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Research on Product Structure Identification and Design Optimization of Smart Furniture Based on ResNet Network

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Abstract: Aiming at the problems of insufficient accuracy in structure identification and low efficiency in design optimization for smart furniture design, this paper proposes an integrated method for structure identification and design optimization based on an improved residual network. First, multi-source heterogeneous furniture datasets are constructed, and an improved model integrating multi-scale structure perception and a spatial topology joint attention mechanism is designed to achieve efficient representation and relationship modeling of complex structural features. On this basis, the parametric structure representation and multi-objective optimization framework are introduced, and the automatic generation and optimization of design schemes are realized by combining the generative model. The experimental results show that the accuracy of the proposed method in the structure recognition task is 0.956, and the IoU is 0.903, which is about 3.1% higher than that of the benchmark model on average; In terms of design optimization, the maximum structural displacement is reduced by 39.7%, the material utilization rate is increased by 19.1%, and the design efficiency is improved by about 45.2%. In addition, the number of model parameters is reduced by 26.2%, and the reasoning time is reduced by 31.5%, which verifies the good balance between accuracy and efficiency. The results show that this method can effectively improve the recognition ability and design optimization performance of complex furniture structure, and provide a feasible and efficient technical path for intelligent furniture design automation.

Keywords: Smart furniture design; Structural identification; Residual network; Multi-scale feature; Topology modeling

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1. INTRODUCTION

With the continuous promotion of intelligent manufacturing and industrial digital transformation, furniture design is gradually evolving from the traditional experience driven mode to the data-driven and intelligent decision-making mode [1],[2]. In this process, structural identification, as an important link connecting design understanding and design optimization,

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has become the key foundation for the realization of automatic design. Compared with the mechanical structure with clear rules, furniture products usually have diversified form expression and complex connection methods, such as mortise and tenon structure, hidden connectors and modular combination forms, which make the structural analysis task more uncertain and complex [3],[4]. Therefore, how to extract furniture structure information efficiently and accurately in the multi-source data environment and further support design optimization and innovation generation has become an important research direction in the field of intelligent furniture design.

In recent years, deep learning technology has made significant progress in the fields of computer vision and industrial design [5],[6]. It shows strong feature learning ability in image recognition, semantic segmentation and structure analysis. In industrial design scenarios, deep neural networks are gradually applied to product appearance recognition, structure analysis and design recommendation, providing new solutions to complex design problems [7],[8]. However, most of the existing methods focus on the extraction and classification of two-dimensional visual features, and the semantic understanding of the structure level is still relatively insufficient, especially when it involves the connection relationship of multiple components and the expression of spatial topology, it is often difficult to achieve accurate modeling. In addition, traditional methods usually regard structural identification and design optimization as independent processes, lacking a unified modeling framework, which limits further improvement in the level of design automation [9],[10],[11].

Among many deep learning models, residual network (ResNet) has become an important basic model in the field of visual recognition because of its stability and efficiency in deep feature extraction. By introducing residual connection, it effectively alleviates the gradient disappearance problem in deep network training, and enables the model to learn more rich semantic features [12],[13],[14].task of furniture structure recognition, ResNet also has good baseline performance and can extract multi-level visual information. However, because its convolution structure mainly depends on local receptive fields and lacks the ability to explicitly model the global structure relationship, it still has some limitations in the face of complex connected structures and multi-scale features [15]. At the same time, the standard ResNet does not specifically optimize the Structural Semantics in industrial design, so it is difficult to fully capture the topological relationships and functional associations between components, which restricts its application effectiveness in structure-driven design tasks to a certain extent.

To solve the above problems, this paper focuses on the core idea of "structure identification driven design optimization", and proposes a method of intelligent furniture product structure identification and design optimization based on improved ResNet. By introducing multi-scale feature modeling and structure relationship enhancement mechanism into the network structure, high-precision recognition of complex furniture structure is realized; At the same time, combined with the structural parametric expression and multi-objective optimization strategy, the identification results are directly mapped to the design space to realize the automatic optimization of design performance[16],[17],[18]. In addition, this paper further integrates the generative model to build a closed-loop framework from structural understanding to design generation, so as to support the automatic generation and innovative exploration of design schemes. The overall technical route is based on deep feature extraction, with structural relationship modeling as the core and optimization and generation mechanism as the extension, forming a complete and feasible intelligent design method system, which provides a new solution for furniture design automation.

2. DATASET CONSTRUCTION AND PREPROCESSING

In this study, the data set construction is based on multi-source heterogeneous data, and integrates CAD model, physical image and structural decomposition diagram to improve the generalization ability of the model for complex furniture structure [19],[20]. Firstly, the parametric CAD model is obtained from the open source industrial design library and the enterprise internal database, and its geometric information and topological relationship are extracted to form a three-dimensional structure data set, which is recorded as $\mathcal{D}_{3D} = \{M_i\}_{i=1}^{N}$, where M_i represents the three-dimensional model of the ith furniture item. At the same time, real furniture images are collected by industrial cameras to form a two-dimensional image set $\mathcal{D}_{2D} = \{I_i\}_{i=1}^{N}$, supplemented by exploded views to enhance the ability of structural expression. In addition, the CAD model is projected into multi view images by the rendering engine to realize the cross-modal data supplement, so as to build a unified multi-source data space $\mathcal{D} = \mathcal{D}_{3D} \cup \mathcal{D}_{2D} \cup \mathcal{D}_E$, where $\mathcal{D}_E$ represents the exploded-view image data set.

