learning has undergone a transformation from its initial perceptron model to the contemporary DNN. This advancement has led to remarkable breakthroughs in fields such as image recognition, speech recognition, and generative modeling.

The objective of this research is to investigate the integration of DNN in multimedia interactions within mechanical CAD models. Our aim is to devise an efficient and intuitive interaction system that elevates user experience and enhances work productivity. The importance of this study lies in its potential to propel the multimedia interactive capabilities of mechanical CAD models forward, offering fresh technical support for industrial design and manufacturing processes. Additionally, it contributes to advancing the utilization of DNNs in multimedia processing and provides valuable insights for future research in related domains.

The novel contributions of this study are threefold: (1) We introduce a DNN-based processing method for mechanical CAD models, which boosts the precision of model identification and classification; (2) We design an intuitive multimedia interactive interface that accommodates diverse interaction modes and seamlessly integrates multimedia elements; (3) Simulation results demonstrate the superiority and practicality of our proposed methodology and system.

To begin, this paper outlines the research background, significance, current landscape, future trends, key content, and innovations presented. Subsequently, we delve into the fundamentals of DNN theory and analyze the requirements for a multimedia interactive system tailored to mechanical CAD models, providing a roadmap for system design. We then delve into the specifics of our DNN-based CAD model processing technique and offer a comprehensive description of the multimedia interactive system's design philosophy and implementation details. Ultimately, we validate the system's efficacy through simulation experiments and summarize our findings.

2 RELATED WORK

The parameterized interactive intelligent design method based on mechanical CAD holographic models has become a major innovation in the field of mechanical design due to its efficiency, accuracy, and convenience. Liu et al. [6] conducted in-depth discussions on this method in order to promote the intelligent development of mechanical design. Mechanical CAD holographic model is a comprehensive model that integrates multi-dimensional information such as three-dimensional geometric information, physical properties, and material properties. It can not only display the geometric shape and size of mechanical parts but also reflect their physical properties such as mechanical and thermal properties. The construction of holographic models provides a solid foundation for parameterized interactive intelligent design. The parameterized interactive intelligent design method is based on the mechanical CAD holographic model, which defines a series of parameters and constraint relationships to achieve automation and intelligence in the design process. Designers only need to set initial parameters and rules, and the system can automatically modify, optimize, and validate the model based on these parameters and rules. Makransky et al. [7] explored the interactive motivation and cognitive benefits of immersive virtual reality training from the perspective of multiple evaluations. VR technology can provide highly realistic virtual environments for trainers, allowing them to experience training scenes firsthand. This immersive experience can stimulate the curiosity and exploratory desire of trainers, thereby enhancing their interactive motivation. Secondly, VR training can simulate various complex scenes and situations, providing trainers with diverse training tasks. This rich and diverse training content can stimulate the interest and challenge of trainers, and encourage them to participate more actively in the training. Finally, VR training has high interactivity and real-time feedback. Trainers can interact with the virtual environment through gestures, voice, and other means and immediately receive feedback. This real-time interaction and feedback can enhance the trainer's sense of participation and achievement, further stimulating their interaction motivation.

In order to improve the efficiency and user experience of 3D model design, Malik et al. [8] proposed a multimedia interaction system based on mixed reality technology and deep learning. It aims to provide a powerful set of design tools for designers and engineers in the field of additive manufacturing. By wearing hybrid reality devices, users can freely operate, observe, and modify 3D models in a virtual three-dimensional space. This interactive approach enables designers to have a more intuitive understanding of the shape, structure, and details of the model, thereby improving the accuracy and efficiency of the design. Deep learning, as an important branch of artificial intelligence, has powerful feature extraction and learning capabilities. In 3D model design, deep learning models are used to learn from a large amount of design data, extract useful features and patterns, and guide model generation and optimization. At the same time, the system can also support multiple formats of model import and export, facilitating data exchange and sharing with other design platforms and manufacturing equipment. The application of VR technology in the manufacturing industry not only changes traditional working methods and improves production efficiency, but also brings new ideas to the design of human-machine workspaces. Malik et al. [9] focused on exploring the immersive and collaborative applications of virtual reality in human-machine workspace design in the manufacturing industry. Immersive virtual reality technology provides operators with a highly realistic virtual environment, allowing them to experience the manufacturing process firsthand. The application of this technology greatly enhances the operator's understanding of manufacturing processes and equipment, thereby improving work efficiency and accuracy.

