Journal of Civil Engineering and Management
ISSN 1392-3730 / eISSN 1822-3605
2022 Volume 28 Issue 6: 497–508
https://doi.org/10.3846/jcem.2022.16994

# APPLYING AI TECHNOLOGY TO RECOGNIZE BIM OBJECTS AND VISIBLE PROPERTIES FOR ACHIEVING AUTOMATED CODE COMPLIANCE CHECKING

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Received 15 September 2021; accepted 14 April 2022

**Abstract.** Automated code compliance checking is an effective approach for assessing the quality of building information modeling (BIM) models. Various automated code compliance checking systems have emerged, wherein users need to input all information accurately according to BIM modeling guidelines, in order to ensure the accuracy of checking results. However, as this process involves human inputs, it is difficult to ensure that each input is accurate. In the case of errors or missing inputs, the checking results will be erroneous. Although automated checking systems can be developed accurately, it is difficult to apply these systems practically. Therefore, this paper proposes the application of AI technology to recognize BIM objects and visible properties, in order to improve the operability of automated code compliance checking. The two necessary elements – object names and properties – could be automatically extracted to a certain extent, following the application of the proposed method to the automated code checking process. The error rate of the input could also be reduced, thus making the application of the code checking system more practically feasible. The proposed recognition method for BIM objects and visible properties is also expected to be used widely in BIM-based building e-submission systems and BIM-based forward designs.

**Keywords:** Building Information Modeling, automated code compliance checking, artificial intelligence, industry foundation classes (IFC), BIM object recognition, visible property recognition.

## Introduction

With the advances in big data and artificial intelligence (AI), countries are devoting increasing attention toward the incorporation of digital technologies into industries. Accordingly, the application of building information modeling (BIM) is the most representative use of digital technology in the construction industry (Alashmori et al., 2020; To et al., 2021). The quality of the BIM model is a crucial aspect in the application of BIM. More specifically, the information within the BIM model should meet various standard naming systems, such as space and object classifications. Moreover, the BIM model should also meet the requirements of various building codes.

Different countries have adopted various measures to implement BIM. Numerous countries have issued modeling guidelines that specify the modeling methods and naming standards for elements, in an attempt to standardize modeling. Additionally, various countries are actively adopting mandatory measures to promote the submission of BIM models. For instance, in 2015, Singapore mandated BIM for all public facilities with an area of more than 5000 m$^2$. With regard to the contract process related to public building designs, in 2006, the General Services Administration [GSA] of the United States was obliged to submit design drawings as BIM design information based on industry foundation classes (IFC). Furthermore, in South Korea, BIM has been compulsory for all public sector projects since 2016 (Cheng & Lu, 2015; Edirisinghe & London, 2015; Sun et al., 2018; Kim et al., 2020).

Some countries have been actively attempting to develop a BIM-based building e-submission system to conduct automated quality checking for the submitted BIM models; in such a system, the core aspect is the automated code compliance checking. Singapore is leading the world in terms of practical applications in this field. Under the iGrant project of the Building and Construction Authority [BCA], an automated code compliance checker was developed to check building accessible code. Urban Redevelopment Authority [URA] developed the GFA Autochecker,

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whereas the Public Utilities Board [PUB] developed a PUB BIM checking system. Currently, the BCA is leading the CORENET X project, which aims to integrate the automated code checking systems of seven agencies. Additionally, South Korea is implementing the KBIM project and developing a building e-submission system based on openBIM (Kim et al., 2020; Amor & Dimyadi, 2021).

According to Eastman et al. (2009), the operation of an automated code checking system primarily depends on the identification of names and properties. The existing information inputting method principally depends on manual inputs, which require significant efforts from users. Consequently, incorrect information input (such as incorrect inputs of object names or properties) or a lack of information is inevitable during this manual input process; this, in turn, could lead to inaccurate automated code checking results. Therefore, although automated code checking systems can be accurately developed, it remains difficult to apply these systems in practice.

Several studies have focused on enhancing the semantic integrity of a BIM model. For instance, Kim and Lee (2019) and Koo et al. (2021a) applied the CNN-based three-dimensional (3D) object recognition method in the automated recognition of BIM objects. This 3D BIM object recognition method was proposed for use in automated code checking. In these studies, the confidence probability was obtained. Furthermore, as designs are creative, building elements will inevitably appear in a variety of forms. Therefore, it is difficult to achieve a prediction rate of 100%. However, building code approval requires a high accuracy, which, in turn, necessitates a more accurate recognition of BIM objects. Therefore, in this study, the authors propose to further judge the recognition results by combining the relationship between the recognized object and space on the basis of AI-based recognition results.

Generally, an object corresponds to multiple properties in building code documents. Such properties are specified in the modeling guide for cooperate the use of an automated code checking system. However, in practical applications, users are required to input a large amount of text information. As this process involves human inputs, there is a higher likelihood for certain inputs to be missing or incorrect. Besides, the existing commercial software, IFC exporter function, still has scope for improvements. Thus, there exist various problems associated with missing property data or the requirement of separate specific settings (Choi & Kim, 2011; Lee et al., 2021). Moreover, the property appears in the form of text; hence, it cannot appear in the 3D model view, making it more difficult for users to reconfirm the information. Therefore, the authors propose adding a logo to the surface of the BIM object for properties that can be visualized, which can be followed by the use of AI technology to recognize these properties (Sun et al., 2019).