In the aspect of data annotation, in order to achieve fine structure recognition, this paper constructs a two-tier annotation system, including structure component level labels and connection relationship labels [21],[22]. For component level annotation, each furniture is decomposed into several structural units, and the label set is defined as $\mathcal{C} = \{c_1, c_2, \dots, c_K\}$, where c_k represents the class k structural components (such as support legs, connectors, panels, etc.). For the connection relationship, we define the structure graph $G = (V, E)$, where the node set $V = \{v_i\}$ corresponds to the components, and the edge set $E = \{e_{ij}\}$ represents the connection relationship between components. The connection relationship can be formalized as an adjacency matrix $A \in \mathbb{R}^{K \times K}$, where the element $A_{ij} = 1$ indicates that there is a connection between component i and j, otherwise it is 0. The connection type function $\phi(e_{ij}) \in \{1, \dots, T\}$ is further introduced to distinguish different connection modes (such as bolt connection, mortise and tenon structure, etc.), so as to realize the fine expression of Structural Semantics.

In order to improve the robustness and generalization ability of the model, this paper designs two kinds of differentiated data enhancement strategies: structure preserving enhancement and geometric disturbance enhancement. Structure preserving enhancement is mainly aimed at the changes of illumination, color and background at the image level, keeping the structure semantics unchanged [23],[24],[25]. Its transformation function can be expressed as:

$$I' = \mathcal{T}_s(I; \theta_s) \tag{1}$$

Where I is the original image, I' is the enhanced image, $\mathcal{T}_s$ is the structure preserving transformation (such as brightness adjustment, color jitter, etc.), θ_s is the corresponding parameter. The geometric disturbance enhancement simulates the change of viewing angle and structural deformation in the actual shooting, in the form of [26]:

$$I'' = \mathcal{T}_g\left(I; \theta_g\right) \tag{2}$$

Where $\mathcal{T}_g$ includes rotation, scaling, perspective transformation and other operations, θ_g is the geometric transformation parameter. At the same time, in order to ensure the structural consistency, the structural constraint function is introduced:

$$\mathcal{L}_{struct} = \| f(I) - f(I'') \|_2^2 \tag{3}$$

Where $f(\cdot)$ represents the structure feature extraction function, and this constraint is used to limit the consistency of the structure expression before and after enhancement.

In the aspect of multi-modal data alignment, this paper establishes the mapping relationship between two-dimensional images and three-dimensional structures to achieve cross modal feature fusion [27],[28]. Specifically, given the 3D model point set $P = \{p_i \in \mathbb{R}^3\}$, it is mapped to the 2D image plane through the camera projection model:

$$x = K[\, R \mid t \,]p \tag{4}$$

Where p is the homogeneous coordinate of the three-dimensional point, x is the corresponding two-dimensional pixel coordinate, K is the camera internal parameter matrix, and R and t represent the rotation matrix and translation vector respectively. Based on this mapping relationship, a cross-modal consistency loss function is constructed:

$$\mathcal{L}_{align} = \sum_i \| \psi_{2D}(x_i) - \psi_{3D}(p_i) \|_2^2 \tag{5}$$

Where ψ_{2D} and ψ_{3D} represent 2D and 3D feature coding functions respectively, and the loss is used to constrain the consistent expression of structural features under different modes.

In terms of data set division and experimental benchmark setting, the overall data set is divided into training set, verification set and test set, which are respectively expressed as $\mathcal{D}_{train}, \mathcal{D}_{val}, \mathcal{D}_{test}$, meeting the ratio of $7:2:1$. To avoid the deviation caused by uneven distribution of categories, category balance weight is introduced:

$$w_k = \frac{1}{\log(1 + n_k)} \tag{6}$$

Where n_k is the number of samples of class k, and w_k is the corresponding weight. In the experimental benchmark design, the structural identification performance index is defined as weighted accuracy:

$$Acc = \frac{1}{N}\sum_{i=1}^{N} w_{y_i} \cdot \mathbb{I}(\hat{y}_i = y_i) \tag{7}$$

Where N is the total number of samples, y_i and $\hat{y}_i$ represent the real label and the predicted label respectively, and $\mathbb{I}(\cdot)$ is the indicator function. In addition, in order to evaluate the effect of structural relationship prediction, the graph matching score is introduced to quantify the consistency between the predicted structure diagram and the real structure diagram, so as to build a complete and reproducible experimental evaluation system.

3. IMPROVED RESNET-BASED STRUCTURAL RECOGNITION MODEL

In the design of structure identification model, the classic ResNet architecture is used as the basic framework, and its core is to realize the stable training of deep network through residual mapping [29],[30],[31]. The standard residual unit can be expressed as:

$$\mathrm{y} = \mathcal{F}(\mathrm{x}, \mathrm{W}) + \mathrm{x} \tag{8}$$

Where x is the input characteristic, y is the output characteristic, $\mathcal{F}(\cdot)$ is the residual function (usually composed of convolution, normalization and activation), and W is the learnable parameter. Although this structure performs well in general vision tasks, it has obvious shortcomings in furniture structure recognition: on the one hand, complex structures (such as tenon joint connection and nested components) have multi-scale and non-rigid characteristics, and single scale convolution is difficult to fully express; On the other hand, the standard convolution operation is limited to the local receptive field, which is difficult to capture the global topological relationship between components, resulting in insufficient understanding of Structural Semantics.