Traditional text and keyword-based retrieval methods are no longer able to meet the requirements of complex 3D model retrieval. Therefore, Manda et al. [10] analyzed a multimedia interactive system for 3D CAD model retrieval based on deep neural networks. It utilizes deep neural networks to extract features from the preprocessed model. These features can be the shape features, structural features, or semantic features of the model, which can comprehensively describe the attributes and characteristics of the model. Encode and index the extracted features to build an efficient retrieval database. By using indexing techniques, candidate models that are similar to the query model can be quickly located. Users can input query conditions through the multimedia interactive interface, and the system searches in the index database based on the conditions and returns a list of models that match the query conditions. Users can browse, edit, and download retrieved models through the interactive interface, and can also perform model comparison, analysis, and visualization operations. Traditional text or keyword-based retrieval methods often struggle to meet complex and refined search requirements. Therefore, Manda et al. [11] analyzed a sketch-based 3D CAD model retrieval system. It proposes a deep learning-based method for enhancing and correcting 3D CAD model retrieval system query sketches. The core idea of this method is to utilize the powerful feature extraction and learning capabilities of deep learning models to enhance and correct query sketches, making them closer to real 3D CAD models, and thereby improving the accuracy and efficiency of retrieval. Specifically, it can use Generative Adversarial Networks (GANs) or other generative models to supplement details, optimize shapes, and other operations on sketches, making them closer to real 3D CAD models.

Mechanical designers have more tools and choices in the design process. Geometric CAD and parametric CAD are two main design methods, each with its own advantages and disadvantages in mechanical design. Pekta and Tunger [12] compared the interactive cognitive behavior and its impact on designers in these two design environments. Geometric CAD design mainly relies on the designer's direct operation and editing of geometric shapes. In this design environment, designers usually need to use drawing tools to build and modify models based on their own experience and imagination. This requires designers to have high spatial imagination and drawing skills. In terms of interactive cognition, designers in geometric CAD design environments rely more on visual and spatial perception. In addition, as modifications typically require manual intervention, designers need to invest more cognitive resources to ensure the accuracy and rationality of the design. Technologies such as augmented reality (AR) and digital twins have been widely applied in the manufacturing industry. The combination of these technologies provides a new solution for multimedia interactive assembly, greatly improving assembly efficiency and accuracy. Qiu et al. [13] reviewed multimedia interactive assembly technology based on CAD augmented reality and digital twins, in order to provide a reference for research and application in this field. CAD technology, as a core tool in the manufacturing industry, provides strong support for product design and manufacturing. During the assembly process, CAD technology can achieve precise modeling and simulation of assembly components, helping engineers predict and optimize the assembly process. Through CAD software, detailed assembly drawings and process files can be generated to guide workers in precise assembly operations. Digital twin technology achieves full lifecycle management of products by constructing virtual models that correspond to actual products. During the assembly process, digital twin technology can monitor the assembly progress and quality in real-time, providing optimization suggestions for the assembly process.

In the field of modern interactive system design, the combination of the function behavior structure design process model and recurrent neural networks provides a new perspective and method for design decision-making. Rahman et al. [14] optimized the user-system interaction experience through deep learning and recursive processing. Traditional design process models are no longer sufficient to meet the design requirements of complex interactive systems. At this point, the introduction of Recurrent Neural Networks (RNNs) provides new ideas for design decision-making. In interactive system design, RNN can be used to learn and predict user interaction behavior, thereby optimizing the system's response and feedback mechanisms. In the design decision-making process, this learned knowledge can be used to guide the functional and behavioral design of the system. For example, based on user operating habits and feedback, the system's interface layout, button positions, or feedback methods can be adjusted to improve user satisfaction and efficiency. In the field of human-computer interaction, gesture recognition has attracted widespread attention as an intuitive and natural way of interaction. With the continuous development of technology, gesture recognition systems based on inertial measurement units (IMUs) are becoming increasingly mature, providing users with a more convenient and efficient interactive experience. Valarez et al. [15] focused on exploring how to use Recurrent Neural Networks (RNNs) to design gesture recognition interactions using IMU data. By processing and analyzing this information, it can recognize the user's gesture actions and perform corresponding interactive operations based on them. In gesture recognition, the user's gesture actions are usually a continuous process that includes a series of time series data. Recurrent neural networks can capture the temporal dependencies in these data, thereby more accurately identifying gesture actions.