The remainder of this paper is organized as follows. The relevant background information is provided in Section 1, including the automated code checking and the modeling guide required for automated code checking, IFC and its internal relationship, as well as the importance of information classification and a related summary of semantic integrity enrichment research. In Section 2, the recognition method for BIM objects and visual properties is detailed. Furthermore, a case study and a discussion regarding the proposed method are presented in Section 3. Finally, the conclusions of this study are presented in the last Section.

## 1. Background

### 1.1. Automated code checking system and BIM modeling guide

With the in-depth research into BIM technology, numerous studies have focused on assessing the quality of BIM data, and different types of automated code checking systems have been proposed. CORENET's ePlancheck, which was introduced in Singapore, represents an early, large-scale attempt at developing an automatic regulatory system (Eastman et al., 2009; Amor & Dimyadi, 2021). Recently, the BCA, URA, and PUB in Singapore successively completed their agencies automated code checking system. Currently, the BCA is integrating seven government agencies to develop the next generation of automated code checking systems, called CORENET-X (Professional Engineers Board Singapore [PEB], 2019; Kim et al., 2020; Amor & Dimyadi, 2021; BCA, 2021). Meanwhile, the Korean government funded the KBIM building e-submission system project to enhance its existing e-submission system, SEUMTER, in order to enable BIM-based e-submissions and automated code compliance checking (Lee et al., 2016; Kim et al., 2020; Amor & Dimyadi, 2021).

To ensure smooth operation of the automated code checking system, the submitted BIM model needs to carry the required properties, names, and objects (Eastman et al., 2009). Moreover, it is necessary to formulate a separate BIM modeling guide for an automatic code checking system, to ensure that users input the necessary BIM model data for automated code checking.

For instance, in Singapore, the URA developed an automated code checking system called GFA Autochecker to automatically check the gross floor area. Combined with the checking system, the GFA Autochecker BIM modeling guide was developed to outline the BIM modeling requirements and standards. More specifically, this guide defines detailed data requirements, including the project information, space provision and classification, schedules, special BIM objects, and other general requirements from other agencies (URA, 2020).

The PUB developed the PUB BIM checking system to check designs in accordance with the code of practice for sewerage and sanitary works, surface water drainage, and water services. Furthermore, a BIM modeling guideline for the PUB BIM checking system was provided to guide users in preparing BIM models that satisfy the checking requirements, including the necessary properties, space naming convention, and standard BIM objects with predefined types (PUB, 2020).

Users need to input the correct information specified in the modeling guide to ensure the accuracy of the results of an automated code checking system; otherwise, the checking results will be inaccurate. However, there are many BIM object names and properties that need to be input, and as these data are input manually, there will inevitably be errors. Moreover, the design process is often accompanied by various changes, making it more challenging to confirm the real-time update of the BIM model information.

### 1.2. IFC and its internal relationship

Regarding the format of the checked BIM data, different authoring tools produce native BIM files in different formats (Harty et al., 2015). If each native BIM files needs to be checked, it is a burden on system development, upgrade, and maintenance (Kim et al., 2020). Most software companies support IFC as it is a widely recognized open specification for data exchange in the fields of architecture, engineering, construction, and facility management (Eastman et al., 2010; Zhou & El-Gohary, 2021; Eastman et al., 2011; Malsane et al., 2015). Moreover, IFC is the official international standard for BIM data (International Organization for Standardization [ISO], 2018); it has been developed and maintained by buildingSMART International since the 1990s. Therefore, most automated code checking systems adopt IFC as the checked BIM file format.

The IFC schema is defined in the EXPRESS schema with the ISO 10303 standard (ISO, 2020) for the exchange of project model data (STEP) (Patacas et al., 2020). IFC is highly robust and offers various methods for defining objects, relationships, and attributes. The IFC model can also represent tangible building elements, such as walls, doors, and elements. In addition, it can represent abstract concepts such as activities and spaces (Motamedi et al., 2016). Several relationships are defined within the IFC schema. Specifically, 49 entities in IFC2×3 (47 in IFC4) are derived from IfcRelationship (Solihin et al., 2017a). Currently, many studies have used the relationship within the IFC. For instance, Lee and Kim (2014) used the objectified relationship, IfcRelSpaceBoundary, to derive circulation information from IFC. Solihin et al. (2016) proposed a novel concept for extending IFC relationship entities to integrate federated models. Moreover, Solihin et al. (2017b) used a relational database to support multiple representations of BIM 3D geometric data to support high-performance code checking-related queries.

When a physical connection does not exist, the connections between the spatial and physical entities can be presented using the "IfcRelContainedInSpatialStructure" relationship in IFC (Liebich, 2009; Alshehri et al., 2017; Kwon et al., 2020). In the present study, the authors used the relationship between spatial and physical entities in IFC for identifying the space to which a 3D BIM object belongs.

### 1.3. Importance of information classification in BIM models and research on semantic integrity enrichment

Eastman et al. (2009) established that the ontology of names and properties is crucial for code checking. Accordingly, some code checking items tend to rely on explicit space classifications, such as circulation evaluations. A large part of the code clause depends on the classification assigned to the component to uniquely represent the type of current information, such as the usage function of a room. Although there are more than 70 major classification systems, a consenting agency can only classify the components in a BIM model using one or two nationally acceptable classification systems (Amor & Dimyadi, 2021). The IFC data model allows for the customization of properties in the existing list of IFC classes. Currently, in addition to the Corenet-X project, the Singapore government is implementing the IFC-SG project to enhance the IFC data model by adhering to local regulatory requirements (Nova Group, 2020).