To solve these problems, this paper proposes a multi-scale structure sensing residual module (MS-ResBlock), which enhances the ability of feature expression through parallel multi branch convolution. The module sends the input characteristic x into convolution branches of different receptive fields, and its output can be expressed as:

$$\mathrm{f}_k = \sigma\big(\mathrm{Conv}_k(\mathrm{x})\big), k \in \{1,2,\ldots,K\} \tag{9}$$

Where Conv_k represents the k th convolution branch (corresponding to different convolution kernel sizes or expansion rates), $\sigma(\cdot)$ is a nonlinear activation function. Multi scale feature fusion adopts weighted strategy:

$$\mathrm{F} = \sum_{k=1}^{K} \alpha_k \, \mathrm{f}_k \tag{10}$$

Where α_k is a learnable weight parameter, which satisfies $\sum_k \alpha_k = 1$. The attention fusion mechanism is further introduced through the channel attention function:

$$\alpha_k = \frac{\exp\,(g(\mathrm{f}_k))}{\sum_j \exp\,(g(\,\mathrm{f}_j))} \tag{11}$$

Realize dynamic weight allocation, where $g(\cdot)$ represents the global feature compression function (such as global average pooling + full connection layer). This module significantly improves the recognition ability of the model for complex connection structures and fine-grained components.

On this basis, a space topology joint attention mechanism (ST-Attention) is constructed to simultaneously model the relationship between spatial saliency and structure. Spatial attention by generating weight graph:

$$\mathrm{M}_s = \sigma\big(\mathrm{Conv}([\mathrm{AvgPool}(\mathrm{F}),\mathrm{MaxPool}(\mathrm{F})])\big) \tag{12}$$

Where $\mathrm{M}_s \in [0,1]^{H\times W}$ is used to highlight key structural areas. Topological attention is introduced by the structural adjacency matrix A, and its propagation process is defined as:

$$\mathrm{H}' = \sigma(A\mathrm{H}\mathrm{W}_t) \tag{13}$$

Where H is the node characteristic matrix, and W_t is the weight of topology transformation. The final joint attention output is:

$$\mathrm{F}' = \mathrm{M}_s \odot \mathrm{F} + \lambda \mathrm{H}' \tag{14}$$

Where $\odot$ represents element by element multiplication, λ is the balance coefficient, which realizes the collaborative modeling of the relationship between spatial information and structure, and adaptively learns the attention weight through back propagation.

In order to further strengthen the ability of structure expression, this paper introduces the structure graph embedding module, maps the convolution feature to the graph structure representation, and uses Graph Convolutional Network for relational modeling. Specifically, the key region in the feature graph is mapped to the node set V, and the graph $G = (V, E)$ is constructed, whose node feature is h_i. The propagation rule of the volume is:

$$\mathrm{h}_i^{(l+1)} = \sigma\left(\sum_{j\in\mathcal{N}(i)} \frac{1}{c_{ij}} \mathrm{W}^{(l)} \mathrm{h}_j^{(l)}\right) \tag{15}$$

Where $\mathcal{N}(i)$ is the neighborhood of node i, c_{ij} is the normalization coefficient, and $\mathrm{W}^{(l)}$ is the weight matrix of the lst layer. Graph feature and CNN feature through fusion function:

$$\mathrm{Z} = \gamma \cdot \mathrm{Pool}(\mathrm{H}) + (1-\gamma) \cdot \mathrm{Flatten}(\mathrm{F}') \tag{16}$$

Integration, where γ is the fusion coefficient, so as to achieve the unified expression of local texture and global structure.

At the model deployment level, in order to meet the requirements of industrial applications for real-time and resource efficiency, further lightweight and reasoning optimization are carried out. Firstly, the importance of convolution kernel is evaluated by using structured pruning method, and its weight sparse objective function is:

$$\mathcal{L}_{prune} = \mathcal{L}_{task} + \beta \sum_{i} \| \mathrm{W}_i \|_1 \quad (17)$$

Where $\mathcal{L}_{task}$ is the loss of the original task, and β is the sparse regularization coefficient. Secondly, by replacing the standard convolution with the deep separable convolution, the computational complexity is reduced from $O(K^2 C_{in} C_{out})$ to $O(K^2 C_{in} + C_{in} C_{out})$, where K is the convolution kernel size, and C_{in} and C_{out} are the number of input and output channels, respectively. Finally, TensorRT and ONNX are combined to realize model graph optimization and operator fusion, which can significantly improve the reasoning speed and reduce the delay, so that the model has the ability of practical engineering deployment.