However, the research of applying DNN to the multimedia interactive system of mechanical CAD models is still in the primary stage. Most of the research focuses on theoretical discussion and algorithm optimization, lacking the realization and application of the actual system. Therefore, this study is devoted to filling this gap and promoting the development of this field by designing and implementing a multimedia interactive system of mechanical CAD models based on DNN.

3 MECHANICAL CAD MODEL PROCESSING BASED ON DNN

3.1 Model Construction

DNN typically comprises numerous hidden layers, each populated with multiple neurons. These networks employ the forward propagation algorithm to systematically transmit input data from the input layer to the output layer, undergoing nonlinear transformations at each hidden layer to extract meaningful features. The backpropagation algorithm is then utilized to fine-tune network parameters based on output errors, aiming to minimize the loss function and enhance overall network performance. Additionally, optimization algorithms such as gradient descent, stochastic gradient descent, and Adam are employed to expedite the network training process and mitigate the risk of overfitting. DNN plays a pivotal role in model identification and classification tasks, enabling the automatic learning of CAD model feature representations and facilitating accurate model identification and classification through training.

Given the intricate nature of mechanical CAD models and the need for swift processing, this study opts for CNN (Convolutional Neural Network) as the foundational architecture. CNN excels in image data processing, efficiently extracting local features and abstracting them progressively. In this research, CAD model graphic data is converted into an image-like format, facilitating the utilization of CNN for feature learning and classification. Through rigorous training and learning, CNN can discern patterns from vast amounts of unstructured data, adhering to the formula specified below:

$$m = \sqrt{x+y} + R\ 10 \tag{1}$$

In this context, m represents the neuron count in the hidden layer, x denotes the neuron count in the output layer, and y signifies the neuron count in the input layer. Suppose that k filters are employed in the convolution layer to process the input image and yield k fresh feature maps for downstream analysis. If we consider the output feature map within a given layer, then:

$$F_j^n = \sum_i w_{ij}^n * F_i^{n-1} + b_j^n \tag{2}$$

In this scenario, $*$ refers to a two-dimensional convolution, w_{ij}^n represents convolution filters, b_j^n denotes deviations, and F_j^n signifies the j output feature map situated at the n layer. To determine the optimal network configuration, this study adjusts layer depths based on experience and experimentation and carefully selects parameters such as convolution kernel size, step size, and padding. Additionally, a batch normalization layer is incorporated to expedite training and enhance model performance, while the ReLU activation function is utilized to augment the network's nonlinearity. The resulting network architecture is depicted in Figure 1.

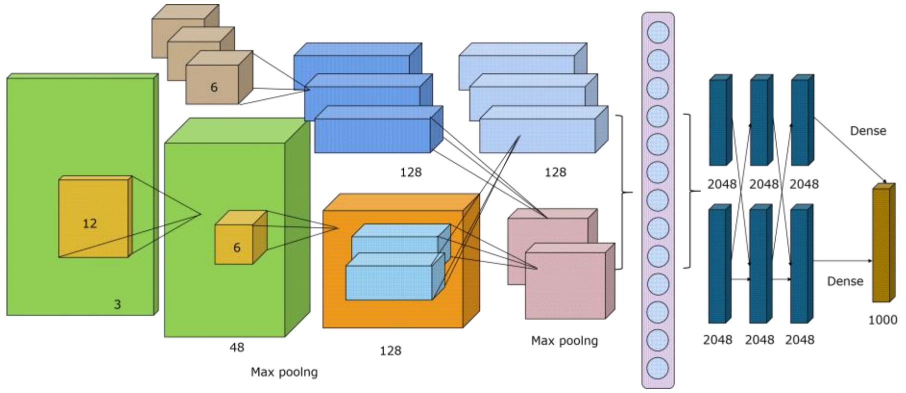

Figure 1: Network structure diagram.

Furthermore, this study performs data augmentation techniques, such as rotating and translating the training dataset, to enhance the model's generalization capabilities. The eigenvector representation of the sample x_i is denoted as follows:

$$a_{i1}, a_{i2}, a_{i3}, \ldots, a_{im} \tag{3}$$

Subsequently, the computation of expectation and variance is conducted for every attribute across all sample points denoted as X :

$$avg\ X\ a_i\ = \frac{1}{g_i}\sum_{j=1}^{g_i} a_{ji} \tag{4}$$

$$std\ X\ a_i\ = \sqrt{\frac{1}{g_i - 1}\sum_{j=1}^{g_i} x_i\ a_i\ - avg\ X\ a_i\ ^{2}} \tag{5}$$

In this context, $x_{i}\ a_{i}$ stands for the value associated with the sample j within the a_{i} attribute. It's worth noting that the aforementioned formula is dimensionless.

$$x_{j}\ a_{i}\ =\frac{x_{i}\ a_{i}\ -avg\ X\ a_{i}}{std\ X\ a_{i}} \tag{6}$$

The sample data follows a normal distribution denoted $N\ 0{,}1$ while eliminating dimensional dependencies among the attributes.

