GlobalIFC: Classification of Building Components in IFC Model via Multi-Feature Fusion Method

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Abstract. Industry Foundation Classes (IFC) are a widely used open standard file format for storing and exchanging building information models. Accurate classification of building components within the IFC model is crucial for efficient BIM checks. In this research, we propose GlobalIFC, a multi-feature fusion method based on mesh representation, for the classification of IFC-based building elements into seven types, including walls, beams, slabs, columns, doors, windows, and others. The proposed method takes into account various features, such as geometric shapes, positions, dimensions, and relationships between components, to achieve accurate classification. Additionally, we introduce rule-based abstract domain knowledge features to assist deep neural networks, demonstrating the feasibility of integrating rule-based reasoning with deep learning methods. The performance of the proposed method is evaluated on a test dataset, achieving perfect classification accuracy of 97.87%. Moreover, we integrate the method into BIM check software and verify its accuracy of 82.96% in practical AEC projects. The proposed method also demonstrates a fast inference speed of 175 objects/s on home-grade computers, making it suitable for deployment on client computers.

1. Introduction

Building Information Modeling (BIM) is a rapidly evolving technology that is transforming the Architecture, Engineering, and Construction (AEC) industry. With the widespread adoption of BIM, the IFC format has become a widely used intermediate format in various BIM technology scenarios, particularly in BIM checks. However, BIM checks based on IFC can be challenging due to the complexity and variability of the data involved. There are practical issues associated with using IFC for BIM checks, including insufficient property information, improper entity usage, and classification errors. Among these issues, classification errors are particularly critical as they pose a significant limitation for accurate BIM checks.

Classification tasks based on deep neural networks can encompass diverse 3D shapes and representations(Gezawa *et al.*, 2020), including images(Su *et al.*, 2015), point clouds(Wang *et al.*, 2019), voxels(Mao *et al.*, 2021), meshes(Feng *et al.*, 2019). The aforementioned studies have made remarkable advancements in the domain of general classification tasks. Consequently, researchers have extended their applications to the AEC field, specifically in the classification of BIM elements, such as binary classification of doors and windows(Koo, Jung and Yu, 2021), and room type classification(Wang, Sacks and Yeung, 2022). However, it is worth noting that these studies primarily focus on individual features, such as geometric shapes, while neglecting important local features, such as relationships among elements, and global features, such as absolute positions, which could potentially enhance the accuracy and comprehensiveness of the classification task.

In this research, we propose GlobalIFC, a multi-feature fusion method based on mesh representation, for the classification of IFC-based building elements. The proposed method leverages deep learning techniques to automatically learn features from mesh-based representations of building components, considering various geometric shapes, positions, dimensions, and relationships between components. Additionally, we introduce rule-based abstract domain knowledge features to assist deep neural networks, combining the strengths of both rule-based reasoning and deep learning methods. The proposed method aims to achieve accurate and efficient building component classification in BIM, with potential applications in BIM checks, quantity take-offs, and constructability analysis.

2. Related Work

Numerous approaches have been proposed to address practical classification challenges in the field. These approaches can be broadly categorized as rule-based and machine learning-based, specifically DNN-based.

2.1 Classification Based on Rule Inferencing

The classification of building components has been the subject of numerous rule-inferencing methods. One proposed method is an integrated approach that leverages domain experts' knowledge of shape features and pairwise relationships of 3D objects, combined with a tailored matching algorithm, to classify objects effectively. The presented approach demonstrated 100% accuracy in classifying all 3D objects in two concrete girder example bridges(Ma *et al.*, 2018). Additionally, a seven-step iterative method has been designed to classify BIM objects in IFC models. This method consists of multiple sub-algorithms, each depicting a pattern-matching rule that utilizes inherent features of the geometric representation of a building object(Wu and Zhang, 2019).

Although these methods have demonstrated the feasibility of rule reasoning based on domain knowledge and conceptual abstraction for building object classification, they have two primary limitations. Firstly, the inference rules differ across different classification problems, requiring manual customization of the classification rules for each problem. Secondly, for complex classification problems, the classification rules are challenging to enumerate, and conflicts may arise between the rules, leading to a quagmire of rules.