Automated code checking will stop for cases that involve missing classification codes or an unapproved classification system. It is difficult to check whether the classification code of spaces or components is correct, as this requires a comprehensive understanding of buildings and their components (Amor & Dimyadi, 2021). Moreover, users need to remember these names and properties, which can lead to a large burden in the case of substantial amounts of inputs. Moreover, in the case of manual inputs, there is a higher likelihood for the information to be missing. Alternatively, if substantial amounts of information are used in the inputs, it becomes difficult to recheck the input information. As a solution, AI methods have recently been tested to ensure the correctness of classification information (Amor & Dimyadi, 2021).

Recent studies have also explored the use of machine learning and deep learning methods to alleviate the semantic enrichment problem in BIM models. For instance, Krijnen and Tanke (2015) proposed an anomaly detection method for checking IFC classifications; this approach is a form of machine learning (ML) technology (Koo & Shin, 2017). Koo and Shin (2018) adopted a novel detection method to detect misclassified BIM elements. Kim et al. (2019) adopted a two-dimensional (2D) CNN technology to identify the BIM elements that are a part of architectural objects constituting the residential space in South Korea. Furthermore, Bloch and Sacks (2018) employed ML to classify rooms using a rule-inferencing approach. Wu and Zhang (2019) proposed the use of a data-driven iterative method to classify common building BIM elements. Moreover, Koo et al. (2021b) used a geometric deep learning method (MVCNN and pointNet) to classify infrastructure BIM elements.

Most of these previous studies only applied existing AI technology to recognize BIM elements and determine the confidence probability. There is no further integration of unique knowledge of building areas. Moreover, there is also a lack of research on enhancing the semantic integrity of properties. Therefore, in this study, the authors will further strengthen the use of AI to solve the semantic problems associated with BIM models and further explored the application of AI technology in the automated code checking process. The authors explore the application of AI for the two necessary elements (BIM object name and properties) in automated code compliance checking.

## 2. Proposed method for recognizing BIM objects and visible properties based on AI

This paper proposes a method for recognizing BIM objects and visible properties through the use of AI, in order to explore solving the semantic integrity problem of BIM models and promotes automated code compliance checking technology to be more humanized in line with the user habits. In this section, the proposed method is introduced in detail via two aspects: BIM object recognition by combining "AI-based object recognition" and "space–object relationship," and the process of applying visible feature recognition in automated code compliance checking.

### 2.1. BIM object recognition by combining AI-based object recognition and space–object relationship

#### 2.1.1. Composing image database of BIM object and training the learning model

For 3D BIM object recognition, if 3D BIM objects are recognized based on images, numerous studies have adopted the multi-view CNN (MVCNN) method proposed by Su et al. (2015) (Figure 1) to explore the application of CNNs in the BIM field. In this study, for AI-based 3D BIM object recognition, the authors also use the MVCNN method for recognition. The specific processes are as follows. First, BIM objects were collected from various resources, including BIM models, libraries, and various online BIM model resources. Subsequently, the BIM objects were classified and labeled. Notably, these should be named according to the standard BIM object naming system required for automated code checking. Subsequently, 12 photos were captured at intervals of 30° for the objects suitable for MVCNN. Lastly, the sample sets were divided in a ratio of 8:2 for training and testing the learning model (Kim & Lee, 2019; Koo et al., 2021b).

#### 2.1.2. Composition of space–object relationship database

Herein, the authors propose the construction of a "space–object relationship database" (Figure 2). Conventionally placed objects exist in each space, which could be called common sense (McCarthy, 1959). For instance, there is a cabinet, refrigerator, and dining table in the kitchen, and a basin, bathtub, shower booth, and water closet in the bathroom. The objects placed in these spaces vary according to the customs of each country or the owner's personal preferences. Generally, this part can be adjusted appropriately according to the specific situations. The names of the spaces and the objects in the "space–object relationship database" should also comply with the standard naming system required for automated code checking, in order to standardize building information.

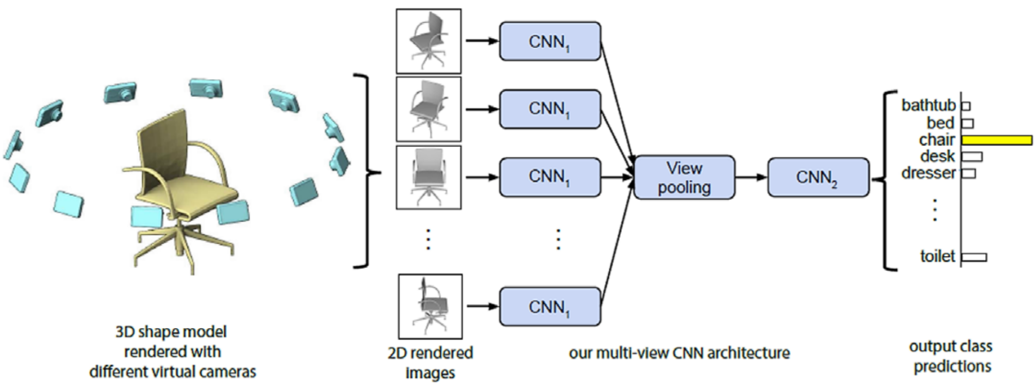


Figure 1. MVCNN architecture (Su et al., 2015)