In the output layer of the model, the corresponding classification or regression layer is set according to the specific task requirements. For classification tasks, the model uses the Softmax function to transform the output into a probability distribution. For the regression task, the linear activation function is directly used to output the predicted value. The output formula of the model is as follows:

$$O_{L}=g\ I_{L} \tag{7}$$

Where O_{L} is the output of layer L, g is the nonlinear activation function, and I is the input of layer L.

The formula for backpropagation error is as follows:

$$E=\sum_{L} O_{L}-Y\ ^{2} \tag{8}$$

Where E is the output error, O_{L} what is the actual output, and Y what is the expected output.

Mechanical CAD models are usually stored in specific file formats, such as STEP, IGES, and STL, or proprietary formats such as DWG of AutoCAD. These formats include geometric information, topological structure, material properties, and possible assembly levels of the model. When dealing with these models, it is first necessary to parse these file formats, extract the key information of the models, and convert them into data structures that can be processed internally. In this paper, the processing flow includes the following steps: (1) File analysis: read the CAD model file, analyze the geometric data and attribute information in it, and convert it into the data representation inside the system. (2) Data cleaning and preprocessing: clean the parsed data, remove redundant information, repair possible errors, and carry out necessary preprocessing operations, such as unit unification and coordinate transformation. (3) Model streamlining and refinement: Streamline the intricate CAD model to minimize data quantity while preserving its geometric traits and topological framework intact. The refinement process is geared towards enhancing the efficacy and precision of subsequent operations. (4) Feature extraction: Extract pertinent features from the refined model, which will serve as the foundation for subsequent identification, categorization, or other analytical endeavors. (5) Data storage and management: store the processed model data and extracted features in the database, and establish an index and query mechanism for subsequent data retrieval and analysis.

3.2 Modelling Verification

In order to verify the effectiveness of the above methods and techniques, a series of experiments and analyses are needed. The experiments in this section include: (1) Data set construction: Collect and sort out a large number of CAD model data, and build a data set for training and testing. The data set contains different types of CAD models to verify the universality and robustness of the method. (2) Experimental design: Design a reasonable experimental scheme, including selecting a suitable DNN model, determining training strategies, setting up comparative experiments, etc. The experimental scheme should fully consider all possible influencing factors to ensure the reliability of the experimental results. (3) Evaluation of results: Evaluate the experimental results with appropriate evaluation indicators (modeling speed, F1 score). At the same time, visual analysis is carried out to show the processing effect and performance of the method intuitively. (4) Discussion and improvement of results: According to the experimental results, discuss and analyze the advantages and disadvantages of the method. Through continuous iteration and optimization, the accuracy and efficiency of CAD model processing are improved. The modeling speed of the algorithm is shown in Figure 2.

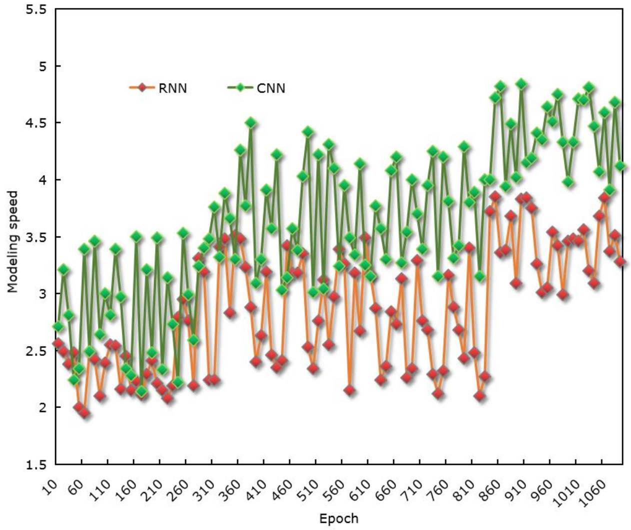

Figure 2: Modeling speed.

The F1 score is shown in Figure 3.