2.2 Classification Based on Machine Learning

The application of machine learning algorithms for semantic enrichment classification tasks has become increasingly popular in recent years. Using the SVM method, a two-staged approach has been proposed to automatically classify BIM elements using geometric and relational data to check the semantic integrity of mappings between BIM elements and IFC classes(Koo *et al.*, 2019). Based on 2D CNN, the method of recognizing and classifying unknown BIM objects is proposed. Their approach included two recognition models, with the first aimed at recognizing the category of a building element and the second aimed at recognizing the sub-type of certain building elements(Koo, Jung and Yu, 2021). Based on 3D CNN, the SpaRSE-BIM method was designed as a more efficient and lightweight model architecture for the classification of IFC-based geometry, which improves the runtime performance of the model and makes it to be used in plug-ins or middleware for BIM tools(Emunds *et al.*, 2022). A recent study proposed a geometric-relational deep learning framework for BIM object classification, which took into consideration shape and relationship features. The study demonstrated that considering relationships between building components and their surroundings improved the classification task. However, the method did not account for dimension and position features, which could be potential areas for optimization from a scientific perspective(Luo *et al.*, 2023).

Although these methods have established deep neural networks as a promising approach for distinguishing BIM element subtypes, it is important to acknowledge that machine learning methods are reliant on the availability and quality of the dataset, and may encounter limitations such as poor generalization. Additionally, existing DNN-based classification methods often prioritize individual features, neglecting the significance of local and global features. This limitation can potentially impact the accuracy of classification tasks that necessitate the incorporation of both local and global information.

The research presented in this paper aims to overcome the limitations of existing methods by integrating machine learning and rule reasoning to develop more accurate and efficient classification methods for building components. To leverage the advantages of both approaches, we propose a novel method of multi-feature fusion based on mesh, which improves classification accuracy and efficiency in real-world projects. Our research takes into consideration multiple factors, including geometric shapes, dimensions, positions, and the relationship between components. Specifically, we consider the shape and size of components as their individual characteristics, the relationships between building components and their surroundings as local features, and the position and orientation of components as global features within a building. The integration of multiple features, including individual, local, and global features, is a novel approach proposed in this paper to enhance the accuracy of component classification.

3. GlobalIFC Architecture

The primary objective of this research is to introduce a more efficient classification architecture for the classification task of building components in the AEC project. This proposed classification technique involves the information integration of mesh-based geometry, IFC-based relations, and domain-based knowledge. The architecture consists of two main stages: feature extraction and feature fusion. In the feature extraction stage, different feature extraction methods were introduced to extract the size, position, relationship, and domain knowledge features. These features were not obtained through an end-to-end method but were found to significantly improve classification accuracy. In the next stage, the extracted features, including geometry shape features and other features obtained from relationship and domain knowledge, are combined into a single feature set for more accurate classification. Finally, the proposed GlobalIFC architecture is based on the above work, which can be used for the classification task of building components in the AEC project.

3.1 Multi-Feature Extraction

1) Dimension

The MeshNet-based deep learning model extracts building element features by focusing on individual elements and considering only their geometric shape information while disregarding global information such as the element's position and direction in the entire building. Additionally, during data processing, size information is ignored due to the normalization of the mesh data. To address the diverse geometric shapes of architectural elements, we incorporate the size and direction vector information of the Oriented Bounding Box (OBB) in the three directions as the dimensional feature of building objects. As a result, we generate a 12-dimensional feature vector for the size and orientation characteristics.

2) Position

In addition, the location of the components within the building can provide valuable insights into their classification. For instance, components located at the top of the building are more likely to be roof members, while those situated at the bottom are often foundation members or piles. To address the impact of spatial positioning on classification accuracy, we have developed two types of location features: relative and absolute position features. The relative position feature includes both horizontal and vertical position features. The former indicates the proportion of the component's central point position relative to the two directions of the rectangular bounding box of the floor. The latter represents the percentage of the component's vertical minimum and maximum heights relative to the floor height and these heights are calculated concerning the elevation of the current building floor. On the other hand, the absolute position feature pertains to the building elevation and represents the percentage of the component's vertical minimum and maximum heights relative to the total building height. These heights are calculated concerning the lowest point of the building. Finally, a 6-dimensional vector presents the essential spatial position characteristics of building components.