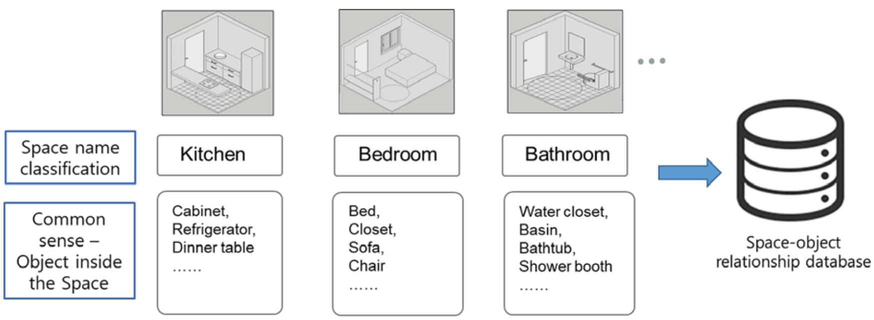


Figure 2. Composition of space–object relationship database

There is "IfcRelContainedInSpatialStructure" relationship in the IFC structure, which can be used for finding the IFCspace in which the 3D BIM object is located. Based on the IFCspace name, the general category of the BIM object can be determined according to the "space–object relationship database".

### 2.1.3. Overall automated BIM object recognition process

First, the MVCNN method mentioned in Section 2.1.1 is used to predict 3D BIM objects, and the results were the confidence probabilities. As the design is creative, building elements will inevitably appear in a variety of forms. Therefore, it is difficult to achieve a prediction rate of 100%, particularly for those elements defined using custom shapes, such as BIM objects made by mass in Revit (a BIM software). However, automated code compliance checking is rigorous and serious, and building officers need to approve the results according to the output of the automated code checking system. Therefore, during the code checking process, a high recognition accuracy for the BIM objects is required. Therefore, the authors propose that the objects should be further judged according to the "space–object relationship" after recognizing the BIM objects using AI technology in the first step; this approach is expected to help improve the accuracy of the results of BIM object recognition. The general process is illustrated in Figure 3 (Sun et al., 2018).

## 2.2. Applying visible feature recognition in automated code compliance checking

### 2.2.1. Extracting properties that can be represented visually and expressing visible properties via a logo similar to actual scenes

The checking requirements written in natural language are analyzed to extract the properties that need to be identified by the automated code checking system. Generally, these properties can be classified as quantitative or functional, among others. In this study, the authors extracted properties that could be represented visually. For instance, "The number of parking lots for the disabled should be at least one out of every 50" is a requirement in the example of parking lots. To define 'the disabled', the previous general method is adding the property of 'accessible' to the BIM object. The proposed method involves adding the "accessible" logo to the object (Figure 4) and using AI technology to recognize the property (Sun et al., 2019).

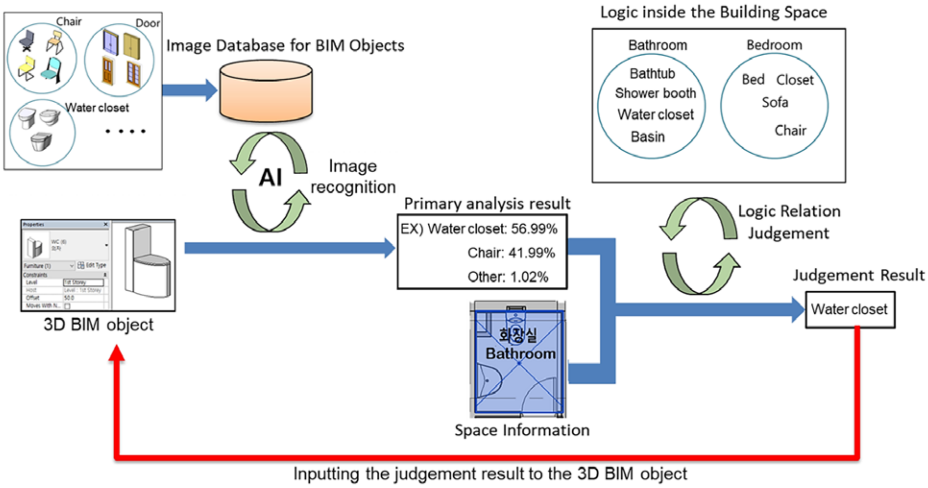


Figure 3. BIM object name recognition process

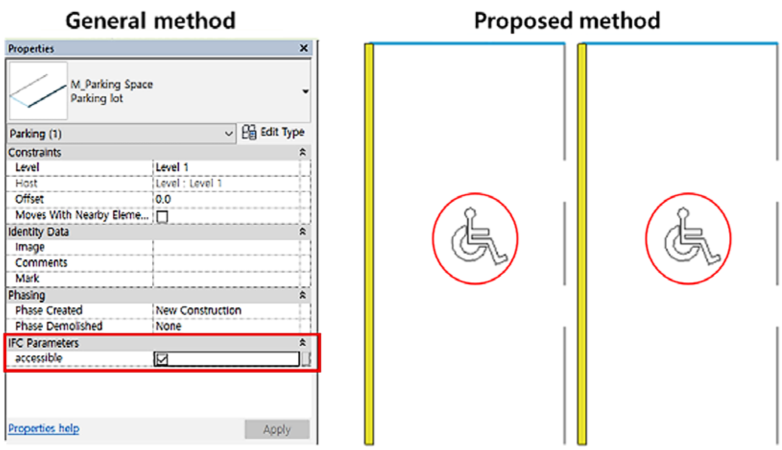


Figure 4. General method (adding "accessible" property to BIM objects) and proposed method (adding visible features to BIM objects) (Sun et al., 2019)

Figure 5. Example of "accessible" door in reality

Following the extraction of visual properties, feasible logos combined with the actual scenes for visible properties need to be determined. For instance, in an actual scene, an accessible door can be expressed using the following method (Figure 5). Adding a similar logo to the actual scene will be more acceptable to designers, as compared with adding the property of "accessible" in the text style to the "door" BIM model.

