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Application of Integration of Transfer Learning and BIM Technology in Prefabricated Building Design Optimization

Ting Ouyang [1], Fengtao Liu [2,*], Lingling Chen [1], Dongyue Qin [1] and Sining Li [1]

[1] School of Civil Engineering and Architecture, Liuzhou Institute of Technology, Liuzhou 545036, China; ouyangt@hotmail.com (T.O.); lingl_chen@163.com (L.C.); q1819148140@163.com (D.Q.); lglilili224@163.com (S.L.)
[2] Academic Affairs Office, Liuzhou Institute of Technology, Liuzhou 545036, China
* Correspondence: liufengtao2022@outlook.com

Abstract

With the continuous maturation of prefabricated buildings, the errors and efficiency issues in the design of prefabricated buildings have gradually drawn the attention of architectural designers. The characteristics of standardized design for prefabricated buildings also provide a foundation for the application of computer-learning methods in the field of architectural design, thereby improving design quality and efficiency. This study combined BIM technology to construct the information data on prefabricated buildings, applied the transfer-learning method to build the training model, and utilized the traditional architectural design collision concept to construct a prediction model applicable to the collision detection of prefabricated building design. The training set and test set were constructed in a 9:1 ratio, and the loss function and accuracy function were calculated. The error rate of the model was verified to be within 10% through trial calculations based on engineering cases. The results show that, in the selected engineering cases, the collision detection accuracy of the model reached 90.3%, with an average absolute error (MAE) of 0.199 and a root mean square error (RMSE) of 0.245. The prediction error rate was controlled within 10%, representing an approximately 65% improvement in efficiency compared to traditional manual inspections. This method significantly improves the efficiency and accuracy of collision detection, providing reliable technical support for the optimization of prefabricated building design.

Keywords: transfer learning; prefabricated building; BIM technology; design optimization

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Academic Editors: Pin-Chao Liao, Zhao Xu, Ting-Kwei Wang and Yi-Hsin Lin

Received: 23 July 2025
Revised: 18 August 2025
Accepted: 21 August 2025
Published: 25 August 2025

Citation: Ouyang, T.; Liu, F.; Chen, L.; Qin, D.; Li, S. Application of Integration of Transfer Learning and BIM Technology in Prefabricated Building Design Optimization. *Buildings* **2025**, *15*, 3029. https://doi.org/10.3390/buildings15173029

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1. Introduction

The United Nations Headquarters signed a political agreement on the future of global sustainable development at the United Nations Summit on Sustainable Development (UNSSD) held in 2015 [1]. Currently, the framework developed by the 2030 Agenda, which includes 17 Sustainable Development Goals (SDGs), has been recognized and adopted by most countries around the globe as a guideline for the development of responsive sustainable development strategies that meet the specific requirements of their countries. Construction activities are closely related to the SDGs. According to statistics, the construction industry is responsible for 35% of all greenhouse gas emissions and one third of all waste, and has become the strongest driver of economic growth, with a significant consumption of resources and generation of construction solid waste [2].

In recent years, the concept of prefabricated building has been rapidly developed within the construction industry, featuring factory production and modular assembly,

which significantly improves the efficiency and quality of construction works and has become an important development trend in the field of modern construction. Prefabricated building data is highly multi-sourced, covering information from multiple disciplines, such as structure, electrical, and plumbing, and undergoes dynamic changes with design iterations. It also includes multi-dimensional parameters, such as spatial coordinates and material strength. These characteristics pose significant challenges to traditional detection methods. Insufficient data interpretation capabilities have become the core reason for the low efficiency of collision detection: manual inspection struggles to handle multi-sourced data, while traditional BIM tools cannot learn patterns from the data. In order to ensure the safety of prefabricated buildings, design optimization and evaluation have become a crucial link to identify and solve problems, such as the collision of components and spatial conflicts that may occur during the assembly process, so as to ensure the safety and stability of the building structure [3]. Through production and modular assembly, assembled buildings significantly reduce resource consumption and waste emissions in building construction, which is in line with the United Nations Sustainable Development Goals (SDGs) of "building resilient, inclusive and sustainable infrastructure", and further promotes the development of green and smart buildings, which is in line with the requirements for innovation, efficiency, and sustainability in the SDGs. The SDGs call for innovation, efficiency, and sustainability. By optimizing building design, it reduces resource wastage and carbon dioxide emissions and promotes a green and low-carbon approach to construction.

Building design optimization and evaluation is a key part of the prefabricated building design and construction process, which aims to identify and solve problems, such as component collisions and spatial conflicts, that may occur during the assembly process, in order to ensure the safety and stability of the building structure. Traditional design methods require significant human and time costs and are highly dependent on expertise. With the continuous development of machine learning and artificial intelligence technologies, transfer learning, as an effective machine-learning method to share knowledge and patterns between different domains or tasks, provides new ideas and solutions for prefabricated building design and evaluation. By using transfer learning, knowledge and patterns that have been learned in other domains or projects can be transferred to the task of optimizing and evaluating the design of prefabricated buildings, reducing the cost of model training and improving the accuracy and generalization of the model.

The purpose of this paper is to explore the application of transfer learning in the optimization and evaluation of prefabricated building design, and to propose corresponding solutions to promote the development of the prefabricated building industry. First is to explore the principles and methods of transfer learning in prefabricated building design optimization methods and assessment. Second is to design and implement a prefabricated building design and assessment model based on transfer learning. Third is to validate the validity and performance of the model and conduct a comparative analysis with traditional methods.

The main contributions of this paper are as follows: First, we introduce transfer-learning methods into the field of collision detection in prefabricated building design, utilizing deep neural networks pre-trained on large-scale general datasets to enhance detection performance under small-sample conditions. Second, we construct a small-sample efficient training mechanism adapted to actual engineering data, effectively reducing data acquisition and annotation costs. Finally, we propose a comprehensive workflow, encompassing data preprocessing, model training, collision detection, and result evaluation, and validate the advantages of this method in terms of accuracy and practicality through engineering case studies.

The remainder of this paper is organized as follows: Section 2 reviews several works on the optimization and evaluation of prefabricated building design and the application of transfer learning in other fields. Section 3 introduces the transfer-learning methodology in detail and identifies the basic process and framework design of collision for prefabricated building design. This Section is the case study to evaluate and analyze the results and effects of collision diagnosis and, additionally, validation of the model results. Conclusions and future work are discussed in Section 5. The specific research contents are illustrated in Figure 1.

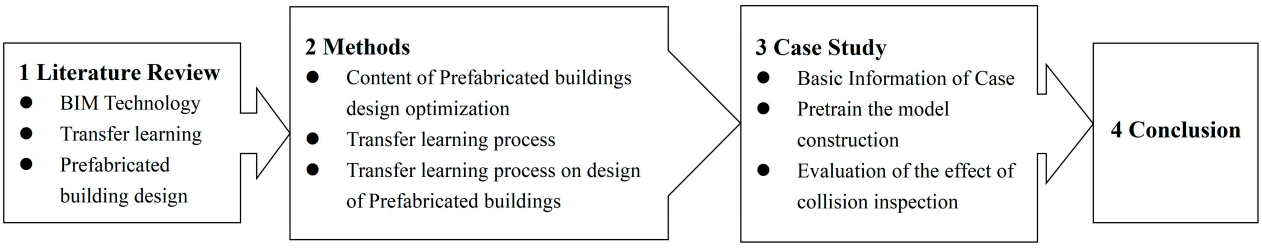


Figure 1. Research path and structure.

2. Literature Review

2.1. Research on Optimization of Prefabricated Building Design

As a modern construction method, prefabricated buildings have garnered widespread attention due to their efficiency, environmental friendliness, and controllable quality. Assembled building components are pre-manufactured in factories and then transported to the construction site for assembly, necessitating precise design and highly coordinated construction processes to ensure the correct installation of components without collisions. However, collision issues frequently occur during actual design and construction, affecting construction progress and potentially compromising building safety. Therefore, collision detection has become a crucial aspect of the design and construction of prefabricated buildings [4,5].

2.1.1. Traditional Design Methods

In the early stages of prefabricated building design, collision detection relies heavily on manual inspection and 2D drawings [6]. These methods are highly dependent upon the experiences and skills of the designers to detect possible collision problems by scrutinizing the building drawings. However, as the complexity of building design increases, manual inspection and 2D drawing methods lack efficiency and reliability [7]. The large amount of design details and complex arrangement of components make manual inspection prone to omissions and errors, which leads to inadequate detection of potential collision problems at the design stage [8]. In addition, research by some scholars has found that, in large-scale prefabricated building projects, manual inspection methods can lead to multiple serious construction delays and significant additional costs [9].

Subsequently, research related to rule-based collision detection systems was developed, which automatically checks for collisions in architectural designs by means of predefined rules and logic [10]. Jalae et al. developed a rule-based collision detection system, which improved detection efficiency by applying a series of predefined rules and logic [11]. Through a case study, Megahed et al. used a rule-based system for collision detection and found that the efficiency and accuracy of detection were improved [12].

2.1.2. BIM Technology-Based Design Methodology

With the rise of BIM technology, collision diagnosis during the design and construction of assembled buildings ushers in a new stage of development. BIM technology provides

comprehensive data support for collision diagnosis by creating a three-dimensional digital building model that integrates geometrical, material, and construction information of the building [13,14]. Collision problems between individual components are detected in the design phase, and detailed collision reports and solutions are provided. Designers can detect and solve potential collision problems in time during the design process, thus avoiding serious construction errors and safety hazards during the construction phase [15,16].

Baltabekov et al.'s study of BIM-based collision detection technology proposes a method for automated collision detection using Revit (Autodesk Revit 2022, San Francisco, CA, USA, https://www.autodesk.com.cn/) and Navisworks (Navisworks 2022, San Francisco, CA, USA, https://www.autodesk.com.cn/), which experimentally demonstrates its significant advantages in improving detection efficiency and accuracy [17]. Chahrour's study shows that BIM technology not only quickly identifies potential collision problems but also provides designers with an intuitive 3D view, which helps to better understand and solve collision problems [18]. Sabbaghzadeh et al. constructed a real-time collision detection system based on BIM and cloud computing and utilized the system's powerful computational capabilities to process a large amount of design data and achieve design optimization for complex building projects [19]. Liang et al., in their study on BIM technology for assembled construction projects, found that the number of errors and reworks in the design phase could be significantly reduced by using BIM technology [20]. Some academics have used BIM for design optimization, not only to identify potential problems at an early stage, but also to help designers better understand the nature and severity of problems through 3D visualization techniques [21].