These low-level features are leveraged by a Multi-Layer Perceptron (MLP) model to extract high-level features for the classification task. Section 3.2 provides further information on how these descriptors, along with shape feature descriptors obtained by MeshNet, are employed to classify building elements.

3) IFC relationship prior

The classification accuracy of building components depends on various factors. Research has shown that relationships between building components and their surroundings are instructive to the classification task(Luo *et al.*, 2023). Therefore, in this paper, we utilize a statistical-based approach oriented towards the total IFC file, that takes into consideration the related impact on classification. Most relationships defined in the IFC standard have two direct attributes, Related and Relating, representing the two sides of the relationship. During feature extraction, we record the number of different relationships in which each object participates as either side, creating a relationship feature vector for each component. In the seven classification problems addressed in this paper, we focus mainly on four types of relationships: IfcRelAggregates, IfcRelVoidsElement, IfcRelFillsElement, and IfcRelConnectsElement. Therefore, each object eventually forms an 8-dimensional feature vector. Based on these, we use an MLP with batch normalization and ReLU to gradually extract high-level relational descriptors.

4) Domain knowledge prior

In this paper, we attempt to tackle a 7-classification problem involving walls, beams, slabs, columns, doors, windows, and others. Through multiple attempts, we ultimately identified two sets of abstract concepts that significantly improved experimental results: rod members and surface members, horizontal components, and vertical components. In the field of architecture and structural engineering, building elements are divided into surface or rod members based on their size ratio and into horizontal or vertical members based on their load-bearing form. These two sets of abstract concepts were based on three eigenvectors (Vector1, Vector2, Vector3) and three eigenvectors (Value1, Value2, Value3), which were extracted from the mesh representation of the building element through Principal Component Analysis (PCA) and sorted based on the magnitude of the eigenvalues. The inference of these abstract concepts is divided into two steps, as shown in Figure 1. Firstly, a set of rules based on eigenvalues is used to determine abstract concepts between rod members, surface members, and others. Secondly, based on the rod and surface members, we have developed a second set of rules using eigenvectors to determine whether a component is horizontal, vertical, or other.

The abstract concept information can be transformed into feature vectors and utilized by a deep learning model to determine their weight proportions. When focusing only on the concepts of horizontal and vertical members and surface and rod components, each component generates a 2-dimensional domain knowledge feature vector.