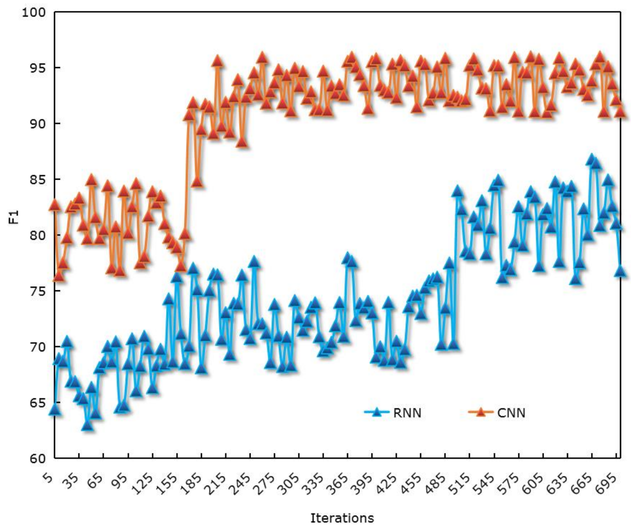

Figure 3: F1 score.

The results of the above figure indicate that the algorithm in this article has a fast modeling speed and a high F1 score. This result indicates that the proposed algorithm has high computational efficiency when processing large amounts of data. This high efficiency stems from the optimization design of algorithms and effective data processing strategies. Meanwhile, the results indicate that the DNN model has excellent performance in identifying positive examples and avoiding false positives. This performance stems from the model's deep understanding of the data, effective feature selection, and appropriate model parameter settings.

4 DESIGN OF MULTIMEDIA INTERACTIVE SYSTEM FOR MECHANICAL CAD MODEL

4.1 Demand Analysis of Multimedia Interactive System for Mechanical CAD Model

The mechanical CAD model is the core element in the field of industrial design, which has the characteristics of accuracy, complexity, and information richness. These models usually contain detailed geometric information, material properties, and assembly relations, which provide designers with comprehensive design references. With the development of technology, users put forward higher requirements for the interactivity of mechanical CAD models, hoping to understand and operate the models more intuitively and efficiently through multimedia means. In order to meet the needs of users for multimedia interaction of mechanical CAD models, the system needs to have the following core functions:

(1) Model import and analysis: The system should support the import of mechanical CAD models in various formats, and can accurately analyze the geometric information, material attributes, and assembly relations in the models.

(2) Multimedia elements fusion display: The system should be able to effectively integrate multimedia elements such as text, image, audio, and video with mechanical CAD models, so as to provide a richer information display and interactive experience.

(3) Interactive operation support: The system should support users to rotate, zoom, and translate the mechanical CAD model through various input devices such as mouse, keyboard, and touch screen, and provide advanced interactive functions such as measurement and annotation.

(4) Real-time rendering and performance optimization: The system should have efficient real-time rendering ability to ensure that users can get a smooth visual experience in the interactive process. In addition, the system should also reduce the rendering burden and improve the running efficiency through reasonable performance optimization means, such as Levels of Detail technology and model simplification.

(5) Model data management and update: The system should establish a perfect model data management mechanism to support the functions of model storage, retrieval, and version control. At the same time, the system should also be able to update the model data in real-time to ensure that users always get the latest and most accurate model information.

At the same time, user experience is one of the key factors to evaluate the success of a multimedia interactive system. In order to meet the user's requirements for ease of use, intuition, and aesthetics, the system interface design should follow the following principles (as shown in Table 1).

User experience requirements	*Interface design principle*	*Specific content*
Usability	Concise and clear	Interface layout should be concise and clear to avoid redundant information and complicated operations. Important functions and information should be placed in a conspicuous position.
	Consistency	The system should maintain a consistent interface style and operating habits, and provide necessary help documents and tutorials.
	Quick response	The system should respond to user interaction quickly, give feedback in time, and deal with possible delays or errors.

Intuition	Concise and clear	Important functions and information are conspicuous, making it easy for users to find what they need quickly.
	Consistency	Maintain the consistency of operating habits and reduce the learning cost and difficulty of users.
Aesthetics	Elegant appearance	Interface design should conform to modern aesthetics, with reasonable color matching, and elements such as icons and buttons should be beautifully designed and moderately sized.

Table 1: Correspondence table of interface design principles and user experience requirements of a multimedia interactive system.

In addition to meeting the basic functional and user experience requirements, the multimedia interactive system of the mechanical CAD model also needs to consider the requirements of performance and security:

(1) System performance requirements: In order to ensure a smooth user experience and efficient workflow, the system needs to have a high processing speed and a stable running state. This requires the system to make reasonable design and selection in hardware configuration, software architecture, and algorithm optimization.