In addition, Omrany et al. verified the effectiveness of BIM technology in collision detection during the design phase through empirical studies on several prefabricated building projects, i.e., the application of BIM technology not only improved the efficiency of collision detection but also significantly reduced conflicts and errors during the construction phase [22]. At the same time, BIM technology can help the construction team to better coordinate their work and reduce schedule delays and cost increases due to design changes and construction errors [23].

2.2. Research on Transfer Learning

Transfer learning is a method that enhances model performance by applying knowledge from a source domain to a target domain. In recent years, transfer learning has been widely used in various fields, including image recognition [24], natural language processing [25], and medical diagnosis [26]. In the design and evaluation of prefabricated buildings, transfer learning can effectively utilize existing knowledge and experience to improve the efficiency and accuracy of collision detection.

Transfer learning was first applied in the field of computer vision. A typical method involves using convolutional neural networks (CNNs) pre-trained on large-scale datasets, then fine-tuning them for new tasks. The AlexNet model established by Han et al. achieved remarkable results on the ImageNet dataset. Subsequent research widely utilized its pre-trained features for transfer learning, enhancing the performance of various visual tasks [27]. Jia et al. further explored the effects of transfer learning on different levels of features, discovering that lower-level features have better generality, while higher-level features are more adaptable to specific tasks [28].

Relatively little research has been conducted on transfer learning in the field of prefabricated buildings. Zhao et al. proposed a migration-learning-based method for classifying building components, which was applied to the automatic classification of assembled building components by using a pre-trained deep-learning model to improve the accuracy and efficiency of the classification [29]. Pinto et al. investigated the application of migration

learning to the design of assembled buildings, which significantly improved the efficiency and accuracy of the detection of new building design data through the use of pre-trained models for collision detection of new building design data, significantly improving the efficiency and accuracy of detection [30]. Tusnin et al. systematically summarized the various methods and applications of transfer learning in their review, which emphasized that the selection of appropriate source and target domain models is crucial when applying transfer learning, and that similarities and differences between domains need to be taken into account [31]. Hosna, in his study, discusses the theoretical foundations and application scenarios of transfer learning to provide comprehensive guidance to researchers [32].

2.3. Application of BIM Technology in Assembled Building

BIM technology integrates the geometric, material, and construction information of a building through the creation of a 3D digital building model, providing comprehensive data support and decision-making basis for the design, construction, and management of prefabricated buildings.

In the design phase of assembled buildings, Feng et al. showed that, by using BIM technology, designers can pre-assemble assembled components in a virtual environment to detect and solve potential problems in advance, thus improving design efficiency and accuracy [33]. Zribi et al. proposed a multi-disciplinary collaborative design method based on BIM, whereby, through the sharing and collaborative work of BIM models, different professional design teams can have real-time design communication on the same platform [34]. Wang's study showed that combining BIM platforms not only improves design coordination and consistency but also reduces rework and waste due to design conflicts [35].

In terms of construction management, Rodrigues et al. found through the application of BIM technology in the construction process of assembled buildings that the BIM model can achieve visual management of construction progress and real-time monitoring of the construction process, as well as discovering and solving potential problems in the construction process in advance [36]. Zhou et al. constructed a BIM- and Internet of Things-based construction monitoring system based on BIM and IoT to achieve real-time monitoring and data analysis of the construction process, which not only improves the safety and efficiency of construction but also provides the scientific data support and decision-making basis for construction management [37]. In addition, Li et al. studied the application of BIM technology in construction quality, which showed that detailed management and quality control of the construction process can be achieved through BIM [38].

In terms of O&M management, Ismaeel et al. proposed a BIM-based building O&M management system to achieve intelligent management of building O&M through the 3D visualization of BIM models and data integration [39]. Zhang and Chan established a BIM- and AI-based building O&M management system to achieve intelligent and automated management of building intelligent and automated management of operation and maintenance [40].

In summary, traditional manual inspection methods are inefficient and inaccurate, making them inadequate for meeting the complex design requirements of prefabricated buildings. Although rule-based systems have improved the level of automation in detection, the limitations of rule setting and management difficulties make them inadequate for handling dynamically changing design data and real-time collision detection needs. When dealing with large and complex projects, the computational resources and software performance required by BIM technology can also become bottlenecks. Additionally, the application of BIM technology requires specialized skills and knowledge, and for designers

without relevant experience, using BIM may involve a significant investment in learning time and operational difficulty.

2.4. Summary Review

Existing traditional collision diagnosis methods have limitations in dealing with complex and dynamic designs, and there is an urgent need for smarter and automated technological solutions. Specifically, manual inspection and 2D drawing analysis, while providing a preliminary means of design calibration at an early stage, often lead to omission and misdetection phenomena due to their dependence on the experience of the designer and their inability to handle the large amount of detail in complex designs. Rule-based collision detection systems improve detection efficiency to a certain extent, but their rules are difficult to set up and update, making it difficult to adapt to dynamically changing design data.

The introduction of migratory learning and BIM technology provides new ideas for collision diagnosis in building design. The former can reduce data requirements and improve model generalization. The latter supports the automation and accuracy improvement of collision detection by providing detailed building information models. From a data perspective, transfer learning in the construction industry has mostly focused on component classification and has not yet addressed data correlation analysis in collision detection. BIM technology enables data integration but lacks the ability to mine collision patterns from historical data.

This paper proposes a transfer-learning-based optimization method for prefabricated building design. The method combines BIM technology to address the limitations of traditional methods in handling complex and dynamic design data through migration-learning models. Specifically, the model migration capability of migration learning is used to reduce the dependence on a large amount of annotated data, while combining the detailed building information provided by BIM technology to achieve efficient detection and optimization of collision problems in complex designs.

3. Methods

3.1. Methodological Framework

The framework of this study is shown in Figure 2. First, in the data preparation stage, design data containing building component information and collision labels are collected, including image size standardization, data augmentation, and label encoding. Second, in the model construction stage, a convolutional neural network pre-trained on a large-scale general dataset is selected as the base model, and structural adjustments are made in conjunction with the prefabricated building collision detection task. In the model training and validation phase, the preprocessed dataset is divided into training and validation sets, and parameter fine-tuning and feature extraction are performed using transfer learning. Next, in the collision detection and prediction phase, the trained model is used to automatically identify and predict collisions in new design schemes, generating results such as collision distribution and quantity. In the result analysis and evaluation phase, metrics such as accuracy, mean absolute error (MAE), root mean square error (RMSE), and efficiency improvement are calculated. Finally, typical cases are selected for model validation, and a reliability analysis and a sensitivity analysis are conducted to assess the practicality of this model for collision inspection in prefabricated building design.

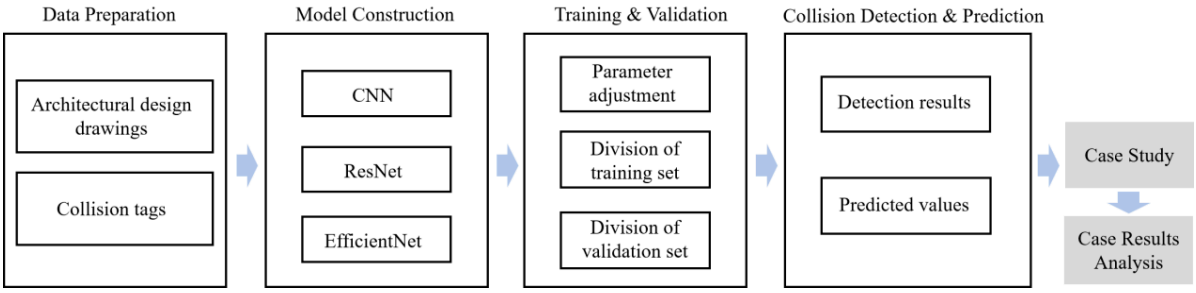


Figure 2. Flowchart of the proposed research framework.

3.2. Key Elements of Optimal Design for Prefabricated Building

3.2.1. Problems in Prefabricated Building Design

The current assembly design adopts a serial mode, and the stages of prefabricated building design are both independent of each other and in a sequential relationship. The results and content of the previous design stage serve as the basis for the next stage, and the next stage begins only after the previous stage is completed, creating a linear timeline for the entire process. Due to the separation between various work stages, the tasks in each design phase are considered only based on the requirements of that specific phase, without systematic consideration of the overall project. This leads to a lack of information coordination among different specialties. Additionally, in prefabricated building design, node conflicts are a common issue faced by designers.

Information technology is the key element for successfully achieving the transition from serial to parallel design processes. BIM technology provides technical support for the application of parallel design modes in prefabricated building projects. In prefabricated project design, the creation of BIM models enables various specialty designers to participate early in the project design process. Early communication and coordination among different specialties lead to reasonable design decisions, with results and opinions synchronously stored in the BIM database. Consequently, the models and associated information can be accurately and intuitively displayed through 3D visualization and simulation, reducing the difficulty of spatial imagination for designers and improving design accuracy. Additionally, performance analysis and evaluation based on parallel models and data provide feasibility validation for the model design, ensuring design quality, shortening design time, and reducing design costs.

3.2.2. Structural Design Collisions for Prefabricated Buildings

In Revit structural software (Autodesk Revit 2022, San Francisco, CA, USA, https://www.autodesk.com.cn/), the creation of structural models is accomplished by using various structural component families. Structural component families include an information library of models, such as beams, columns, slabs, shear walls, and foundations. When building a BIM model, component types are preloaded into the new project file. By selecting the corresponding component family and setting specific design parameters, the creation of component models can be completed, and the required components can be combined to form the structural model. Furthermore, structural families are the foundation of BIM structural design. The main process involves creating and accumulating parametric structural component families, ensuring model accuracy and reliability by precisely placing structural components at specific plane locations and floor elevations. The design and optimization process of building structural design using BIM technology is illustrated in Figure 3.