#### 2.2.2 Specifying unified features in modeling guide and setting them as feature targets for machine learning

As architectural design is a creative process, the emergence of various designs is inevitable, and it is difficult to ensure the accuracy of machine learning recognition for such arbitrary visual features. Moreover, code compliance checking is rigorous, and the accuracy of a systematic judgment is critically important. Therefore, it is necessary to improve the accuracy of visual feature recognition and ensure the reliability of code checking. Furthermore, the recognition target should be limited (Sun et al., 2019).

Therefore, the authors propose the sorting of visual features to create a unified feature library, stipulate this library in the modeling guide, and set the visible features as the feature targets for machine learning. The authors use AI technology to recognize the surface of the BIM object with visual features to obtain the property information for automated code compliance checking. This entire process is illustrated in Figure 6.

## 3. Case study for proposed method and discussion

Herein, the authors present a case study using two examples to illustrate the proposed method. The first involves recognizing the "water closet" 3D BIM object, whereas the second involves recognizing the "accessible" property of a door.

### 3.1. Recognizing 3D BIM objects to obtain object name

There are some building code requirements in the Singapore "Code on accessibility in the Building Environment 2019"; these requirements are primarily related with the water closet, such as, the minimum space in front of the water closet should be more than 1000 mm. For checking this item, the code compliance checking system needs to first identify the BIM object named "water closet". There-

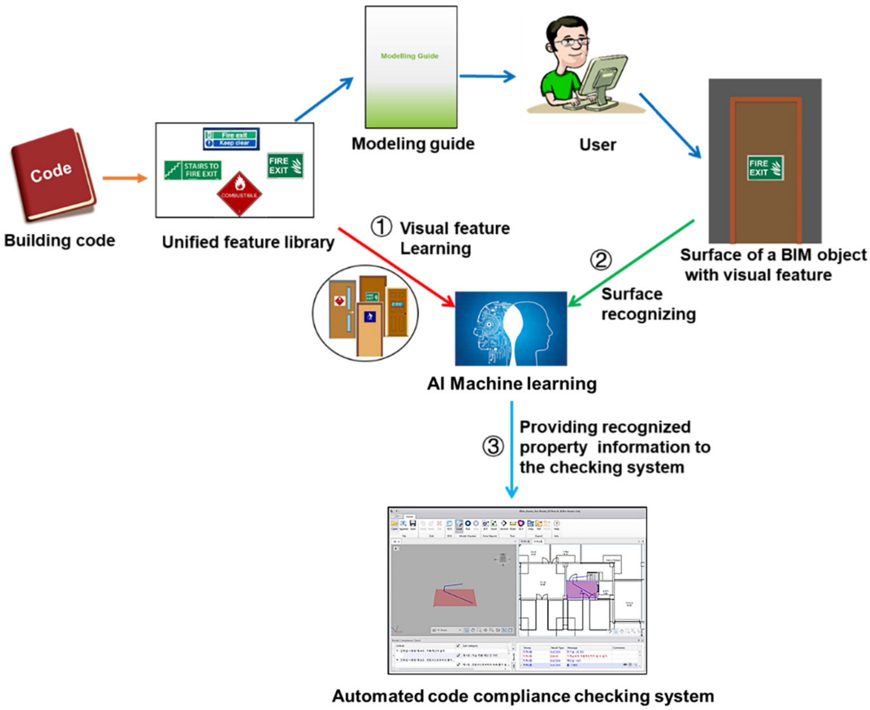


Figure 6. Automated code checking using visual feature recognition (Sun et al., 2019)

after, the minimum space in front of "water closet" should be checked using the internal position and dimension information of IFC.

It is well known that the "water closet" falls under the "Plumbing Fixture" in Revit. This type of plumbing fixture includes sinks, water closets, tubs, drains, and various appliances. After being exported to IFC, all the fixtures will exist as "IfcFlowTerminal." Therefore, designers should input the name in the 3D BIM object to distinguish between sinks, water closets, tubs, drains, and other similar objects.

These 3D BIM objects should be assigned specific names in the modeling guide to cooperate with the use of automated code checking systems, such as "water closet". However, during the design process, these names may be input incorrectly or omitted, or the designers may not follow the names specified in the modeling guide; in such cases, they may name the BIM objects according to their personal preferences. For example, designers may use customary names such as "toilet" or "WC". In such cases, if the system cannot identify the specified name, the checking process will not proceed successfully. Moreover, this will also lead to inaccurate results of the automated code compliance checking (Sun et al., 2018; Kim & Lee, 2019; Koo et al., 2021a).