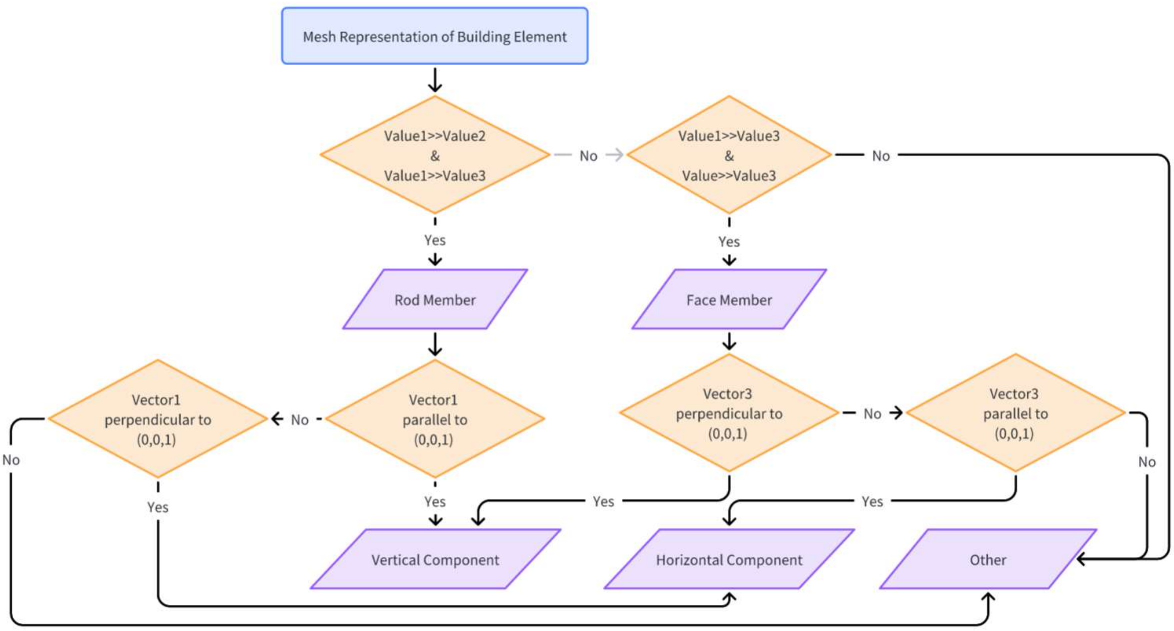


Figure 1: Rules for Abstract Domain Concept

3.2 Multi-Feature Fusion

The GlobalIFC method comprehensively considers multiple features, including geometric features, relational features, and domain features to solve the problem of classification accuracy. Among these features, shape features are automatically generated by the MeshNet model, and dimension and position features are acquired via geometric computation. Relation features are obtained through IFC information retrieval, and domain features are derived from rule-based inference.

Different extraction methods lead to significant differences in the levels of these features, with shape features extracted by neural networks being high-level, while manually extracted dimensions, locations, relationships, and domain features are low-level. To address this, we propose two modules, namely feature extraction and feature fusion, to fuse the features of different dimensions. The process in Figure 2 is divided into two steps:

First, the features in the low-dimensional feature space are expanded using the feature extraction module to form features in a high-dimensional feature space. We use an MLP with batch normalization and ReLU to gradually embed the input 28-dimensional vector into a high-level feature space of 128 dimensions. Then we concatenate the feature of the first and second layers to the feature of the last layer to form the final feature descriptor of 448 dimensions.

Then, the feature fusion module merges the 1024-dimensional shape features with the 448-dimensional other features and further studies a unified feature descriptor for BIM objects. The feature fusion module consists of three linear layers that map the 1472-dimensional descriptor to a 512-dimensional, then to a 128-dimensional, and finally to a 7-dimensional feature space, respectively. The resulting features are then passed through a softmax function to obtain the final 7-category score.