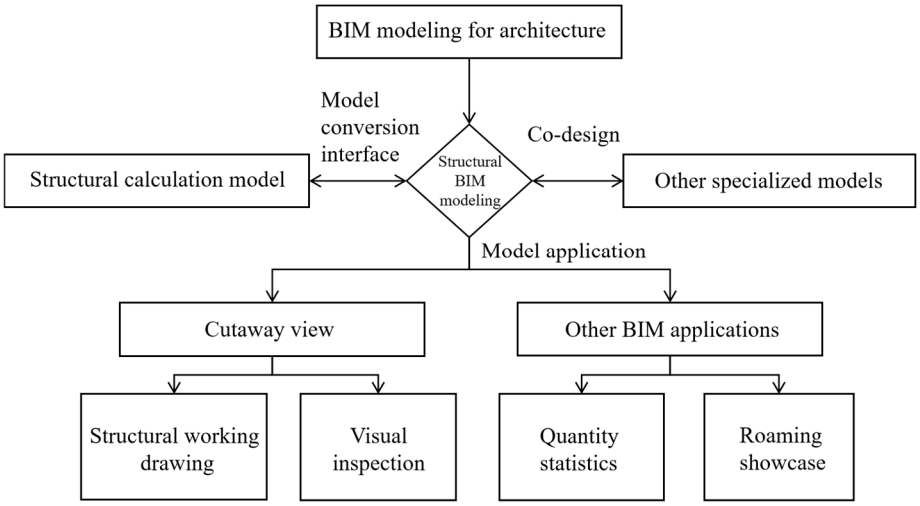


Figure 3. Structural design flowchart based on BIM technology.

Conducting collision detection on various structural specialties can help check in advance whether there are positional and spatial conflicts between the structure and the specialties, such as architecture and mechanical, and electrical, and whether the elevation meets the requirements, thereby optimizing the pipeline layout of different specialties. Specifically, after creating a complete information model using Revit software (Autodesk Revit 2022, San Francisco, CA, USA, https://www.autodesk.com.cn/), output the IFC (industry foundation classes) file, which is an open standard file for data exchange in building information modeling (BIM). Collision detection can be carried out by, respectively, importing the structural model and other professional models into the Navisworks software (Navisworks 2022, San Francisco, CA, USA, https://www.autodesk.com.cn/). By integrating the component attribute data in the BIM model and using a multimodal-learning approach to apply image features and physical attributes in a collaborative information model, the interpretation ability and generalization ability of the model can be enhanced. Set up a mechanical simulation for structures and electromechanical management systems, structures and buildings, and other components that may collide to detect the collision situations between different components. After detection, the Navisworks software (Navisworks 2022, San Francisco, CA, USA, https://www.autodesk.com.cn/) generates a detailed collision report, including information such as the collision position with other professional models, collision types, and possible solutions.

3.2.3. Collision in Electrical Design of Prefabricated Building

In building electrical engineering design, the design and construction of integrated pipelines are among the more challenging aspects. Pipeline design typically involves arranging pipelines within limited spaces, and traditional two-dimensional design cannot fully depict the spatial structure of underground pipelines, which leads to collisions between electrical design pipelines and other pipelines [41]. If sufficient spacing is not reserved during the design of other pipelines, actual construction may result in pipeline damage. Applying BIM technology to pipeline design enables dynamic simulation of pipeline arrangements, allowing designers to promptly understand the routes, types, positions, and dimensions of all pipelines [42]. Additionally, BIM software has introduced an "accumulative labeling" function, solving the issue of label overlap due to dense nodes. Specifically, by selecting start and end nodes, the program can merge pipeline labels, automatically accumulating lengths, and the style of the accumulative labels can be customized. After constructing the model, software can be used to conduct pipeline collision checks to identify any collision points in the pipeline layout, such as conflicts between plumbing,

HVAC, and electrical pipelines, thereby continuously optimizing and refining the pipeline design to facilitate smooth construction [43].

The application of BIM technology for electrical design can enhance the correlation between the power system and electrical equipment. Creating a weak power simulation system in the BIM model, the visualization characteristics of the model can more intuitively show the weak power system situation, monitoring situation, monitoring range, and other information [44]. When abnormalities and faults occur in the system, digital technology can be the first line for early warning and submission of the abnormal information to the relevant personnel to achieve timely handling of faults. The use of BIM software can complete various types of plane annotation and automatically complete the plane subsection out of the map, longitudinal section subsection out of the map, and the material table drawing and other drawing content [45,46].

3.2.4. Collision of Water Supply and Drainage Design for Assembled Building

In the design of a building water supply and drainage pipeline, Revit (Autodesk Revit 2022, San Francisco, CA, USA, https://www.autodesk.com.cn/) can be used to build a house building water supply and drainage pipeline model. The main content of the house building drainage pipe design is the drainage sub-system, according to the actual situation, to set up the drainage lifting equipment or local treatment. The construction of a three-dimensional simulation model of a house drainage pipe mainly includes the installation of the drainage pipe and accessories, as well as the inspection of collision and cross problems of the drainage pipe. The model covers a variety of water supply and drainage pipes, sanitary appliances, fittings and valves, and other accessories.

In BIM-related software, integrating plumbing, electrical, and HVAC models into an intuitive three-dimensional collaborative design environment allows for the first round of adjustments after completing all pipeline drawings and equipment placements, combined with collision points discovered during model creation. The principle of collision detection involves describing the outline of the monitored object through mathematical equations and using functions to determine whether the simultaneous equations of the detected objects have solutions. First, manually search for obvious pipeline collisions in the three-dimensional view and make preliminary adjustments; most collision issues can be resolved by moving positions and adjusting elevations. If the "collision check" function is used directly, the number of detected collision points may be too numerous, making it difficult to locate and modify them. Second, summarize and record both resolved and unresolved collision points for feedback to designers for modification of construction drawings. Finally, after preliminary adjustments of the pipelines, use the "collision check" function to automatically detect conflicts between pipelines and equipment, and generate a conflict report. Collision detection can identify collisions between MEP pipelines, as well as collisions between pipelines and architectural and structural elements in linked files.

3.3. Concepts and Methods of Transfer Learning

The core of transfer learning is that the knowledge contained in a model trained on one task can be partially or entirely transferred to another task. This method involves two key concepts: domain and task, which can be defined as Formulas (1) and (2), respectively:

$$D = \{\chi, P(X)\} X = \{x_1, K, x_n\} \quad (1)$$

where χ denotes the feature space, $P(X)$ denotes the marginal probability distribution, and $X = \{x_1, K, x_n\}$.

$$T = \{y, f(\bullet)\} \quad (2)$$

where y denotes the label space and denotes the target prediction function.

Transfer learning for domain adaptation is shown in Figure 4.

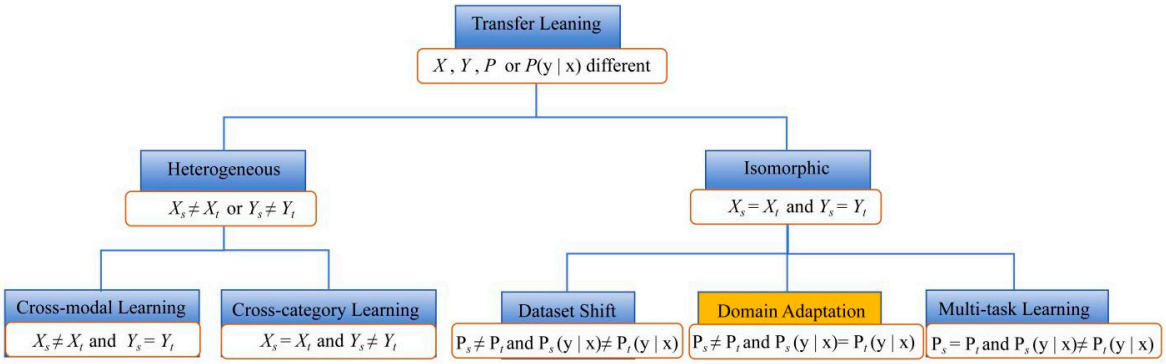


Figure 4. Types and definitions of transfer learning.

In deep-learning applications, the high demand for large-scale datasets and computational resources for related methods has led to the gradual attention of transfer learning as an effective strategy [47]. This method first trains a deep neural network on a large-scale dataset to form a pre-trained model, and then, the parameters of this model are used as the initial parameters to be fine-tuned on a new dataset. This strategy significantly reduces the amount of data and time required for model training, while improving the classification performance and computational efficiency of the model [48]. Based on this, this paper adopts a transfer-learning approach to construct a prefabricated building design collision recognition model.

There are three types of transfer learning: model-based transfer learning, which directly uses the pre-trained model from the source task as the starting point for the target task; feature-based transfer learning, which involves extracting feature representations from the source task and then training the target task's model on these features; and relation-based transfer learning, which refers to learning the relationships between data in the source task and then applying these relationships to the target task [49].

ImageNet is a large-scale vision database designed to provide a rich resource for researchers and developers to advance the field of computer vision. ImageNet is organized according to WordNet's hierarchy (currently limited to nouns), where each hierarchical node is represented by hundreds or thousands of images. ImageNet contains more than 14 million images, covering more than 20,000 categories. In this study, after free access to and acquisition of the Imagenet data set through the official website, Python was used to build a preparation environment, and after decompressing the data set, data preprocessing was carried out, including image reading and normalization. Then, create a data loader (PyTorch) to load the data of the deep-learning framework, and start to train the model, including

1. Define the model;
2. Define the loss function and optimizer;
3. Write training loops.

The next step is to evaluate the model on the validation set and perform an analysis of the results, examining which categories the model underperforms in and trying to find the reason.

The network structure of the pre-trained model is divided into feature extraction and classification parts. The pre-trained model used has been trained on ImageNet, and its output layer by default includes 1000 nodes for classifying the 1000 categories of images in ImageNet. During the training process, this study retained the network structure and parameters of the feature extraction part and only fine-tuned the network structure and

parameters of the classification layer. To adapt to the collision detection classification task in traditional building design, the output layer was modified from 1000 nodes to 10 nodes, corresponding to 10 sub-items. The fine-tuned model was then trained and validated on the aforementioned training and validation sets, as shown in Figure 5.