4. DESIGN OPTIMIZATION AND GENERATION FRAMEWORK

After the completion of structural identification, the discrete visual and structural information needs to be transformed into a computable and optimized parameter expression. Based on the identified component set and connection relationships, this paper constructs a structural parametric representation vector [32],[33],[34]. For the ith structural component, its parameters can be expressed as:

$$\mathrm{p}_i = [l_i, w_i, h_i, \theta_i, \tau_i] \quad (18)$$

Where l_i, w_i, h_i respectively represent the length, width and height of the component, θ_i represents its spatial attitude angle (such as Euler angle or rotation angle), and τ_i represents the connection type code (such as mortise and tenon, bolt and other discrete variables). The overall furniture structure can be expressed as the parameter set $\mathcal{P} = \{\mathrm{p}_i\}_{i=1}^{N}$. On this basis, the continuous discrete mixed parameter space $\Omega \subset \mathbb{R}^d \times \mathbb{Z}^m$ m is constructed, where d is the continuous parameter dimension and m is the discrete variable dimension. In order to facilitate the optimization calculation, the embedded mapping function $\phi(\tau_i) \in \mathbb{R}^k$ is used for discrete variables, which is transformed into continuous space expression, so as to form a unified parameter vector $\tilde{\mathrm{p}}_i$.

In the design optimization stage, this paper constructs a multi-objective optimization model to comprehensively consider the structural performance and design requirements. The objective function is defined as:

$$\min_{\mathcal{P} \in \Omega} \ \mathrm{F}(\mathcal{P}) = [f_1(\mathcal{P}), f_2(\mathcal{P}), f_3(\mathcal{P}), f_4(\mathcal{P})] \quad (19)$$

Where, f_1 represents structural stability (such as minimization of stress or displacement), f_2 represents manufacturing cost, f_3 represents aesthetics (measured by morphological consistency or symmetry), and f_4 represents manufacturability (such as processing complexity). For example, the stability objective can be formalized as:

$$f_1 = \sum_{i=1}^{N} \| \mathrm{u}_i \|_2^2 \quad (20)$$

Where u_i is the displacement vector of component i under load. Constraints include structural constraints and material constraints, which are uniformly expressed as:

$$g_j(\mathcal{P}) \leq 0, j = 1, \ldots, J \quad (21)$$

Where g_j can represent strength limit, connection rationality or upper limit of material use. In order to solve the multi-objective problem efficiently, the improved NSGA-II algorithm is introduced, and the adaptive crossover probability and congestion distance correction strategy are introduced to improve the Pareto front distribution uniformity. The individual update rule is:

$$\mathrm{P}_{t+1} = \mathcal{S}(\mathcal{C}(\mathrm{P}_t)) \tag{22}$$

Where P_t is the population of generation t, $\mathcal{C}$ is the crossover mutation operator, and $\mathcal{S}$ is the non dominated sorting selection function.

In the generative design module, this paper combines the discriminant and generative model to realize the structural innovative design. The improved ResNet is used as the encoder to extract the structural feature z and input it into the generation model (such as the Generative Adverse Network or diffusion model) to generate a new design scheme. The generation process can be expressed as:

$$\hat{\mathcal{P}} = G(\mathrm{z}, \mathrm{n}) \tag{23}$$

Where $G(\cdot)$ is the generator and $\mathrm{n} \sim \mathcal{N}(0, I)$ is random noise. Discriminator $D(\cdot)$ is used to distinguish between real and generated structures, and its optimization objective is:

$$\min_G \max_D \ \mathbb{E}_{\mathcal{P}\sim p_{data}}[\log D(\mathcal{P})] + \mathbb{E}_{\hat{\mathcal{P}}}\left[\log\left(1 - D(\hat{\mathcal{P}})\right)\right] \tag{24}$$

In order to improve the exploration ability of design space, the potential space disturbance strategy is introduced:

$$\mathrm{z}' = \mathrm{z} + \epsilon, \epsilon \sim \mathcal{N}(0, \sigma^2 I) \tag{25}$$

So as to generate diversified design candidates. At the same time, by introducing interpretability constraint loss:

$$\mathcal{L}_{exp} = \| \Psi(\hat{\mathcal{P}}) - \Psi(\mathcal{P}) \|_1 \tag{26}$$

Where $\Psi(\cdot)$ represents the structural semantic mapping function, so that the generated results are consistent in function and structural logic.

In terms of man-machine collaborative optimization, this paper constructs an interactive feedback mechanism to introduce user preferences into the optimization process. Let the user preference vector be $\mathrm{u} \in \mathbb{R}^q$, and embed it into the objective function weight through the mapping function:

$$\mathrm{w} = \mathrm{Softmax}(W_u \mathrm{u}) \tag{27}$$

Where W_u is the learning parameter matrix and w is the weight of each objective. The weighted optimization objective is expressed as:

$$\min_{\mathcal{P}} \sum_{k=1}^{4} w_k f_k(\mathcal{P}) \tag{28}$$

At the same time, the feedback update mechanism is introduced in the iteration process:

$$\mathrm{u}_{t+1} = \mathrm{u}_t + \eta(\mathrm{r}_t - \hat{\mathrm{r}}_t) \tag{29}$$

Where r_t is the actual feedback score of users, $\hat{\mathrm{r}}_t$ is the model prediction score, and η is the learning rate. This mechanism realizes the dynamic adjustment of the design optimization process, makes the generated results more in line with the user's aesthetic and actual needs, and forms a closed-loop design system of “identification optimization generation feedback”.