(2) Data security requirements: Mechanical CAD models often contain important design and manufacturing information of enterprises, so the data security of the system is very important. To ensure the security of model data during transmission, storage, and utilization, the system must incorporate encryption technology, access controls, and other security measures. Additionally, a robust data backup and recovery mechanism should be established to mitigate potential data loss or corruption due to unforeseen circumstances.

(3) Regarding system stability and reliability, the multimedia interactive system must be capable of sustained operation and handling a substantial volume of user requests and data interactions. This necessitates a high degree of resilience against various anomalies and attacks. Accordingly, the design and implementation of the system should prioritize exception handling, fault tolerance, and load balancing mechanisms.

4.2 System Design

The overall architecture design of a multimedia interactive system of mechanical CAD model is the basis of system development, which determines the stability, expansibility, and ease of use of the system. The overall architecture of the multimedia interactive system of the mechanical CAD model in this paper includes the following levels: data layer, business logic layer, user interface layer, integration, and interface layer. See Table 2 for details.

Level	*Describe*	*Functional subdivision*
Data layer	Responsible for storing and managing the basic data of mechanical CAD model	Model file storage and retrieval
	Include model files, multimedia resources, user data, etc.	Storage and access to a multimedia resource
	Design efficient data storage structure and access mechanism	User data storage and management
	Ensure data integrity and security.	Data backup and recovery mechanism
Business logic layer	Realize the core functions of the system.	Analysis and processing of CAD model
	Including CAD model analysis, processing, feature extraction, and multimedia interaction.	Feature extraction and recognition

	Work closely with the data layer to complete data reading, processing, and storage operations.	Fusion of multimedia elements and CAD model Identification and handling of interactive operation
User interface layer	Responsible for showing the processed CAD model and multimedia information to users.	Intuitive user interface design
	Receiving user's interactive operation An intuitive and easy-to-use user interface and interactive logic are designed to improve the user experience.	Easy-to-use interactive logic design Real-time feedback and response mechanism
Integration and interface layer	Responsible for system integration and interaction with external systems.	Seamless connection between internal modules
	Define a unified interface standard Achieve seamless connection between modules within the system and between the system and external systems.	The interactive interface between the system and the external system Interface security and stability guarantee

Table 2: Hierarchical subdivision of overall architecture of multimedia interactive system for mechanical CAD model.

The multimedia interactive module is the core part of the system, which is responsible for realizing the integration and display of CAD models and multimedia elements, as well as supporting the user's interactive operation. Specifically, it includes: (1) Multimedia elements management: Design the storage, retrieval, and updating mechanism of multimedia elements to ensure the effective association between multimedia elements and CAD model. (2) Fusion display strategy: Study the fusion method of CAD model and multimedia elements, such as texture mapping on the model surface, augmented reality technology, etc., in order to achieve a more abundant and intuitive display effect. (3) Interactive operation support: Design the recognition and processing mechanism of the user's interactive operation, such as gesture recognition and voice recognition, to provide a more natural and convenient user experience.

User interface and interactive logic design are the key links to improve user experience. According to the user's needs and operating habits, this paper designs a reasonable interface layout to ensure that important information and functions are easy to reach. At the same time, the complete process of interaction between users and the system is defined, including operation steps, feedback mechanism, and exception handling, so as to ensure that users can successfully complete various tasks. Finally, feedback is collected through user testing, and the interface and interaction logic are continuously optimized and improved to improve user satisfaction and efficiency.

5 SYSTEM IMPLEMENTATION AND SIMULATION EXPERIMENT

5.1 System Development Environment and Tool Selection

The choice of system development environment and tools has an important impact on development efficiency and system performance. Specific choices include development environment: choose a suitable development environment, such as an operating system, programming language, and development framework. These environments should be able to provide rich library and tool support to simplify the development process. Modeling and simulation tools: Select professional modeling and simulation tools to build and test mechanical CAD models and multimedia interactive systems. These tools should have powerful modeling, rendering, and interactive functions. Debugging and testing tools: Select effective debugging and testing tools to locate and solve problems in the development process. These tools should be able to provide detailed log information, performance analysis, and error location.

The implementation details of key modules are the core part of system development. The specific implementation includes:

(1) CAD model processing module: Realize the functions of importing, parsing, processing, and feature extraction of CAD models. Pay attention to the compatibility of data formats, processing efficiency, and accuracy of feature extraction.