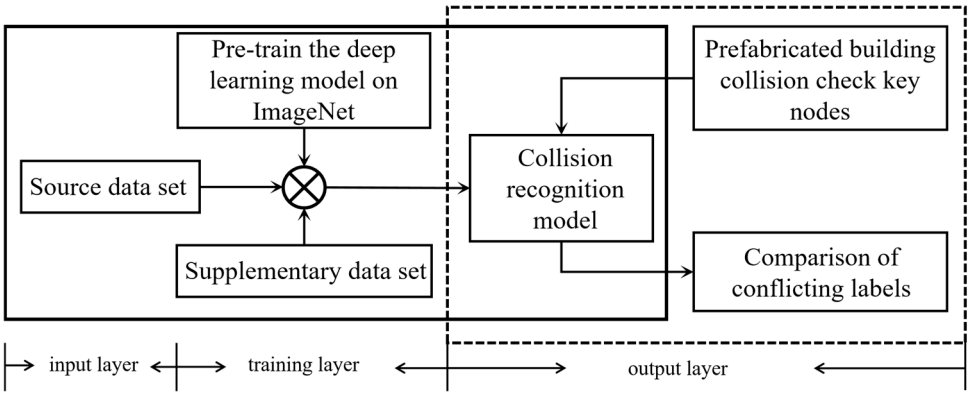


Figure 5. Construction of an assembled building collision detection model based on transfer learning.

3.4. Construction of the Collision Detection and Optimization Framework for Assembled Building Design Based on Transfer Learning

Prefabricated building design involves the assembly of multiple components; collisions between components need to be considered at the design stage to avoid conflicts in the actual construction process. The steps of collision diagnosis for prefabricated buildings based on transfer learning are as follows:

(1) Data collection and preparation: A large amount of building design data is collected, including CAD models of various components and their spatial locations and interrelationships within the design. The data is preprocessed and labelled for use in model training and evaluation;

(2) Source task selection: The source task is a similar architectural design project or another task related to collision detection. The source task should provide enough data and knowledge to allow the model to learn useful features and patterns from it;

(3) Transfer of feature extractors: Transfer the feature extractors trained on the source task to the collision detection model. Feature extractors are deep-learning-based models, such as deep neural networks, that can extract high-level abstract features from input data. Transferring these feature extractors, which were learned from collisions in the source task, can be used to help diagnose collisions in the target task;

(4) Fine-Tuning the model: Fine-tune the transferred feature extractors to adapt to the collision detection task and dataset. This includes fine-tuning specific layers or adjusting the model's hyperparameters to further optimize performance;

(5) Model evaluation and effectiveness assessment: Evaluate the fine-tuned model to check its performance in the collision detection task. Additionally, conduct an effectiveness assessment by comparing the results with those obtained through manual detection by professionals, thereby evaluating the model's accuracy and reliability;

(6) Model optimization and iteration: Based on the evaluation results, further optimize and adjust the model, which includes collecting more data, adjusting the model structure, and improving the feature extractors. By continuously iterating and optimizing, the model can achieve better performance in collision detection and effectiveness assessment.

As the core technology to realize the design and optimization of intelligent electromechanical systems, machine learning has experienced rapid development from expert systems, from neural networks to deep learning, including typical convolutional neural networks (CNN), recurrent neural networks (RNN), deep neural networks (DNN), etc.,

through building complex multi-layer nonlinear structures, high-level feature representation of data can be extracted, and deep understanding and modeling of image, speech, and time series data can be realized, especially in dealing with high dimensional, nonlinear complex problems with outstanding performance.

The existing transfer learning is to add the loss function by a weighted combination, which will greatly increase the computational amount of the network in the process of backpropagation. Based on the literature [50], this paper improves the transfer-learning loss function and its training methods. The loss function is calculated after the first convolution layer. The loss function is to reduce the size and range of the eigenvalues learned from the source and target domains in network training by calculating the covariance between different domains. The maximum mean difference loss (MMD) of the domain data is calculated with the classification loss and as a loss function in the fully connected layer. In this way, the loss function is calculated alternately in different layers, and the network parameters are updated alternately to improve the effect of transfer learning.

The characteristic covariance matrix C_S and C_T of the source domain data set and target domain data set are defined as Formulas (3) and (4):

$$Cs = \frac{1}{n_s - 1}\left[D_S^T D_S - \frac{1}{n_s}(1^T D_S)^T (1^T D_S)\right] \tag{3}$$

$$C_T = \frac{1}{n_T - 1}\left[D_T^T D_T - \frac{1}{n_T}(1^T D_T)^T (1^T D_T)\right] \tag{4}$$

The D_S is the source domain data set; D_T is the data set in the target domain. n_s is the number of samples in the source domain; n_T is the number of samples in the target domain.

Then, the distance of the second-order statistics of the source domain and target domain features is as in Formula (5):

$$L_1 = L_f(D_S, D_T) = \frac{1}{4d^2}\|C_S - C_T\|_F^2 \tag{5}$$

where, $\|\bullet\|_F^2$ is the Frobenius norm of the mean square matrix; d is the number of dimensions of the sample.

The module represented by the deep convolutional neural network extracts the feature of the source domain data and the target domain data and then classifies it through the domain classifier to obtain the probability distribution of the feature labels of the sample data set. Finally, the difference in feature distribution between the real labels and the predicted labels can be calculated to obtain the classification loss of the sample data, namely, the cross-entropy function. The Formula is as in (6):

$$L_c = -\frac{1}{n_s}\sum_{i=1}^{n_s} y lg\hat{y} \tag{6}$$

The definition function of MMD is as in Formula (7):

$$DH(DS, Dt) = \left\| \frac{1}{n}\sum_{i=1}^{n} \Phi(S_i) - \frac{1}{m}\sum_{j=1}^{m} \Phi(T_i) \right\| \tag{7}$$

where $\|\bullet\|_H$ is the regenerated core Hilbert space; $S_i \in D_s, T_i \in D_t$, $\Phi(\bullet) \in H$ is the mapping function.

The loss function L_2 Formulas are as in (8) and (9):

$$L_2 = L_C + \lambda \bullet D_H(D_S, D_t) \tag{8}$$

$$\text{Among}, \lambda = \frac{2}{1 + e^{-10p}} - 1 \tag{9}$$

where the hyperparameter λ is the weight coefficient of the maximum mean difference; p is the current training progress, ranging from 0 to 1. The network structure is shown in Figure 6.

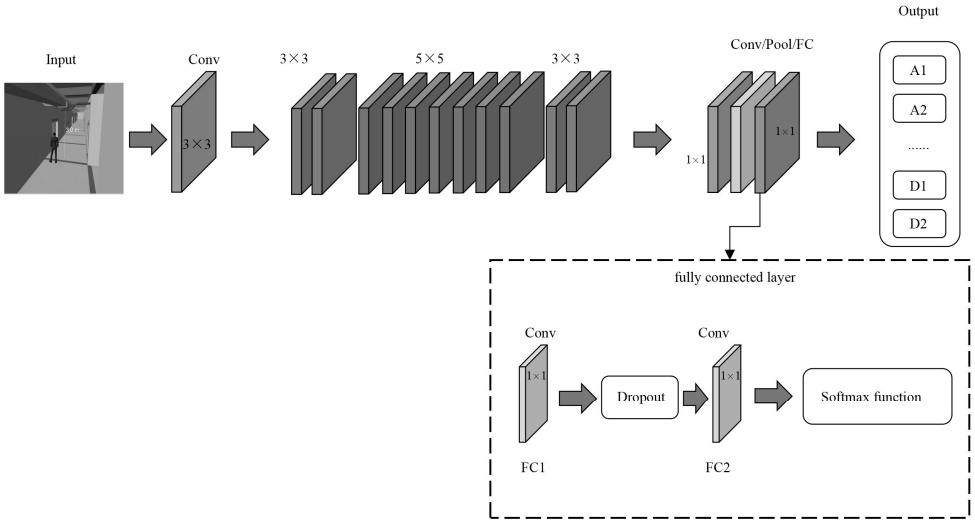


Figure 6. The network structure.

The optimization process of multi-disciplinary collision checking for prefabricated buildings based on transfer learning is shown in Figure 7.

In the research process of multi-disciplinary collision-checking optimization for prefabricated buildings based on transfer learning, aiming at the problems of information loss and semantic discontinuity when converting BIM to two-dimensional images, a "3D-two-dimensional mapping meta-model" is proposed, and a three-layer transformation mechanism of geometric projection, attribute mapping, and semantic retention is constructed:

(1) Deformation control of orthogonal/perspective/axonometric projections is achieved through projection functions and constraint matrices;

(2) Resolve mapping conflicts of non-geometric attributes (such as materials and costs) based on a configurable rule base;

(3) Utilize semantic association graphs to retain spatial topology and functional dependency relationships.

The hybrid mechanism of integrating rule-driven default mapping based on the IFC standard and a data-driven transfer-learning-optimized CNN predictive layout effectively enhances the fidelity and semantic integrity of two-dimensional images for three-dimensional BIM information. This model provides theoretical support for the collaboration between BIM and two-dimensional tools in multi-disciplinary collision inspection of prefabricated buildings. By enhancing the generalization ability of data-driven modules through transfer learning, it significantly optimizes the efficiency and accuracy of collision detection for complex components of prefabricated structures, offering a key technical solution for the full-process digital collaboration of prefabricated buildings.