Researchers have studied this semantic problem associated with BIM models and employed AI to resolve the issue. For instance, Kim and Lee (2019) used the 2D-CNN, which is a deep neural network, to classify furniture BIM elements and developed the BIM object recognition module for automated code checking. Moreover, Koo et al. (2021b) applied MVCNN to classify infrastructure BIM elements and mentioned the practical implications for code checking by assessing the semantic integrity of BIM models. However, they primarily used the MVCNN method to recognize 3D BIM objects and obtain the confidence probability. By contrast, herein, the authors propose that the name of the BIM object should be further judged by combining the "space–object relationship", in order to improve the efficiency of object recognition. In the following section, the authors outline how the proposed method is used to obtain the name "water closet" of a 3D BIM object.

First, the BIM objects in the 3D model to be recognized are visualized individually, and each BIM object is recognized based on the method described in Section 2.1. In this study, a 3D BIM object (Figure 7) was utilized as an example, and twelve photos were captured at intervals of 30° for recognition. The authors also used the MVCNN recognition method based on previous research (Su et al., 2015, 2018; Wu & Zhang, 2019; Kim & Lee, 2019; Koo et al., 2021a).

The image data of twenty different types of BIM objects were collected from online 3D CAD and BIM libraries (Wu et al., 2015; Su et al., 2018), including walls, columns, parking lots, doors, plants, water closets, curtains, tables, and chairs. The collected image data were then divided in a ratio of 8:2 to train and test the training model. In this manner, an accuracy of 85%, precision of 87%, recall of 85%, and an F1 score of 85% were achieved. Subsequently, the 3D BIM object was predicted using the training model. The recognition confidence was 97.6% for "water closet", 1.0% for "plant", 0.3% for "chair", and 1.1% for "others". Notably, this study did not focus on recognition confidence; instead, it focused on methods to integrate the results of AI recognition with the existing knowledge of the specialty.

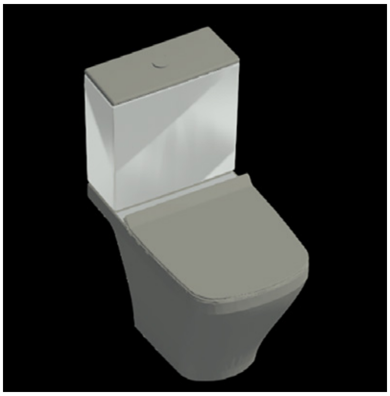

Figure 7. 3D BIM object for recognition

Based on the relationship between the space and object in IFC using "IfcRelContainedInSpatialStructure", the IFCspace name "bathroom" can be determined. Thereafter, depending on the "space–object relationship database" sorted out in advance, the objects in the "bathroom" space could be water closet, basin, or bathtub, among others.

Further judgments can be made by combining the results from the AI recognition and the "space–object relationship". Thus, the 3D BIM object can be judged as a "water closet". This entire judgment process is illustrated in Figure 8.

### 3.2. Recognizing accessible properties through surface of BIM objects with visible logo

The Singapore "Code on accessibility in the Building Environment 2019" includes a building code requirement, according to which the "clear width" of a door for an accessible individual washroom should be more than 850 mm. For checking this item, the code compliance checking system could be developed to find all "Ifcdoor" elements and the "ifc" internal dimension information can then be used to judge whether the "clear width" meets the related requirement.

However, it is likely that different types of doors exist in a single building, such as normal doors and accessible doors. Hence, it is important to ensure that the system can identify different types of doors. Therefore, designers should input information related to the doors, in order to enable the system to distinguish between them. The general method involves specifications in the modeling guideline and requiring the designers to add the "accessible" property to the "door" BIM object. The code compliance checking system can then identify the property information to appropriately perform the checking process.

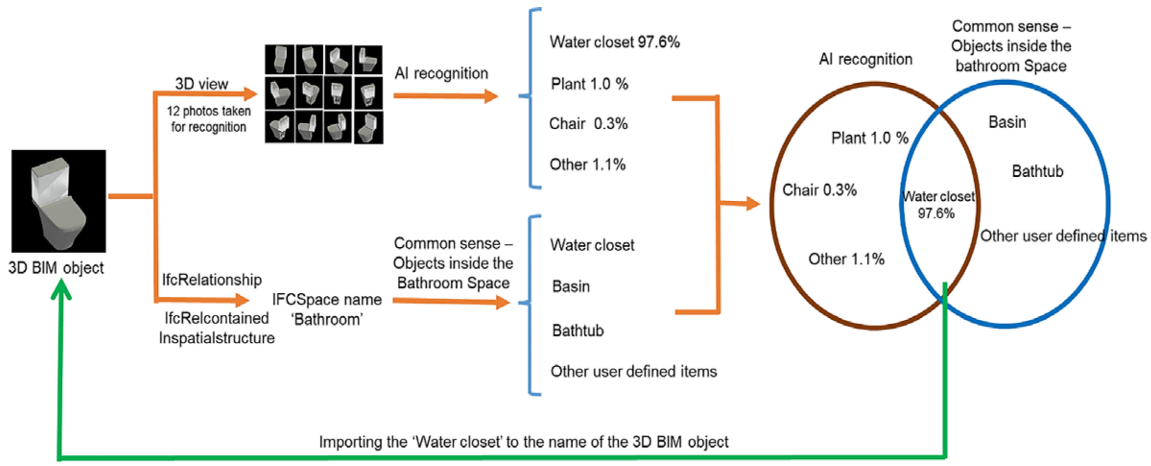


Figure 8. Entire judgment process for 3D BIM object

However, as in the case of the BIM object name input, designers are required to input a large amount of specified model information according to the modeling guide during the design process. As mentioned before, given that this process involves human inputs, it is inevitable that there will be missing or erroneous inputs. Moreover, the properties in the BIM model exist in the form of text; therefore, it is difficult to recheck such properties. Besides, the design activity is accompanied by a large number of design scheme adjustments and design changes, which represent another considerable challenge in terms of inputting the information accurately. Nevertheless, if even one property is entered incorrectly, the result of the entire automated code checking will be inaccurate (Sun et al., 2019). Therefore, the authors herein propose a method of using AI to recognize visual properties, in order to provide the relevant information for automated code compliance checking and to realize a more practical automated code checking approach. In the following section, the authors present an example using the case of a recognizing accessible property through the surface of a door BIM object with a visible logo.