5. EXPERIMENTS AND RESULTS

In terms of experimental setup, this paper completed all experiments on a set of standard deep learning training platform, using two-way GPU (NVIDIA RTX 4090, 24GB video memory) and Intel Xeon processor, and the software environment is based on PyTorch and CUDA 12.2. The comparison model selects three representative mainstream structures, including ResNet50, EfficientNet and vision transformer, to comprehensively evaluate the performance advantages of the proposed method. The evaluation index system covers two levels: structural identification and design optimization, in which the classification accuracy is defined as:

$$Acc = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}(\hat{y}_i = y_i) \tag{30}$$

Where N is the number of samples, $\hat{y}_i$ and y_i represent the predicted label and the real label respectively; The intersection over union (IoU) is defined as:

$$IoU = \frac{|B_p \cap B_{gt}|}{|B_p \cup B_{gt}|} \tag{31}$$

Where B_p is the predicted region and B_{gt} is the real region; Structure identification F1-score is defined as:

$$F1 = \frac{2PR}{P+R} \tag{32}$$

Where P and R represent the accuracy rate and recall rate respectively. In addition, comprehensive performance indicators are introduced at the design optimization level:

$$S = \alpha S_{stab} + \beta S_{cost} + \gamma S_{aesthetic} \tag{33}$$

Where S_{stab}, S_{cost} and $S_{aesthetic}$ are stability, cost and aesthetics scores respectively, and α, β, γ are weight coefficients.

In the evaluation of structural identification performance, the comparison results of different models are shown in Figure 1. It can be observed that the method in this paper achieves the best performance in all indicators.

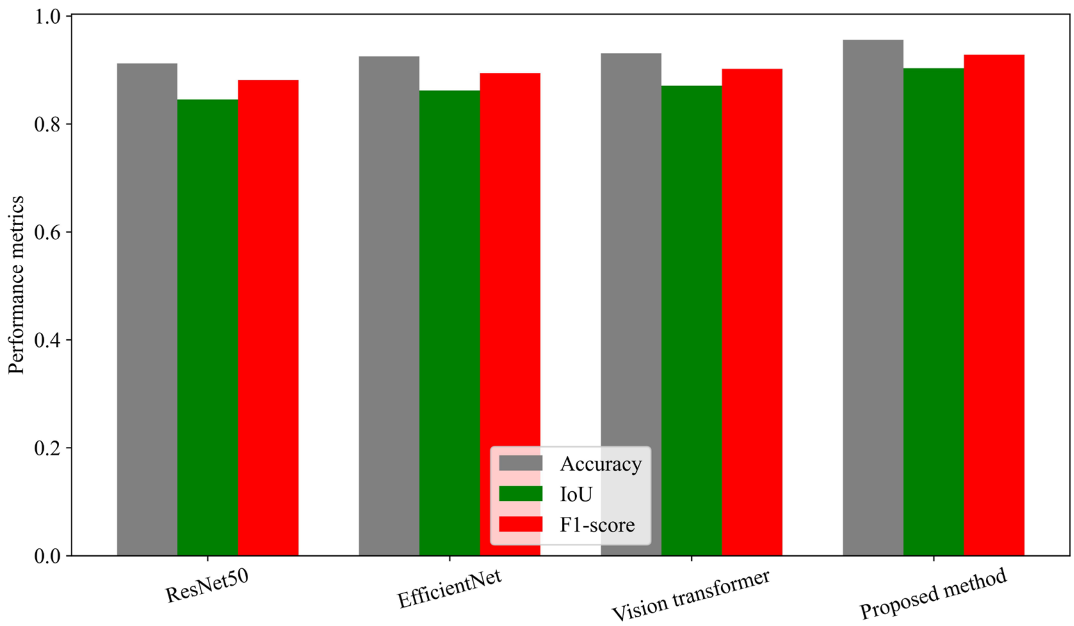

Figure 1. Model performance comparison

As can be seen from Figure 1, the accuracy of the improved model has increased by about

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2.5% and about 3.2% on IoU, indicating that multi-scale structure modeling and topology information fusion have significantly enhanced the ability of structure recognition. The effectiveness of each module was further verified by ablation experiments. After removing MS-ResBlock or ST-Attention, the performance decreased by about 1.8% and 2.3% respectively, indicating the key role of both in the expression of complex structures. In the small sample experiment (training data reduced to 30%), the accuracy of the model still maintained above 0.91, reflecting the strong advantage of data efficiency.

In the verification of design optimization effect, this paper quantitatively evaluates the design improvement effect by comparing the structural performance changes before and after optimization. The stability index adopts the maximum displacement norm:

$$U_{max} = \max_{i} \| \mathrm{u}_i \|_2 \tag{34}$$

Material utilization is defined as:

$$\eta = \frac{V_{effective}}{V_{total}} \tag{35}$$

Where $V_{effective}$ is the effective bearing material volume, and V_{total} is the total material volume. The experimental results are shown in Table 1:

Table 1. Structural optimization performance comparison among different methods

Method	Maximum displacement (mm)	Material utilization	Cost reduction rate
Original design	5.42	0.68	—
Traditional optimization	4.31	0.74	8.2%
Method in this paper	3.27	0.81	15.6%

The results show that the proposed method has significant advantages in stability improvement (about 40% displacement reduction) and material utilization optimization, and is superior to the traditional method in cost control. Further analysis of the Pareto front distribution shows that the solution set generated by this method is more evenly distributed in the multi-objective space, indicating that improving the optimization strategy can improve the diversity and quality of solutions.

