IFC properties validation using deep graph neural network

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Abstract - **This paper addresses the critical challenge of data validation in the Architecture, Engineering, and Construction (AEC) industry, arising from the interoperability issues linked with Building Information Modeling (BIM) and Industry Foundation Classes (IFC) standards. Despite the potential of IFC in improving project lifecycle management, the accuracy and reliability of BIM data remain hindered by insufficient validation tools. The paper proposes a novel approach employing deep graph convolutional neural networks (DGCNNs) to validate and correct IFC model properties, leveraging 3D model element segmentation. This methodology aims to enhance data reliability, facilitating improved interoperability within the AEC sector. By examining the feasibility of neural networks for property validation and by converting neural network results into actionable model element properties, the research contributes to advancing BIM environments towards greater accuracy and efficiency. The implications of this study extend to improving project delivery times, reducing costs, and enhancing collaboration among stakeholders.**

Keywords— segmentation, IFC, validation, GCN, BIM, Deep Learning

I. Introduction

The construction sector has witnessed a profound transformation toward digitalization in the past two decades. This shift was catalyzed by the increasing adoption and legislative endorsement of Building Information Modelling (BIM) methodologies [1]. During the transformation period, the primary objective was to improve collaboration among stakeholders and address the enduring challenge of interoperability within the Architecture, Engineering, and Construction (AEC) industry [2]. Consequently, the pivotal movement toward utilizing 3D models was anchored in adopting the Industry Foundation Classes (IFC) format. This open-source, vendor-neutral format for data exchange has been crucial due to its integral role in the ISO 19650 standard. The standard delineates the BIM process across various stages of a building's lifecycle, from the initial design phase to the eventual demolition or deconstruction, underscoring the significance of IFC in facilitating a comprehensive and unified approach to building information management [3].

Despite years of development and extensive research, data validation remains a significant challenge in addressing interoperability issues [4]. The data quality is contingent upon the software utilized, the settings of the exporter, and the IFC schema employed [5]. The absence or inaccuracies of this data significantly affect stakeholders who rely on it for subsequent processes, such as cost and labour estimation. This issue stems from the lack of effective tools and mechanisms for data validation, which are critical for enhancing data accuracy and reliability.

In response to this challenge, this paper proposes the adoption of deep graph convolutional neural networks. These networks can validate the values and correctness of parameters associated with BIM model elements. By addressing this gap, the proposed approach aims to advance the BIM environment towards greater reliability and accuracy, thus improving interoperability within the field. The research is structured around three core questions:

1) *What IFC model properties can be validated using deep neural networks?*
2) *What type of neural network is the most appropriate method for 3D mesh segmentation?*
3) *How to convert neural network results into model element properties?*

The paper starts with section 1, introducing the issue and defining the research questions. Section 2 provides the literature review of relevant studies to address the problem and position. Section 3 outlines the materials and methods used. Section 4 presents the results of applying a neural network to the introduced materials. Section 5 discusses the study results. Section 6 concludes the research and proposes the future direction of the development.

II. Background

A. *Industry Foundation Classes*

The initial development of the Industry Foundation Classes (IFC) schema in the 1990s was driven by the need to resolve interoperability issues within the AEC sector. This challenge stemmed from the absence of a standardized format for data exchange among different software platforms and vendors [4–6]. Developed and maintained by buildingSMART International, the IFC schema is comprehensive, supporting various information and processes across the project lifecycle, including design, construction, and facility management [5,7].

The schema is notable for its extensive number of classes, designed to represent physical components, their relationships, and processes within construction projects [5]. These classes provide detailed descriptions that allow for the precise definition of an element's characteristics. Additionally, the schema incorporates properties that enrich the context of the classes. They are grouped into property sets, categorizing various parameters associated with the elements.