In Singapore's "Universal Design Guide for Public Places", the BCA provides examples of an "accessible logo" and an "ambulant logo" (BCA, 2016), as shown in Figure 9. In this study, the authors used these two types of logos as an example to express accessible and ambulant doors in the BIM model, following the actual scene. These logos could also be stipulated in the modeling guide.


**Photo:** *Sign for accessible individual washroom with braille markings*

**Photo:** *Sign for ambulant disabled*

Figure 9. Logos mentioned in "Universal Design Guide for Public Places" (BCA, 2016)

Accordingly, visual logos were added to the object to be identified. In this case study, visible logos were embedded into the BIM objects using Revit, as shown in Figure 10.

AI-based image recognition was used to recognize the type of "door" BIM model. In this study, a 2D image classification method (TensorFlow, 2021) was utilized. The authors considered accessible, ambulant, and normal doors as examples to illustrate the performance of the proposed method (Figure 11).

The authors collected 160 images of doors with the accessible logo, 160 images of doors with the ambulant logo, and 160 images of the normal door; these images where then divided in a ratio of 7:3 to train and test the learning model. The validation accuracy could be 100%.

Subsequently, the surface of the target object was recognized, and it was predicted that the type most likely belongs to "accessible" with 100% confidence (Figure 12). As the input logo is stipulated in the modeling guide, the recognition result could be significantly high. Thereafter, the recognized name "Accessible" could be input into the corresponding property of "IfcDoor."

### 3.3. Discussion and limitations

The 3D BIM object name and visible property could be recognized using AI, via the method illustrated in Sections 3.1 and 3.2, without relying on the manual input of text information.

Considering the case of recognition for the 3D BIM object "water closet" as an example, the authors explored using "the results of AI recognition" and the "space–object relationship" to comprehensively judge the name of the 3D BIM object. It was found that this approach could improve the accuracy of recognition. After applying the proposed method to the code checking process, it could reduce the error rate of manually inputting the object names. This method could also be used to recheck the input information of the existing model.