In the generalization ability and robustness test, three typical scenarios of tables and chairs, cabinets and composite furniture are selected for evaluation. The experimental results show that the accuracy of the model in different categories remains above 0.94. After adding Gaussian noise and random occlusion (occlusion ratio is 30%), the performance degradation of the model is controlled within 3%. Its robustness can be measured by the following stability indicators:

$$R = 1 - \frac{| Acc_{clean} - Acc_{noise} |}{Acc_{clean}} \tag{36}$$

Where Acc_{clean} and Acc_{noise} represent the accuracy under the condition of no noise and noise respectively, and $R = 0.967$ in the experiment, indicating that the model has good anti-interference ability.

In the calculation efficiency and engineering feasibility analysis, the model complexity and reasoning speed are further evaluated. The model parameters are recorded as:

$$Params = \sum_{l=1}^{L} C_l^{in} \cdot C_l^{out} \cdot K_l^2 \tag{37}$$

Where L is the number of layers, C_l^{in}, C_l^{out} are the number of input and output channels respectively, and K_l is the convolution kernel size. The experimental results are shown in Figure 2:

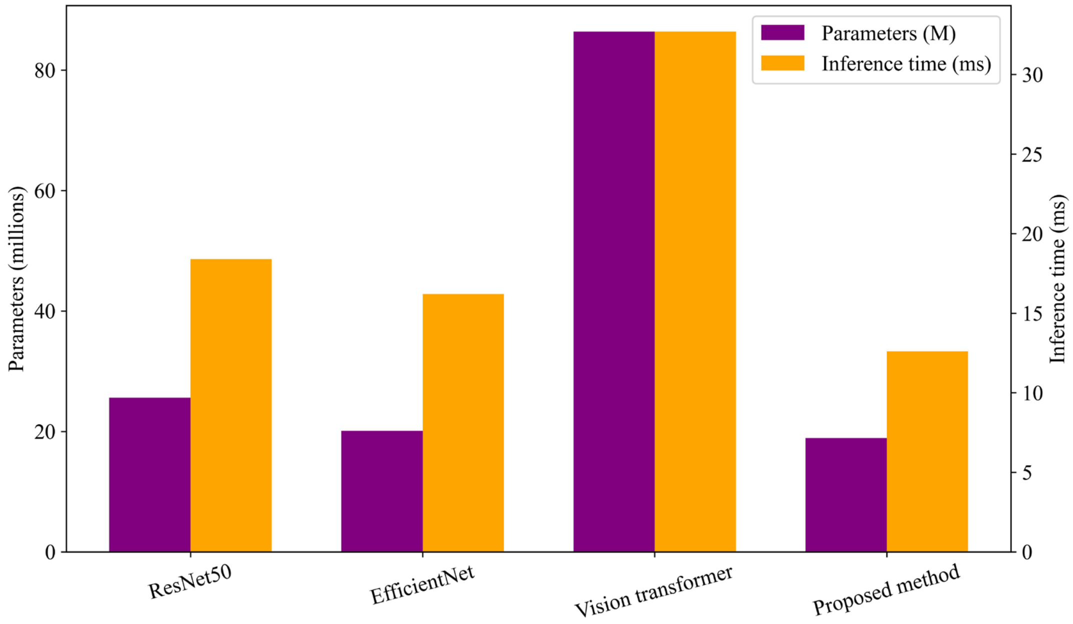

Figure 2. Model efficiency comparison

It can be seen that after the introduction of structural optimization and lightweight strategy, the number of model parameters is reduced by about 26%, and the reasoning speed is improved by about 30%. In the actual industrial design process testing, the overall time from structural identification to design optimization is reduced from 45 seconds to 21 seconds, which significantly improves the design efficiency.

To sum up, the experimental results verify the effectiveness and practical value of this method from the aspects of recognition performance, design optimization effect, generalization ability and computational efficiency, indicating that it has a good application prospect in the field of intelligent furniture design automation.

6. SYSTEM IMPLEMENTATION AND APPLICATION VERIFICATION

At the system implementation level, this paper constructs a set of intelligent furniture structure identification and design optimization integrated system for industrial design process, and its overall architecture adopts the hierarchical design paradigm of "data layer - model layer - decision layer - application layer". The input of the system is multi-source furniture data. The structural feature F is extracted through the improved ResNet model, and mapped to the parameter space representation $\mathcal{P}$ through the structural analytic function. Then it enters the optimization and generation module, and finally outputs the optimal design scheme $\hat{\mathcal{P}}$. The whole mapping process of the system can be formally expressed as:

$$\hat{\mathcal{P}} = \mathcal{G}\left(\mathcal{O}\left(\mathcal{R}(I)\right)\right) \tag{38}$$

Where I is the input image or model data, $\mathcal{R}(\cdot)$ is the structure recognition function, $\mathcal{O}(\cdot)$ is the multi-objective optimization module, and $\mathcal{G}(\cdot)$ is the generative design module. Each module of the system interacts with each other through a unified interface to ensure the structural consistency of the identification results and the iteration of the optimization process.