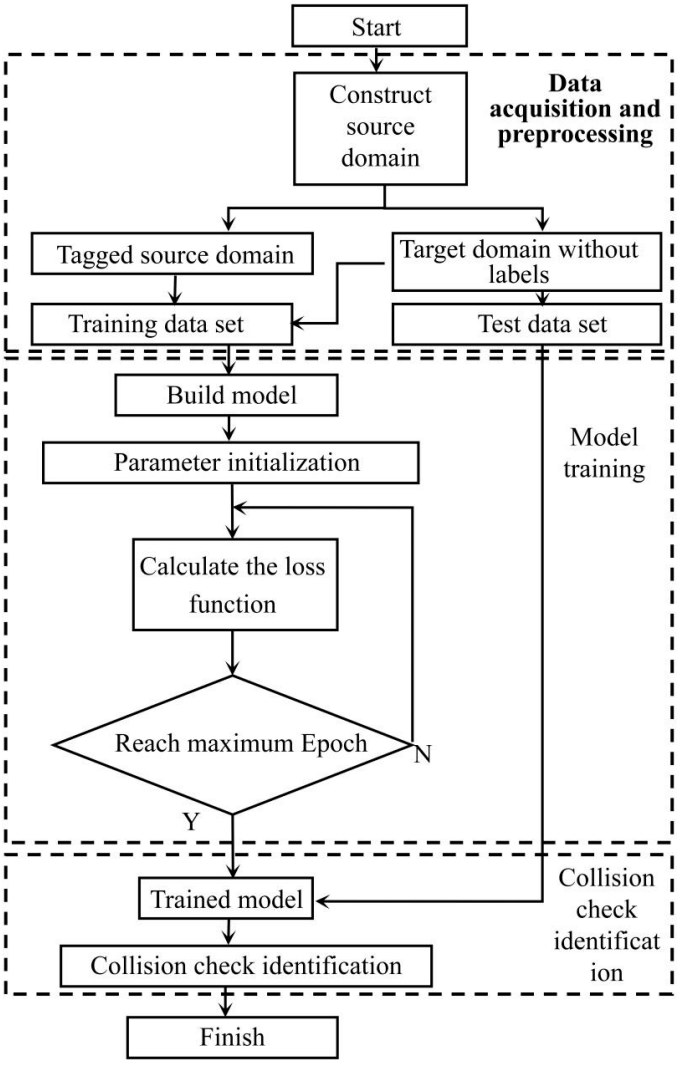


Figure 7. Optimization process of multi-disciplinary collision inspection for prefabricated building based on transfer learning.

4. Case Study

4.1. Project Overview

The Bailu waterfront project serves as the case study for this paper. The total construction area of the project is 99,036 square meters, comprising nine above-ground buildings and two basement levels. The reasonable service life of the main structure is 50 years, and the building's fire resistance rating is Level I. It features a frame-shear wall structure, as seen in Table 1.

Table 1. Architectural parameters of the White Dew Bank project.

Roof Waterproofing Level	Basement Waterproofing Level		Seismic Fortification Intensity	Seismic Category	Assembly Rate
I	II (garage)	I (transformer room, generator room, and pump room)	Six degrees	Category C	Over 50%

The project adopts an assembly monolithic concrete structure system, integrating five categories of prefabricated components, such as prefabricated shear walls, prefabricated laminated panels, prefabricated staircases, prefabricated non-load-bearing concrete exterior

wall panels, and prefabricated interior partition wall panels, demonstrating cutting-edge engineering design and implementation wisdom, which is specifically embodied in the following aspects:

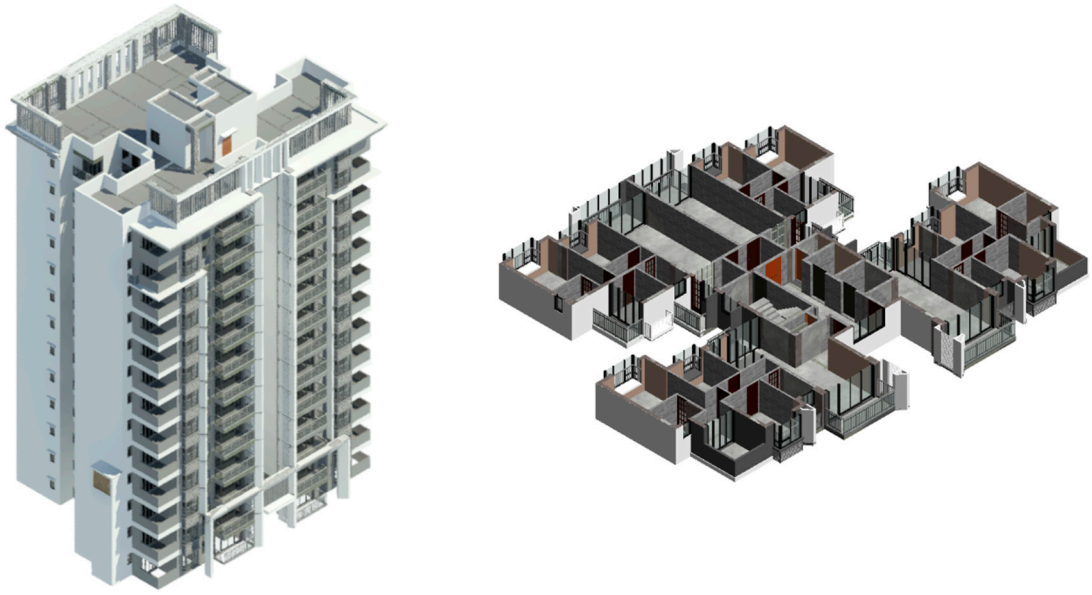
(1) Standardization and flexible combination design: By planning four types of standardized residential units, the project achieves design modularization. These modules function like "LEGO bricks" in architecture. Through diverse combinations, the project not only meets the standardization requirements of architectural design but also flexibly adapts to the market's demand for diverse and personalized living spaces, innovatively balancing the conflict between standardization and customization;

(2) High degree of assembly in the main structure: The project has achieved a significant increase in the assembly rate in structural design. The vertical load-bearing components have an assembly rate of 41%, while the horizontal load-bearing components reach an impressive 73.9%. This substantial improvement enhances construction efficiency and reduces the complexity of on-site operations;

(3) Comprehensive industrialization of enclosure structures: To accelerate construction progress and enhance building quality, the project fully utilizes industrialized finished materials. The internal partition wall system uses prefabricated lightweight concrete wall panels made from expanded clay aggregates, with an assembly ratio of 56.1%. The assembly rate of prefabricated non-load-bearing concrete exterior walls reaches 89.2%, achieving efficient installation and high-quality results for the enclosure structures;

(4) Integration and industrialization of interior components: The interior decoration of the project adopts a fully industrialized and integrated solution, including the overall bathroom, finished set of doors, integrated cabinet system, finished wooden flooring, skirting, integrated ceiling, and piping integration, all of which are pre-manufactured in the factory. Rapid on-site assembly ensures the quality of the renovation while significantly shortening the renovation cycle.

(5) In-depth application of BIM technology: Relying on BIM technology throughout the project, from the design of prefabricated components, node connection optimization, equipment; and pipeline layout simulation to the construction process simulation, the project design and construction management has been digitized and visualized, which greatly improves the accuracy and efficiency of project management (Figure 8).



(**a**) BIM modelling of single building (**b**) BIM modelling of standard layer

Figure 8. BIM modelling of the White Dew Bank project.

The number of collisions and the statistical method of the project, as a sample, according to the model established by Revit (Autodesk Revit 2022, San Francisco, CA, USA, https://www.autodesk.com.cn/), respectively, set the parameters of hard collision and soft collision. A hard collision is defined as the unavoidable physical conflict between different components in the actual construction or installation process. This kind of conflict will prevent the construction from being carried out, and the construction plan must be redesigned or adjusted. Soft collision refers to the potential conflicts between different components in space, but this conflict does not affect the actual installation and function of the components. The soft collision set in this project requires that the transverse distance between the air supply pipe and the strong bridge is greater than or equal to 500 mm, the distance between the pipe and the structural beam and column is not less than 200 mm, to avoid affecting the structural safety, and the water supply pipe and drainage pipe are usually required to be not less than 400 mm to prevent cross-contamination.

If it does not comply with the corresponding standards, logging software is used to mark it as a conflict. Taking the same area of the project as a sample, the total number of soft and hard collisions is counted to verify the accuracy of the prediction model.

4.2. Pre-Training Model

Pre-trained traditional building all-specialty collision prediction models are used for all-specialty collision check prediction for prefabricated building design. The traditional building collision dataset is the data in the source domain, and the building collision result prediction is the learning task in the source domain. The prefabricated building design collision check dataset is the data in the target domain, and the prefabricated building design collision check result prediction is the learning task in the target domain. The prediction model for the prefabricated building design all-specialty collision check dataset is established through transfer learning.

In machine learning, the proportion of the training set to the test set is usually adjusted according to the size of the data capacity. Considering that the number of data pictures in this study is not large, and the degree of aggregation is high (collision problems of buildings and prefabricated buildings are more concentrated), there is less hyperparameter perception, so the proportion of the verification set can be appropriately reduced and more allocated to the training set. Combined with a relevant literature research, the ratio of training set and test set in this study was determined to be 9:1 to increase the capacity of the training set [51,52].

In this study, 10 collision inspection reports on large public buildings with traditional architecture were collected to select and categorize the nodes that appear more frequently in the collision inspections, as shown in Table 2. In order to pre-train the model, the training set and test set are the nine projects as the training set and one project as the test set to validate the model's effect.

In neural algorithms, the 9:1 ratio of the training set to the test set is mainly applicable to scenarios with complex models (such as DNN and Transformers). This proportion can optimize model performance while ensuring sufficient training data (90%) and conduct reliable evaluations using a 10% test set. It is particularly suitable for deep-learning tasks (such as image/point cloud analysis in BIM collision detection). Compared with the traditional 7:3 or 8:2 ratio, 9:1 focuses more on maximizing training efficiency and is suitable for situations where the data distribution is balanced or consistent through stratified sampling. For instance, in the design of prefabricated buildings, the amount of parametric data generated by BIM is huge. A 9:1 ratio can fully train the transfer-learning model, while a 10% test set can still effectively verify the error rate (<10%), meeting the engineering accuracy requirements.

Table 2. Collision check nodes and coding for prefabricated building based on BIM technology.