(2) Multimedia interactive module: Realize the fusion display of multimedia elements and the support of user interaction. Pay attention to multimedia elements's loading speed, display effect, response speed, and accuracy of interactive operation.

(3) User interface and interactive logic module: Realize the design of the user interface and the realization of interactive logic. Pay attention to the aesthetics, ease of use, and rationality of the interactive logic of the interface.

5.2 Design and Implementation of Simulation Experiment

Simulation experiments are an important means to verify the function and performance of the system. The specific design and implementation of the experiment in this section include: (1) Experimental purpose and hypothesis: Define the purpose and hypothesis of the experiment and determine the system functions and performance indicators that need to be verified. (2) Experimental data and scenarios: Select representative experimental data and scenarios to simulate the real application environment. (3) Experimental process and record: Record the experimental process and results in detail, including operation steps, input data, output results, and abnormal conditions. (4) Result analysis and conclusion: Make statistics and analysis on the results to verify whether the function and performance of the system meet the design requirements. According to the experimental results, conclusions are drawn and possible improvement suggestions are put forward.

This section first evaluates the performance of the system by comparing the experimental data and performance indicators. Pay attention to key indicators such as processing speed, memory consumption, and stability, and compare with the expected target. The processing speed of the system is shown in Figure 4.

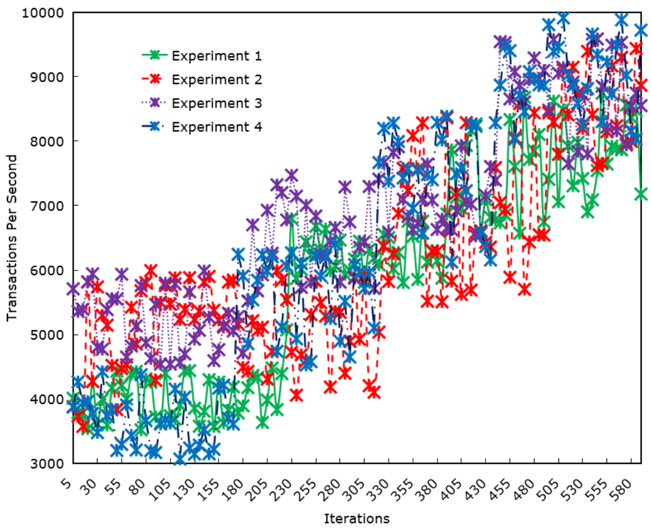

Figure 4: Processing rate.

Figure 4 illustrates that the processing speed of this method is rapid, exhibiting minimal fluctuation. This demonstrates the system's proficiency in efficiently handling input data while maintaining a consistently high performance across diverse scenarios. Meanwhile, Figure 5 presents the system's memory consumption.

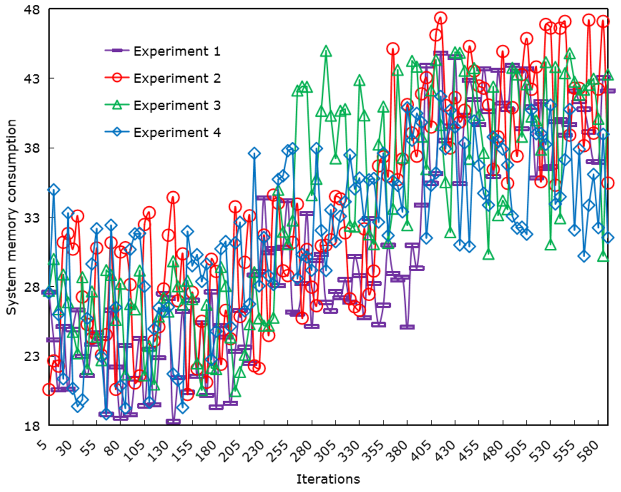

Figure 5: System memory consumption.

Figure 5 shows that the memory consumption of the method in this paper is relatively low and grows slowly, which shows that the system can effectively manage memory resources and avoid unnecessary waste. The system stability is shown in Figure 6.