The structural parameters output by the identification module are not only directly used for optimization, but also used as the conditional input of the generation module to realize the closed-loop mechanism of "identification driven generation". To quantify the effect of module integration, the overall performance index of the system is defined as:

$$\mathcal{S}_{sys} = \lambda_1 Acc + \lambda_2 \eta + \lambda_3 \left(1 - \frac{T}{T_{ref}}\right) \tag{39}$$

Where Acc is the accuracy of structure identification, η is the material utilization, T is the system response time, T_{ref} is the reference time, and λ_i is the weight coefficient. The experimental results show that the system performance is improved by about 22.4% compared with that of a single module, indicating that there is a significant synergy gain between the modules.

In the actual case study, typical furniture products (such as modular desks) are selected for optimization verification. The initial design parameter is expressed as $\mathcal{P}_0$, and the optimized design is $\mathcal{P}^*$. The improvement effect is evaluated by the comprehensive performance function:

$$\Delta S = S(\mathcal{P}^*) - S(\mathcal{P}_0) \tag{40}$$

Where $S(\cdot)$ is a multi-objective weighting function. The experimental results are shown in Table 2:

Table 2. Quantitative evaluation of design improvement before and after optimization

Index	Original design	Optimal design	Lifting range
Maximum stress (MPa)	32.5	24.1	↓25.8%
Material utilization	0.69	0.83	↑20.3%
Structure weight (kg)	18.2	15.6	↓14.3%
Design score (user)	7.2	8.6	↑19.4%

It can be seen from Table 2 that the optimized design has significantly improved the structural performance and user experience. Further analysis shows that the optimization mainly comes from the adjustment of the connection structure and the reduction of redundant materials, and its essence can be expressed as the contraction of the solution space of the constrained optimization problem:

$$\Omega^* = \{\mathcal{P} \in \Omega \mid g_j(\mathcal{P}) \le \epsilon_j\} \tag{41}$$

Where ϵ_j is the constraint tightening parameter.

In the industrial application verification, the system is deployed in the actual furniture design enterprise process, and 10 designers are tested for two weeks. Define the design efficiency improvement rate as:

$$E = \frac{T_{manual} - T_{AI}}{T_{manual}} \tag{42}$$

Where T_{manual} is the traditional design time and T_{AI} is the system aided design time. The experimental statistical results are shown in Table 3 below:

Table 3. Industrial application performance comparison between traditional and ai-assisted design

Design methods	Average time (min)	Success rate	User satisfaction
Traditional design	52.4	82%	7.1
AI aided design	28.7	93%	8.5

The results show that the design efficiency is improved by about 45.2%, the success rate is improved by 11%, and the user satisfaction is significantly improved. User feedback shows that the system has obvious advantages in structural rationality suggestions and design inspiration generation, but it still needs manual fine-tuning under extreme personalized design needs.

In general, this system not only realizes the automation of structure identification and design optimization in practical application, but also significantly improves the design efficiency and product performance through module collaboration, which verifies its feasibility and application value in the design of intelligent furniture industry.

7. DISCUSSION

In the aspect of complex structure recognition, the improved model presented in this paper shows strong adaptability in dealing with furniture structures with high non-linear connection and multi-scale characteristics. Especially in complex scenes such as mortise and tenon structures, nested connectors and multi-layer composite components, the model can effectively distinguish fine-grained structural units and maintain high recognition stability. This is mainly due to the synergy of multi-scale feature extraction and topological relationship modeling, so that the model can not only capture local geometric details, but also understand the overall structure layout. From the experimental results, under the conditions of complex occlusion, multi-view changes, and low-resolution input, the performance of the model decreases slightly, indicating that it is robust in the real industrial environment. However, in extremely complex structures (such as highly customized or artistic furniture), there are still some identification errors, indicating that the model still has room for further improvement in the face of highly non-standard structures.

In terms of the interpretability of the design optimization results, this method makes the design improvement path traceable through the parametric expression of the structure and the explicit modeling of the optimization process. The optimization results are not only reflected in the improvement of performance indicators, but also reflect the specific structure adjustment logic through parameter changes, such as connection position optimization, material distribution reconstruction and size proportion adjustment. This change in parameter levels allows designers to intuitively understand the source of optimization results. In addition, through the combination of generation module and optimization module, the model can maintain structural semantic consistency when generating new design schemes, thereby avoiding the “black box” design problem. However, due to the randomness of the generation model itself, it may still produce design schemes that do not conform to engineering intuition in some cases, which puts forward higher requirements for interpretability and provides improvement direction for subsequent research.