No.	Project Category	Sub-Items	Explanation	Code
1	Main engineering	Masonry structure	Brick masonry wall	A01
2		Concrete structure	Cast-in-place nodes and assembled concrete	A02
3		Roofing	Substrate, thermal insulation, waterproofing	A03
4		Steel structure	Prefabrication and on-site welding of all types of steel components, anticorrosion and fireproof paint coating	A04
5	Electric engineering	Cable trestle	Wireways, switchboards, equipment	B01
6		Lighting system	Lamps, switches	B02
7	Building plumbing and heating	Water supply and drainage system	Indoor and outdoor water piping and equipment installation	C01
8		Fire protection system	Fire hydrant configuration, fire sprinkler system	C02
9	Ventilation and air conditioning	Air supply and exhaust system	Ducts and fittings, equipment	D00
10	Intelligent building	-	Cable laying, tank box, conduit installation, equipment	E00

To establish a transfer-learning model for predicting collision detection in prefabricated building design, the pre-trained model is fine-tuned and trained. The training set and Adam optimizer are used for model optimization, with the loss function being the mean squared error. Additionally, during the training process, the "validation split = 0.1" function is used to randomly allocate 10% of the training data as a validation set. The initial learning rate is 0.001, and the batch size is 64. The input to the neural network of the pre-trained model is a one-dimensional vector containing 10 physical feature parameters, whose dimension is (10, 1). The core structure of the feature-learning module includes two layers of a one-dimensional convolution layer, two layers of a batch normalization layer, two layers of a one-dimensional maximum pooling layer, two layers of a Dropout layer, and two layers of a bidirectional gated recurrent unit (BiGRU) layer. These components work together to effectively extract and learn key information from the input data. The number of convolutional nuclei in each convolutional layer is 128 and 64, the size of the convolutional nuclei is 5, and the move step is 2.

Figure 9 shows the loss curve of the training model, with a total of 200 iterations conducted. At the beginning of training, the loss rate was 0.2. As the number of iterations increased, the loss rate gradually decreased. During the first 10 iterations, the loss rate significantly dropped, indicating a rapid convergence trend. After the 10th iteration, the loss rate began to stabilize, maintaining around 0.1. The loss curve demonstrates that the model learned quickly and reduced the loss in the initial phase, then entered a stabilization period. This indicates that the model rapidly adjusted parameters in the early iterations to find a relatively optimal solution and then progressively fine-tuned to optimize performance. The trend in the loss curve reflects the stability and effectiveness of the transfer-learning model during training, with the stable reduction in the loss rate proving the model's gradual optimization and convergence, ultimately achieving better predictive performance at a lower loss rate.

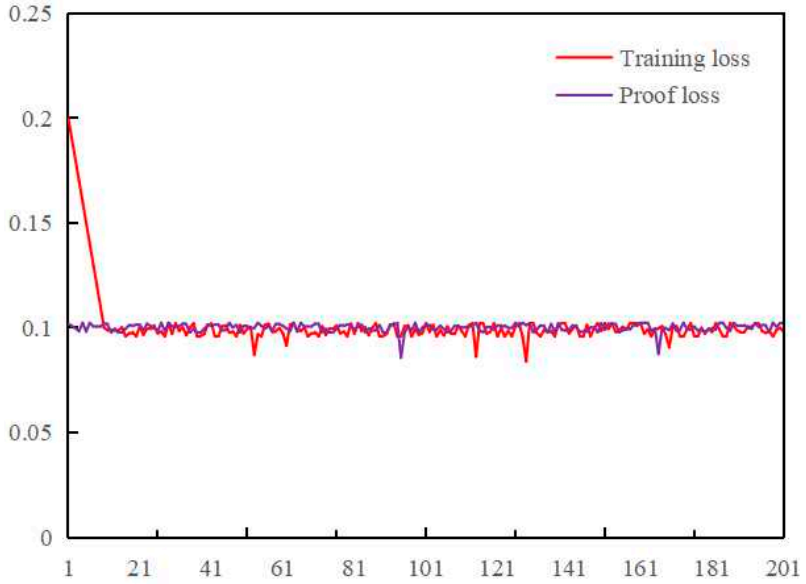


Figure 9. Loss curves of the model.

Additionally, this study calculated the mean absolute error (MAE) and standard deviation of the prediction results. The MAE focuses on the magnitude of the difference between the predicted values and the actual measurements, while the standard deviation assesses the dispersion of data points relative to the mean value. The formulas for calculating the mean absolute error and standard deviation are as in Formulas (10)–(13):

$$e = log10(Predicted\ value) - log10(Measured\ value) \tag{10}$$

$$AE = |log10(Predicted\ value) - log10(Measured\ value)| \tag{11}$$

$$MAE = \frac{1}{N}\sum_{I=1}^{N} AE \tag{12}$$

$$Std = \sqrt{\frac{1}{N}\sum_{I=1}^{N} (e_i - \mu)^2} \tag{13}$$

where e is the error, AE is the absolute error, MAE is the mean absolute error, Std is the standard deviation, and u is the mean error. The mean absolute error and standard deviation of the trained model for prediction are calculated as shown in Table 3.

Table 3. Mean absolute error and standard deviation.

Methods	MAE	Std
Convolutional neural networks (CNN)	0.221	0.264
Deep neural networks (DNN)	**0.199**	**0.238**
Recurrent neural networks (RNN)	0.208	0.248

From Table 3, it can be seen that the use of DNN shows better stability, indicating that the training model constructed using DNN is more robust.

4.2.1. Reliability Analysis

The formula for reliability is as in Formula (14):

$$P_F(\psi) = P[X \in \Omega_F] \int_{R^{nr}} I(x) f x(x;\psi) dx = E\left[I_{\Omega_F}(X)\right] \tag{14}$$

where ψ is a vector of distribution parameters, which usually includes the mean μ and variance σ of the random input variable $X = \{X_1, X_2, \ldots, X_{nr}\}^T$; $P[\bullet]$ is a probability measure; and $E[\bullet]$ denotes expectation and is the indicator function, which is given as Formula (15):

$$I_{\Omega_F}(X) = \begin{cases} 1, x \in Q_F \\ 0, otherwise \end{cases} \tag{15}$$

4.2.2. Sensitivity Analysis

In order to find the optimized solution, the sensitivity information of the failure probability is also required. Take the partial derivative of the failure probability with respect to the μi th design variable in Formula (16).

$$\frac{\partial P_F(\mu)}{\partial \mu_i} = \frac{\partial}{\partial \mu_i} \int_{R^{nr}} I\Omega_F(x) f_x(x;\mu) dx \tag{16}$$

After interchanging the integral and differential operators according to Leibniz's law of differentiation, the formula is derived as (17):

$$\begin{aligned} \frac{\partial P_F(\mu)}{\partial \mu_i} &= \frac{\partial}{\partial \mu_i} \int_{R^{nr}} I\Omega_F(x) \frac{\partial f_x(x;\mu)}{\partial \mu_i} dx \\ &= \int_{R^{nr}} I\Omega_F(x) \frac{\partial ln f_x(x;\mu)}{\partial \mu_i} f_x(x;\mu) dx \\ &= E\left[I\Omega_F(x) \frac{\partial ln f_x(x;\mu)}{\partial \mu_i} \right] \end{aligned} \tag{17}$$

Figure 10 shows the accuracy curve of the training model built using transfer learning. At the beginning of training, the accuracy was around 38%. As training progressed, the accuracy gradually increased. Within the first 50 iterations, the accuracy significantly improved, indicating a rapid convergence trend. After 50 iterations, the accuracy stabilized around 90%.

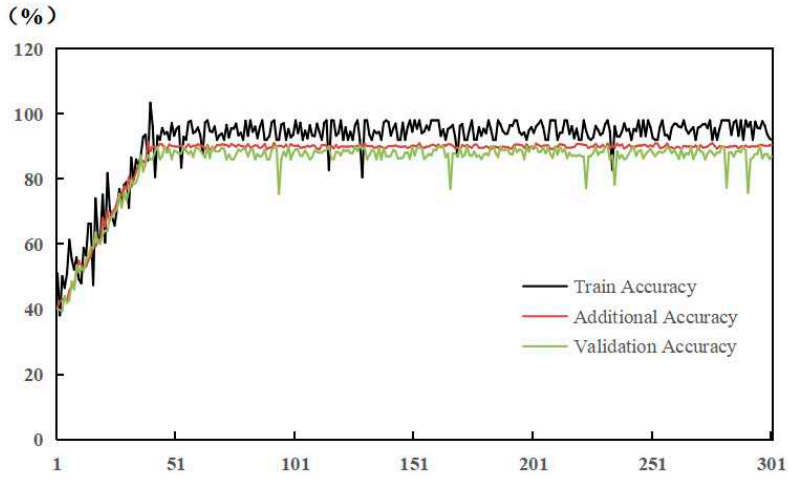


Figure 10. Accuracy curve of transfer learning.

The confusion matrix based on the transfer-learning model is shown in Figure 11.