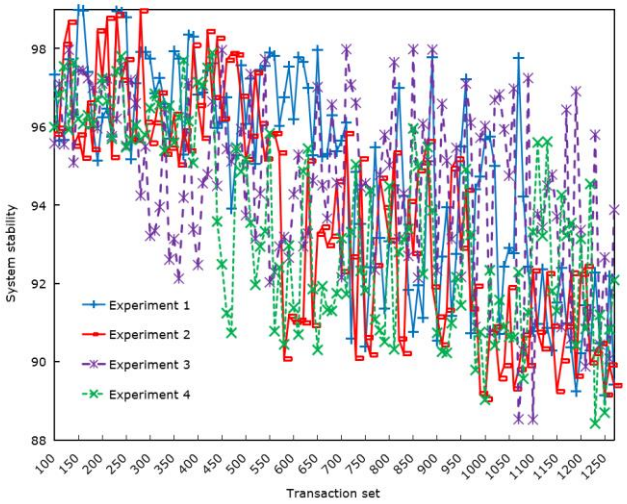

Figure 6: System stability.

Figure 6 shows that the method in this paper has high stability and small performance fluctuation, which shows that the system has good robustness and fault tolerance.

At the same time, this section tests each module separately to ensure that they can work normally according to the design requirements. At the same time, test whether the interface and data interaction between modules are correct. Then, all the modules are integrated to carry out the overall system test to check whether the system can run normally and meet various functional requirements. Focus on performance, security, and stability testing. The test results are shown in Table 3.

Module name	*Separate test*	*Interface and data interaction test*	*Integration testing*	*Performance test*	*Safety test*	*Stability test*
Module 1	Pass	Pass	Pass	Meet the requirements	No loopholes	Stable
Module 2	Pass	Pass	Pass	Meet the requirements	No loopholes	Stable
Module 3	Pass	Pass	Pass	Meet the requirements	No loopholes	Stable
Module 4	Pass	Pass	Pass	Meet the requirements	No loopholes	Stable
Module 5	Pass	Pass	Pass	Meet the requirements	No loopholes	Stable
Module 6	Pass	Pass	Pass	Meet the requirements	No loopholes	Stable
Overall system	Pass	Pass	Pass	Meet the requirements	No loopholes	Stable

Table 3: System module test and overall test results.

In addition, real users are invited to participate in the test to check whether the system can meet the actual needs and expectations of users. Make necessary adjustments and optimizations according to user feedback. Figure 7 shows the user's evaluation results of the system.

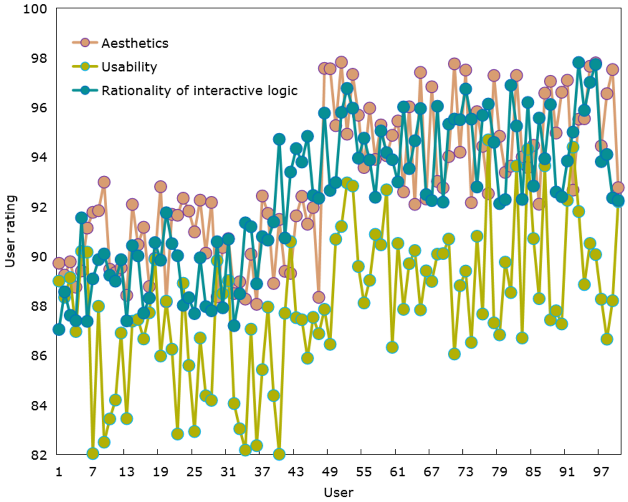

Figure 7: User evaluation results.

The user's evaluation of the system in Figure 7 shows that the system is excellent in aesthetics, ease of use, and rationality of interactive logic. These high scores reflect that the system pays attention to user experience in design and implementation, and can provide users with an efficient, convenient, and pleasant operating environment.

6 CONCLUSIONS

In this paper, a multimedia interactive system of mechanical CAD model is successfully designed and implemented. The system seamlessly integrates DNN technology to efficiently handle CAD models and offers tight integration with multimedia components, delivering an intuitive and engaging interactive experience for users. Here are the key research findings: Firstly, we've introduced a CAD model processing approach leveraging DNNs. This method automatically extracts model features, enabling precise classification and recognition, thus significantly boosting processing speed and accuracy. Secondly, a multimedia interactive module has been devised and implemented. It facilitates the integrated presentation of diverse multimedia elements and offers a plethora of user interaction options, including gesture recognition and voice control. This allows for a more convenient interaction with CAD models. The system's functionality and performance have undergone rigorous simulation testing, revealing excellent results in terms of processing speed, accuracy, stability, and user experience. This bodes well for its future application prospects.

Looking ahead, we'll closely monitor user feedback and demands to continually refine the system's capabilities and performance. Regular user feedback collection and market research will keep us apprised of evolving user needs and industry trends, providing valuable insights for system updates and enhancements.

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