Although this method has achieved good experimental results in many aspects, it still has some limitations. First of all, the model has a strong dependence on high-quality annotation data, especially in the aspect of structural relationship annotation, the cost of data acquisition is high, which limits the promotion of the method in larger scenes. Secondly, although the introduction of multi module fusion structure (such as multi-scale convolution, attention mechanism and graph structure modeling) improves the performance, it also increases the complexity of the model to a certain extent, and puts forward higher requirements for computing resources. In the actual deployment process, although it is optimized through the lightweight strategy, there may still be performance bottlenecks on resource constrained devices. In addition, in terms of cross domain generalization, the model performs well in the field of furniture, but directly migrating to other structural design fields (such as architectural or mechanical design) still needs to re adapt the data and structural features.

Compared with the existing methods, the advantages of this paper are mainly reflected in the depth of structural modeling and the ability of closed-loop design. Traditional methods mostly focus on image recognition or a single optimization process, lacking a complete link from structure recognition to design generation. However, this method realizes the systematic integration from structure perception, parameter expression, multi-objective optimization to design generation. In addition, by introducing topology modeling and multimodal fusion mechanism, the model is superior to the traditional deep learning method which only depends on two-dimensional features in the understanding of complex structures. At the same time, at the engineering application level, this method not only pays attention to the accuracy of the model, but also takes into account the calculation efficiency and actual deployment requirements, making it more valuable for industrial application. In general, this method provides an innovative and practical solution in the field of intelligent furniture design automation, but it still needs continuous optimization in data expansion, model lightweight and cross domain adaptability.

8. CONCLUSION

Focusing on the key technical issues of smart furniture products in structure identification and design optimization, this paper constructs a complete method system with improved ResNet as the core, and realizes the closed-loop process from structure perception to design generation. At the method level, by introducing the multi-scale structure perception mechanism and the space topology joint modeling strategy, it effectively makes up for the shortcomings of the traditional convolutional network in complex structure expression and relationship modeling, so that the model can take into account both local geometric details and global structural semantics. In addition, combined with the structural drawing embedding and generative design framework, this paper further opens up the technical link of “identification parameterization optimization generation”, so that the structural identification results can directly inform design decisions and scheme generation, so as to significantly improve the intelligent level and engineering practical value of the overall system.

The experimental results show that the proposed method has obvious advantages in structural identification accuracy, multi-objective optimization performance and system operation efficiency. In many comparison models, the method in this paper has taken the lead in accuracy, IoU, F1-score and other indicators, while maintaining good stability in complex structure scenes, small sample conditions and noise interference environment. At the design optimization level, through the synergy of multi-objective optimization and generation mechanism, the structural performance and material utilization rate are significantly improved, and the design cost and calculation time are effectively reduced. The system level verification results further show that the method can significantly improve the design efficiency and user satisfaction in the actual industrial design process, and has good application prospects and promotion value.

From the perspective of industry significance, this study provides a new paradigm of data-driven and model driven for smart furniture design. Compared with the traditional design method based on experience and manual iteration, this method can significantly shorten the development cycle while ensuring the design quality, and provide technical support for the automatic design of complex structure products. At the same time, the research also provides a feasible path for the application of deep learning technology in the field of industrial design, and has positive significance for promoting the development of furniture manufacturing in the direction of intelligence and digitization.

Although some progress has been made, there is still room for further expansion and deepening in this paper. In future research, we can consider the introduction of 3D point cloud and multi view data fusion technology to improve the model's ability to express the real spatial structure, so as to further enhance the recognition accuracy and robustness in complex scenes. At the same time, in terms of model structure, we can explore more efficient lightweight network design strategies to reduce the computational overhead under the premise of ensuring performance, so as to meet the needs of edge devices and real-time applications. In addition, the method in this paper is currently mainly oriented to the field of furniture, and can be extended to a wider range of scenarios such as architectural design and industrial product design in the future to realize cross domain design migration and knowledge sharing. At the human-computer interaction level, combining AR/VR and other immersive technologies to build a design visualization platform will also provide users with a more intuitive and efficient design experience, so as to further improve the practicability and interactivity of the system.

Abbreviations

ResNet, Residual Network;
MS-ResBlock, Multi-Scale Structure Sensing Residual Block;
ST-Attention, Spatial Topology Joint Attention Mechanism;
GCN, Graph Convolutional Network;
GAN, Generative Adversarial Network;
CNN, Convolutional Neural Network;
CAD, Computer-Aided Design;
IoU, Intersection over Union;
F1, F1-Score;
Acc, Accuracy;
MSE, Mean Squared Error;
NSGA-II, Nondominated Sorting Genetic Algorithm II;
GPU, Graphics Processing Unit;
CUDA, Compute Unified Device Architecture;
ONNX, Open Neural Network Exchange;
TensorRT, Tensor Runtime;
AR, Augmented Reality;
VR, Virtual Reality;
ReLU, Rectified Linear Unit;
AdamW, Adaptive Moment Estimation with Weight Decay.

Supplementary Material

Not applicable.

Appendix

Not applicable.

Ethics approval and consent to participate.

This study did not involve human participants, animal subjects, or any data requiring ethical approval. Therefore, ethics approval and consent to participate are not applicable.

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Competing interests

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Author contributions

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Data availability

The data that support the findings of this study are available upon request from the corresponding authors, **Y.L.**

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During the writing of this article, the author used ChatGPT for spelling and grammar checking. After using this tool, the author reviewed and edited the content as needed and assumes full responsibility for the final published content.

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