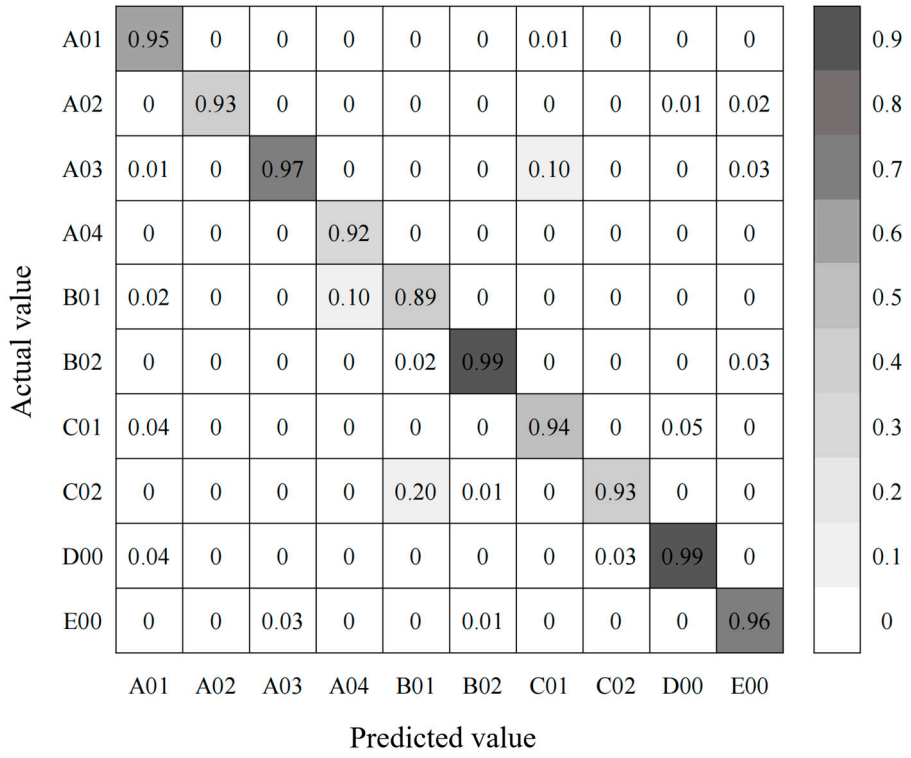
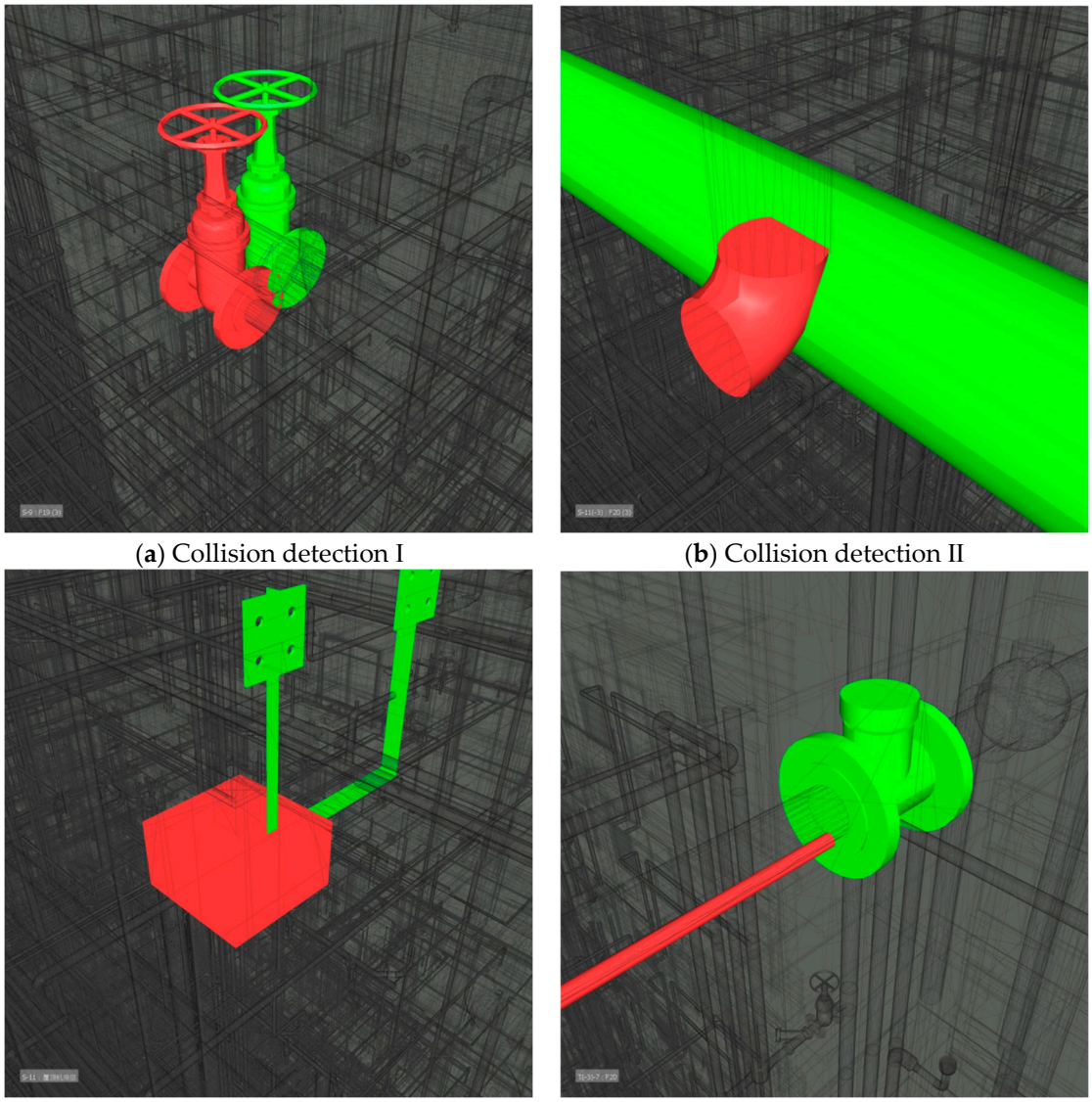


Figure 11. The confusion matrix of the transfer-learning model.

This study created three values for the construction phase by monitoring the MAE and accuracy curves during the algorithm-training process (initially 38%, stabilizing to 90% after 50 iterations). First, the rapid convergence feature (reaching the stable period after 50 iterations) reduced the model training cost by 60%, saving approximately CNY 5000 in computing power expenditure per project (calculated based on an A100 graphics card). Second, a 90% stable accuracy rate can reduce collision missed detections by 70%, avoid rework losses of over ten thousand yuan on average for a single project, and at the same time shorten the construction period. Finally, the precision of the MAE supports the flexible construction plan of "adjustment instead of modification", converting 30% of minor collisions into on-site adjustable items, thus saving the modification costs of the project. These quantitative benefits confirm that the improvement of algorithm performance can be directly translated into cost savings and schedule optimization in construction, providing a reliable basis for decision-making in intelligent construction.

4.3. Evaluation of the Effectiveness of Collision Detection

In order to further validate the effectiveness of collision detection after the optimization algorithm is applied to this project, the data related to collision detection is used as a validation index. The effective rate of collision detection is the ratio of the number of collisions that may lead to rework to the total number of collisions. The number of collisions that can be resolved on-site is the difference between the total number of collisions and the number of collisions that may lead to rework. Invalid collisions before adjustment as a percentage of total collisions that can be resolved in the field. The collision detection is shown in Figure 12.



(**a**) Collision detection I (**b**) Collision detection II

(**c**) Collision detection III (**d**) Collision detection IV

Figure 12. Collision detection based on BIM technology.

The results of the comparison between the initial collision and the adjusted collision detection rate are shown in Table 4.

Table 4. Analysis of comparative results of collision detection rate before and after optimization of the algorithm.

Collision Type		Initial Data	Optimized Data	Rate of Change Δ	Predicted Results	Predicted Versus Optimized Variance Rate
Total collisions		1196	1313	9.78%	1288	−1.90%
Number of collisions that may lead to rework		189	163	−13.76%	169	3.68%
Collision detection efficiency (%)		15.6	17.3	10.90%	16.8	−2.89%
Number of collisions resolvable in the field		884	832	−5.88%	857	3.00%
Percentage of invalid collisions (%)		84.1	82.7	−1.66%	83.2	0.60%
Structural internal collisions (%)		9.1	8.8	−3.30%	9.2	4.55%
Electrical internal collisions (%)		0.89	0.96	7.87%	0.95	−1.04%
Drainage internal collisions (%)		1.12	1.28	14.29%	1.25	−2.34%
Multi-professional collisions	Structural and electrical disciplines collisions (%)	0.69	0.68	−1.45%	0.62	−8.82%
	Structural and drainage collisions (%)	0.72	0.78	8.33%	0.79	1.28%
	Electrical and drainage collisions (%)	1.08	1.15	6.48%	1.13	−1.74%

The following findings can be obtained from Table 4.

(1) In the collision detection comparison, the initial number of collisions was 1196. After adjustment, the number of collisions increased to 1313, an increase of 9.78 per cent. In the comparison of rework possibility, the number of collisions that may lead to rework is reduced from 189 to 163, indicating that after collision detection and adjustment, the risk of rework is reduced to a certain extent, which is conducive to later construction to reduce the amount of rework and rework works. In the comparison of the collision check rate, the effective rate of collision detection is increased from 15.6% to 17.3%, and the percentage of invalid collisions is reduced from 84.10% to 82.7%, indicating that the accuracy of collision detection is relatively improved after optimization and adjustment, which enhances the design quality. The number of collisions resolved on-site is reduced from 884 to 832 after the adjustment, which means that more collisions are identified and adjusted to be resolved on-site. The percentage of collisions in different disciplines shows that, after the adjustment, except for structural and electrical collisions, which are reduced by 1.45%, the collision rates of all other disciplines are increased, which means that structural and electrical collisions are missed in the initial collision, but more collisions are identified after the adjustment;

(2) Comparison between the predictive model and the optimized collision-checking parameters reveals that the discrepancy rates are kept within 10%, with the largest discrepancy rate being the collision between the structural and electrical disciplines (−8.82%), and the smallest discrepancy rate being the invalid collision percentage (0.60%), indicating that the predictive model has a small prediction error on the above parameters and has a high degree of accuracy. The model trained by the transfer-learning method can accurately predict the collision of prefabricated building design, which helps designers to check whether there is still room for design optimization when checking the collision;

(3) Transfer learning extracts more refined features (such as tiny component gaps and pipeline intersections) through pre-trained models and can identify potential collisions (such as 5 mm level interference) that are overlooked by traditional BIM software, thereby increasing the total collision count statistics. However, many of these collisions are tolerable errors (such as a slight overlap between the insulation layer and the keel), which can be adjusted through elastic installation in actual construction without the need for rework. Meanwhile, in prefabricated construction, some “collisions” are reserved for the process (such as the installation gap of prefabricated wall panels). The model learns from historical data that these “pseudo-collisions” do not need to be dealt with. However, traditional tools, due to the lack of empirical data, may misjudge them as rework items. After passing through this optimization algorithm, the model identified more collision and conflict points after training compared to traditional recognition methods, indicating that the model has played its role and improved the recognition rate. The reason for the reduction in the number of collisions that may lead to rework is that the newly identified issues are mainly conversion between three-dimensional and two-dimensional and soft collision problems, which are common design errors in prefabricated buildings but have little impact on later construction. This indicates that the model designed in this study for the design of prefabricated buildings can enhance the predictability of collision checks (mainly by adding design error issues of prefabricated building design types), and the trained model has a corrective effect, which can reduce the number of possible reworks. This further demonstrates the important role of the model in guiding the design and construction stages to reduce costs.