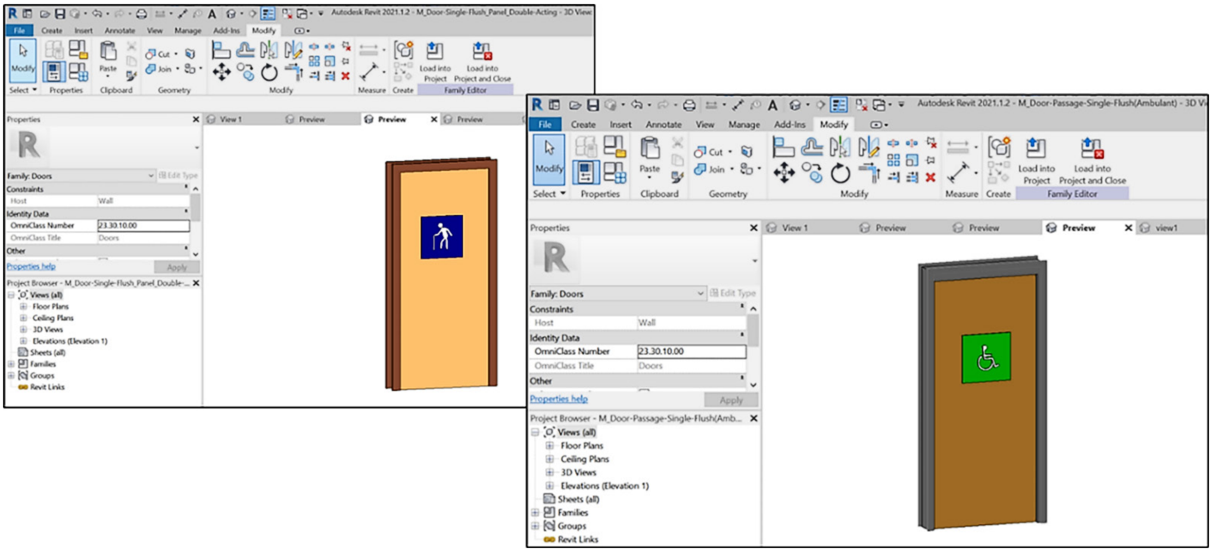

Figure 10. Example of embedding visible logos into BIM objects using Revit

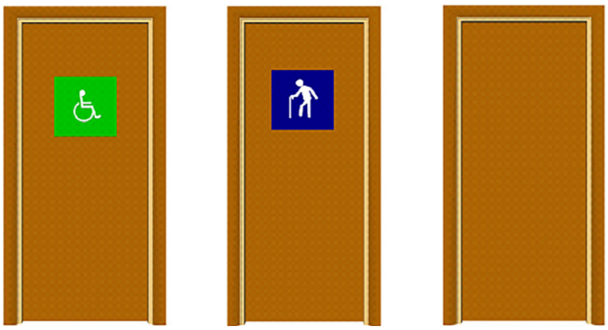

Figure 11. Example of accessible, ambulant, and normal doors

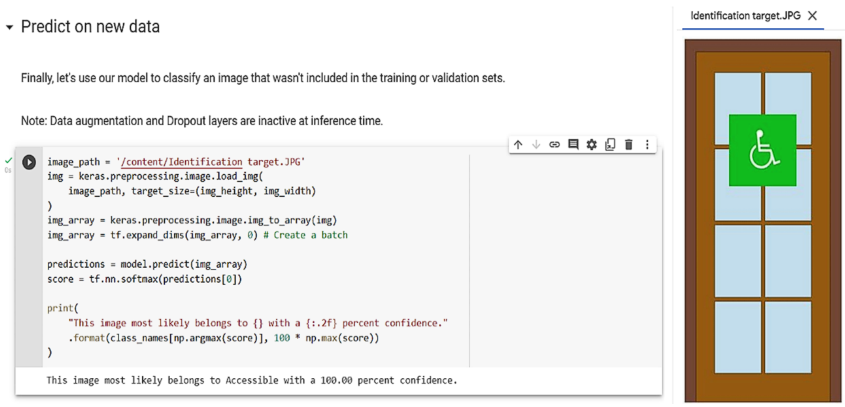


Figure 12. Prediction result using image classification (TensorFlow, 2021)

Considering the case of recognizing the "accessible" property of a door as an example, the properties that could be visualized were stipulated in the BIM modeling guideline to increase the standardization of the BIM model. Adding a visible logo to the object surface could also help designers recheck the designs. Compared with the method of adding the "accessible" information to the BIM object in a textual format (which can be considered "invisible"), the proposed method could reduce the manual input of text information, which, in turn, decreases the input errors. Through the visualization of feature properties, designers could also obtain a better understanding of the design process (Sun et al., 2019).

The proposed method can eliminate the dependency on human input data for information recognition, and the computer can simulate human behaviors. Provided the object or property can be visually perceived by humans and allow for judgments based on common sense, the computer can imitate humans to recognize this information. Designers could focus less on the accurate input of information and pay more attention to the design. Following the application of the proposed method to the automated code checking process, the two necessary elements, i.e., object name and property, could be automatically extracted to a certain extent, and the error rate of the input could be reduced. This could be an effective approach for improving compliance code checking. The authors expect that an automated code checking system should be more operable in practice using the proposed method. The standardized model after the automated code checking will provide important standard building data and contribute toward the standardization of the construction industry.

In this study, the authors only derive further judgments using the space–object relationship based on the AI recognition results for BIM object recognition. In addition to the space–object relationship, other factors should also be considered, such as the relationship between objects as well as the ratio of an object's internal dimensions (Krijnen & Tamke, 2015; Koo & Shin, 2017; Sacks et al., 2017; Koo et al., 2019). If these factors are integrated, the recognition of the system will be more intelligent, which, in turn, would lead to more accurate results.

Furthermore, for property recognition, the authors only implemented properties that could be visualized and often appear in actual scenes. However, there also exist properties that are not easy to visualize, such as quantitative attributes (window opening angles, etc.). Therefore, further research is required to establish methods to express these properties reasonably and recognize them intelligently.

## Conclusions

In the era of big data and AI, it is crucial to obtain a large amount of standardized data. In the construction industry, it is desirable to obtain standard building data through BIM. Recently, automated code checking technology for BIM models has attracted significant attention. It is necessary to input all types of information into this system accurately to ensure the accuracy of the checking results. However, it is challenging for users to input large amounts of information accurately. Therefore, automated code checking is feasible in theory but difficult to apply in practice.

Therefore, in this study, the authors explored the application of AI for extracting two necessary elements (object name and property) for automated code compliance checking. Accordingly, the authors conducted research focusing on the recognition of 3D BIM object names and visual properties.

In terms of BIM object recognition, certain scholars have used existing AI technologies to recognize the names of 3D BIM objects (such as using the MVCNN method). The authors mentioned that, as the design is creative, building elements will inevitably appear in various forms. Therefore, it is difficult to achieve a prediction rate of 100%. On the basis of the AI prediction results, further comprehensive judgments should be made in combination with the inherent knowledge of buildings. The authors proposed further judging the name of 3D BIM objects by combining "AI-based object recognition results" and the "space–object relationship".

Currently, there is a dearth of research on the semantic integrity issue for "property". Therefore, the authors proposed adding visual logos on the BIM object surfaces and using the AI method to recognize visible properties. These visual logos should be specified in the modeling guide to increase the standardization of the BIM model. Moreover, visual logos can also help designers better understand the design in the process of BIM-based forward design.

The proposed recognition method for BIM objects and visible properties is expected to be widely used in BIM-based building e-submission systems and BIM-based forward designs. Accordingly, the feasibility of BIM can be improved significantly. Moreover, the automatically extracted standard data will also serve as a building data basis for big data and AI-based analyses of the construction industry.

## Acknowledgements

This work is supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant 22AATD-C163269-02).

## Funding

This work is supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant 22AATD-C163269-02).

## Author contributions

H. W. Sun was responsible for the paper conceptualization, paper methodology and paper writing, I.H. Kim was responsible for the project administration, funding acquisition, research guidance, paper review.

## Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work described in this paper.

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