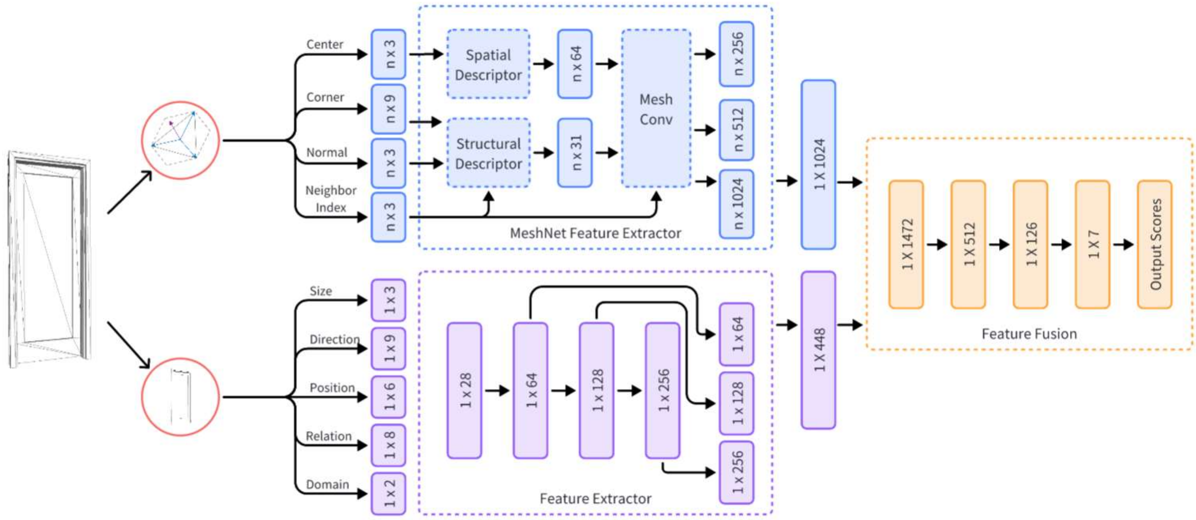


Figure 2: Multiple Feature Fusion

4. Experiment

4.1 Dataset

This work selects 15 representative building models, including residential buildings, public buildings, and industrial buildings, extracts the geometric elements in the models, and initially expands the data set to nearly 150,000, as shown in Table 5. However, these directly extracted data samples are seriously repetitive and unbalanced. Through manual screening to remove duplication and errors, a relatively balanced and representative data set is finally obtained. The processing and screening of data sets are very time-consuming and laborious, but a high-quality and balanced data set is a crucial precondition for training a deep model.

Table 5: Dataset Extended and Balanced.

Dataset	Wall	Beam	Column	Slab	Door	Window	Other
IFCNetCore	537	282	0	507	309	0	0
Extended Dataset	23714	7790	3332	4592	5789	3792	102340
Balanced Dataset	651	890	786	620	2965	2615	12022

4.2 Result

1) Accuracy metrics

After hyperparameter tuning, the final model is trained for 100 epochs with a batch size of 32 on the training dataset. We use the SGD optimizer with a learning rate of 0.0001 and a weight decay of 0.006. Max pooling is applied for feature aggregation, with 64 kernel numbers and a sigma value of 0.3. The performance of several mainstream neural networks and the GlobalIFC model on the training dataset is compared. Table 6 demonstrates that the GlobalIFC model, trained on a balanced dataset, achieves a higher accuracy of 97.87%, providing a strong foundation for its superior performance in real-world projects.

Table 6: Performance results for GlobalIFC compared to previous approaches.

Model	Accuracy(%)	Precision(%)	Recall(%)	F1 Score(%)
MVCNN	82.67	85.32	84.67	82.99
DGCNN	80.12	82.26	81.96	80.65
MeshNet	82.71	85.61	85.21	83.80
GlobalIFC	**97.87**	**99.67**	**99.29**	**97.91**

To compare the performance of different models in real-world projects, we utilized several state-of-the-art neural networks and the GlobalIFC model to perform type inference on the example project, which is an office building with 3147 building components. The results showed a significant improvement in the accuracy of building component classification, increasing from 66.36% to 92.28%, as presented in Table 7.

Table 7: Accuracy metrics on the example project.

Model	Accuracy(%)
MVCNN	67.5
DGCNN	65.52
MeshNet	66.36
GlobalIFC	**92.28**

Furthermore, we conducted tests on nine additional projects, encompassing various types of buildings, such as residential, office, hospital, and industrial facilities. The average accuracy of the model across these projects was 82.96%, with per-class average accuracies detailed in Table 8. Our future work will focus on addressing the challenges faced by the GlobalIFC model in accurately predicting the types of walls and others, which ultimately resulted in lower overall accuracy.

Table 8: Per-class average accuracies on projects.

Model	Wall	Beam	Column	Slab	Door	Window	Other	Total
GlobalIFC	80.1	92.19	96.61	99.12	90.32	92.63	70.57	**82.96**

2) Efficiency metrics

The GlobalIFC algorithm proposed in this study integrates various types of feature extractors, including calculation, retrieval, deep learning, and rule reasoning. However, due to the complexity of the integrated features, the operating efficiency of the algorithm may be a challenge. To evaluate the operational efficiency of the algorithm, we deployed the MVCNN, DGCNN, MeshNet, and GlobalIFC models on a client Windows system and tested their performance on laptops and desktops with different configurations. The experimental results showed that on a laptop, the entire algorithm, including pre-processing and post-processing, and algorithm running time, achieved a speed of 21 objects/s, while on a desktop computer, it reached 175 objects/s, as shown in Table 9. These results demonstrate that the GlobalIFC algorithm via the CPU and GPU acceleration technology meets the requirements for processing in a client application in terms of operational efficiency.

Table 9: Operating efficiency metrics on the example project.