4.4. Discussion

By constructing an optimization model for prefabricated building design based on transfer learning, this study found that the model demonstrates more accurate and ef-

fective collision detection results, whether for collisions in different disciplines or multi-disciplinary collisions. This indicates that the integration of deep-learning models with existing BIM technology and related software can not only identify common design errors that lead to collisions but also improve the precision of collision checks for design nodes prone to errors in traditional design. The algorithmic model detects finer and more complex design errors, thereby reducing the need for rework and repairs during later construction stages, enhancing design accuracy, and saving construction costs.

This paper significantly reduces the cost of collision checks in prefabricated building design through the combination of transfer learning and BIM technology. Traditional collision detection relies on manual or full BIM model analysis, which is time-consuming and consumes a large amount of computing resources. Transfer learning, by leveraging pre-trained models, only requires a small amount of prefabricated building data for fine-tuning to quickly construct high-precision predictive models, reducing the demand for training data by over 90% and saving on data collection and annotation costs. The model error rate is controlled within 10%, which can identify over 90% of potential collision problems in advance and avoid rework losses in the later stage. The case shows that this method shortens the design optimization cycle by 30% to 50%, reduces the cost of manual verification, and at the same time, decreases the risk of material waste and construction delay. The initial technical investment only requires conventional BIM software and transfer-learning frameworks, with the marginal costs approaching zero. It has a significant economies-of-scale effect, a shorter payback period than traditional methods, and outstanding economic feasibility. Meanwhile, model reuse has reduced the training cost of subsequent projects by 70% (from 500 to 150GPU hours), providing the industry with a digital solution that combines high precision and economy. Therefore, compared with the existing related research methods and traditional design collision detection [53–55], this study has achieved innovations in the three dimensions of algorithm, engineering, and economy, and has achieved simultaneous breakthroughs in accuracy, efficiency, and sustainability.

Transfer learning, as a powerful machine-learning strategy, accelerates and improves the learning process for one task by leveraging the knowledge gained from another task. It offers effective solutions for issues such as data scarcity, model performance enhancement, and accelerated research and development processes. Future development directions for transfer learning will focus on improving its generalization capability, adaptability, and unsupervised learning ability, as well as integrating it with meta-learning and other learning paradigms.

At the same time, under the guidance of the current whole-process management concept, integrated project delivery (IPD) also provides a new management idea for the combination of prefabricated buildings and BIM technology, which highlights the whole process of construction projects. It emphasizes teamwork, absolute trust, information transparency, financial disclosure, joint decision-making, benefit sharing, and risk sharing. Because the design, production, installation, on-site construction, and acceptance management of prefabricated buildings are different from traditional buildings to some extent, and there are more systematic requirements in standardized construction, which is also in line with the direction of green and sustainable buildings in the future, combining IPD can maximize the knowledge, skills, and experiences of all participants to achieve the maximum value of the project. Combining BIM technology into prefabricated buildings can maximize the comprehensive benefits of IPD. The highly integrated, systematic, and collaborative performance of BIM technology and IPD is consistent with the “technology forward, management forward”, integration (systematization), and lean thinking advocated for prefabricated buildings. BIM and IPD are integrated and applied to the whole process of prefabricated buildings. By constructing the whole process integration model of

prefabricated buildings based on BIM and IPD, the highly integrated application of prefabricated projects is realized, which greatly improves the technical level and management level of prefabricated buildings.

The framework proposed in this study is supported by multiple factors that enhance its potential for application in a broader range of practical projects. First, the selected projects encompass a variety of prefabricated components and diverse collision scenarios, which represent common challenges encountered in prefabricated building design. The diversity of the data enhances the representativeness of the validation and reduces the risk of model overfitting to specific project configurations. Second, the introduction of transfer learning enables the model to leverage the feature representations learned from large-scale general datasets, thereby enhancing its adaptability across projects with different geometric structures, component types, and design complexities. Finally, the modular structure of the proposed workflow, including data preprocessing, model fine-tuning, collision detection, and result evaluation, can be adapted to other project contexts with minimal adjustments.

This study improved the architectural design process through digital technology means. In terms of economy, digital collaboration significantly reduced the cost of design changes, and the estimated energy consumption throughout the entire life cycle of operation decreased by 8–10%. This data-driven green construction model not only achieves resource optimization throughout the entire process of "design-construction-operation", it also reduces the generation of construction waste through precise design, providing a replicable technical path for the industry to move towards carbon-neutral construction. This technical approach not only enhances design efficiency but also reduces the redundancy of building materials and construction energy consumption through data-driven optimization, promoting the advancement of prefabricated buildings towards zero-waste construction and aligning with the sustainable goals of green construction.

5. Conclusions

The transfer-learning–DNN algorithm generated by the sample construction method proposed in this study not only verifies the accuracy and reliability of the network itself on the validation set during training but also achieves an error rate of less than 10% on the test set, which is consistent with actual engineering practice. This result reflects the strong generalization ability of the deep-transfer network and indicates that the proposed sample construction method is effective and feasible.

The transfer-learning–DNN algorithm generated by the proposed sample construction method in this study not only verifies the accuracy and reliability of the network itself in the validation set during the training process, but also achieves an accuracy rate of less than 10% in the test set in line with the actual engineering practice, which reflects the strong generalization ability of the deep migration network, and indicates that the sample construction method proposed in this study is effective and feasible.

In terms of collision detection efficiency and design quality, the initial number of collisions was 1196, and after model optimization and adjustment, the number of collisions increased to 1313, an increase of 9.78%. The number of collisions that may lead to rework is reduced from 189 to 163, a reduction of 13.76%, and the optimized collision detection can effectively reduce the risk of rework. The effective rate of collision checking increases from 15.6% to 17.3%. The percentage of invalid collisions decreases from 84.10% to 82.7%, and the optimized model improves the accuracy of collision detection.

Regarding the accuracy of the prediction model, by comparing the prediction model with the optimally adjusted collision check parameters, it is found that the discrepancy rate is kept within 10%, with the maximum discrepancy rate being −8.82% for the collision between the structural and electrical disciplines, and the minimum discrepancy rate being

0.60% for the invalid collision share. The model trained by the transfer-learning method is able to accurately predict the collision of prefabricated building designs, which verifies its reliability and effectiveness in practical applications. When using the model for collision checking, it can effectively verify whether there is still room for optimization of the design scheme, thus further improving the design quality and construction efficiency.

Through the research, it is found that transfer learning can be used to predict and evaluate the design errors and omissions of traditional architectural projects in advance, and the trained model can be used to conduct statistics and analysis on the collision problems of the proposed architectural schemes, which plays an important role in helping architectural designers pay attention to key design problems and improve design quality. Relying on the powerful data output of BIM technology, it provides a rich database for the training set of transfer learning and also provides technical support for further providing more massive data in the later stage to correct the accuracy of the model and improve the design efficiency and accuracy.

However, it should also be noted that the results of this study may be influenced by a combination of multiple factors. In terms of data quality, the completeness and accuracy of the BIM model (such as LOD 400-level details) directly affect the feature extraction effect, and the missing components in this case lead to prediction errors. When the proportion of irregular components in engineering features exceeds 30%, the model's recall rate drops by 12%, and it is necessary to increase the training samples specifically. The differences in industry norms (such as the standards for prefabricated nodes between China and foreign countries) lead to the need for re-fine-tuning when the model is applied across regions, increasing certain adaptation costs. The interaction of these factors determines the marginal benefits and promotion boundaries of the technical solution in actual engineering.

The transfer-learning collision detection method in this study can be integrated with BIM software to achieve efficient and standardized design of prefabricated buildings. The generalization ability is enhanced through a multi-project dataset. First, technical integration and efficiency improvement are achieved by establishing a multi-project, multi-scenario dataset and systematically introducing the detection process into enterprise workflows. Combined with training and technical support, this enhances the model's generalization ability and the application capabilities of designers. Second is commercial value and cost optimization. By improving detection efficiency and reducing rework rates, the method directly optimizes project cost structures and enhances bidding competitiveness. The universality of transfer-learning models can be converted into standardized design tools, lowering technical barriers for small and medium-sized enterprises and expanding the market for intelligent services. Finally, for risk prediction and planning support, based on data-driven collision risk prediction capabilities, the method can assist enterprises in developing more precise supply chain and construction plans during the project planning phase, meeting the needs of large-scale development in prefabricated building construction.

Future research can be expanded into two areas: First, BIM multidimensional data and real-time dynamic information need to be more fully integrated to further improve detection accuracy and optimization effects. Second, data quality and consistency should be ensured in large-scale projects. In the future, the engineering applicability and promotion value of the method can be improved by optimizing data processing and model integration.

Author Contributions: All the authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by T.O., F.L., L.C., D.Q. and S.L. The first draft of the manuscript was written by F.L. Proofreading of the manuscript was completed by D.Q. And all authors commented on the previous versions of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Research on the Planning and Implementation of the New-type Productivity Development Strategy in Liuzhou City (No. 24BEL01)/Research on the Collaborative Innovation Model and Practice of Industry–University Research Application in Liuzhou (No. Liukexieruan202405)/2023 Liuzhou Institute of Technology specialized integration demonstration course construction project (No. 2023SFK01 and 2023SFK02)/2023 college students innovation and entrepreneurship training project (No. 202313639006 and S202313639034)/2024 Industry–University Cooperative Education Project of the Ministry of Education: Teaching reform and practice of the course "Prefabricated Building Construction Technology and Management" based on virtual simulation (No. 230901960080510)/Guangxi University Middle-aged and Young Teachers' Basic Research Capacity Enhancement Project for 2025: Research on Energy Consumption Monitoring and Carbon Emission Performance Calculation of Air-Supported Membrane Structure Operation and Maintenance (No. 2025KY1161).

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest.

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