Model	Accelerate	Computer	Pre-process(s)	Predict(s)	Post-process(s)	Total(s)	Throughput (objects/s)
MVCNN	No	1	3931	6657	1	10589	0.3
		2		1683		5615	0.6
DGCNN		1	191	14643	1	14835	0.2
		2		2231		2423	1
MeshNet		1	147	835	1	985	3
		2		325		475	7
GlobalIFC		1	187	842	1	1030	3
		2		331		519	6
	Yes	**1**	**4**	**149**	**0**	**153**	**21**
		2	**3**	**15**	**0**	**18**	**175**

Note: The configuration of Computer1 is an Intel i7 4-core 3.0GHz processor, 16GB of RAM, and Intel Iris Xe graphics card, and Computer2 is an AMD R7 8-core 3.4GHz processor, 32GB of RAM, and Nvidia Rtx 3060ti 8GB graphics card.

3) Case study

In this section, a comprehensive analysis was conducted to evaluate the influence of different features on the accuracy of the classification results, as demonstrated in Figure 3. It was observed that excluding the consideration of dimension features led to an erroneous classification of a 10mm thick glass panel as "Wall", whereas the correct classification in our 7-class task should be "Other". This misclassification could be attributed to the normalization of shape data during the pre-processing stage, which resulted in the loss of crucial dimension information.

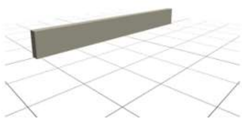
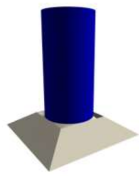
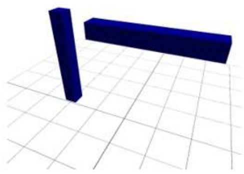
	Dimension	Position	Relationship	Rule
	 glass plate	 short wall	 pipe segment	 column and beam with the same size
MVCNN	Wall(×)	Beam(×)	Column(×)	Column and Beam(√)
DGCNN	Wall(×)	Beam(×)	Column(×)	Column and Column(×)
MeshNet	Wall(×)	Beam(×)	Column(×)	Column and Column(×)
GlobalIFC	Other(√)	Wall(√)	Other(√)	Column and Beam(√)

Figure 3: Effect of different features

Similarly, disregarding positional features resulted in the misclassification of a short wall as a "Beam", which was initially justifiable based on its shape features alone. However, when taking into account the local position of the component within the floor, the correct classification should be "Wall", indicating the importance of positional features in accurate classification.

Furthermore, neglecting relational features led to the misclassification of a pipe segment as a "Column", despite its connection with an air terminal, which would classify it correctly as

"Other". This underscores the significance of incorporating relational features to capture the complete context of the components.

Additionally, omitting the rule based on domain knowledge resulted in the misclassification of columns and beams with the same size. However, with the inclusion of domain knowledge features, the two types could be accurately distinguished, highlighting the importance of leveraging domain-specific knowledge for improved classification performance.

5. Conclusion

In this research, we investigated mesh-based deep learning models to determine their applicability for classifying BIM element types in the actual AEC project. Based on deep learning models MeshNet, we designed GlobalIFC, a multi-feature fusion model based on mesh representation for the classification of IFC-based building elements. We trained and tested the GlobalIFC model on the 7-classification task, including walls, beams, slabs, columns, doors, windows, and others. Results showed that our method had the perfect classification performance in the dataset, with an accuracy of 97.87%, precision of 99.67%, recall of 99.29%, and F1 of 97.91%. Furthermore, experiments on real-world projects showed that the accuracy of this method averaged 82.96%, significantly outperforming deep learning methods that solely rely on geometric shape information. The GlobalIFC method demonstrated state-of-the-art classification performance in both datasets and projects, highlighting the need for multiple feature-based classifications of building components.

While our method has demonstrated promising results, it also has some limitations to be acknowledged. Firstly, the accurate expression of the relationship between building components in the IFC file is required, as the components are divided based on specialties and the correct representation of their relationship depends on this. Secondly, proper division of components at joints, corners, and across floors is necessary for accurate calculation of dimensions and professional information. Failure to do so may result in inaccurate results. Thirdly, the prediction accuracy of curved components is not as robust as that of linear components, which may be the reason for the introduction of bounding box-based features.

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