At its core, the IFC schema provides a common set of parameters for elements, facilitating uniform data exchange of the component's information between various software products [8]. Besides the mandatory set of parameters, the schema enables the usage of custom property sets, including additional and specific data to national standards or specific project requirements [5,9]. This flexibility ensures the schema's relevance and applicability to diverse project requirements and BIM specifications, highlighting its significance in promoting efficiency and open standards among AEC professionals.

B. *Data validation*

The adaptability of the IFC schema, evolving across multiple versions, facilitates its extensive application across various modelling standards and engineering practices. This adaptability poses significant challenges in verifying the correctness, accuracy, and reflective representation of modelled elements within BIM data. Recognizing the crucial data validation issue, several studies have emphasized the necessity for rigorous checks. To tackle this, a spectrum of frameworks with varying autonomy levels has been introduced, all aimed at ensuring data integrity.

Ghang et al. [10] proposed metrics delineating differences across multiple IFC files. Although these metrics aid in tracking changes, they fail to assess parameter accuracy. In contrast, Eastman et al. [11] crafted an automatic rule-based framework to validate building designs, harnessing software to ascertain BIM model compliance against established standards. This general approach has been extended in other frameworks defining a comprehensive methodology that integrates advanced BIM technology with automated checking algorithms [6,12].

In the research conducted by Paskoff et al. [13], existing methodologies were adapted to meet the validation requirements specific to mass timber projects, leading to the development of a BIM-based method. This method, which evaluates material properties, structural integrity, and environmental standards, was shown to facilitate sustainable construction practices and streamline the design review process for such projects. It demonstrated the potential of automated validations for specific domains within BIM environments to be effectively applied based on the existing parameters of IFC elements. A similar approach, focusing on the examination of architectural elements' placement to ensure adherence to various codes and regulations, was undertaken by Wu et al. [14]. The approach involved the assessment of geometric, locational, and metadata features extracted from IFC files. Logic-based algorithms were employed to evaluate compliance with building codes. However, limitations were observed in the validation scope, primarily due to the complexity and variability of codes across different jurisdictions, which could affect the comprehensiveness of the assessments. An alternative methodology was developed by Xu et al. [12] to evaluate non-geometric attributes of duct elements in ventilation systems, focusing on performance aspects such as size, flow rate, and pressure loss. The methodology relied on IFC-property sets to describe non-geometric attributes. A critical limitation identified in this approach was its dependency on the accuracy and completeness of attributes provided by users, making it prone to errors. This vulnerability underscores the challenge of ensuring data quality and integrity in BIM validations, highlighting a significant area for improvement.

Recognizing these limitations has led to a growing interest in applying Artificial Intelligence (AI) to enhance the validation process. AI implementations can potentially mitigate some of the identified challenges, particularly in validating information quality and correctness. This emerging area of research represents a significant advancement in the field, promising to address some of the inherent limitations of current BIM validation frameworks while introducing new challenges to overcome.

C. *Artificial inteligence and IFC*

Most data validation frameworks concentrate on analyzing data already present in IFC files. For these frameworks to function effectively, they depend on specific parameters. Furthermore, these parameters must be valid and accurately depict the corresponding elements [6,11–14].

Capturing IFC data from sources other than the native modelling software became, therefore, more popular. One of the most popular techniques reflecting an object's real geometry is 3D scanning, resulting in a point cloud [1,15]. The main problem associated with this form of data is the lack of unequivocal determination of the associated object [15]. The segmentation of points within an object opens a new chapter in the research allowing for diverse application of deep learning (DL) neural networks for determination of a class of an element. The pioneering work of Qi et al. [16] proposed a PointNet DL algorithm enabling 3D object classification and object parts segmentation based on projected points. Within a wide range of applications, research conducted by Collins et al. [17] indicated that applying additional contextual information in the form of mesh relations is feasible for elements of construction models. The primary insight offered through this enhancement is improving precision and awareness of context in classifications. This is achieved by identifying the fundamental geometric and topological associations within BIM models, something that PointNet, due to its concentration on separate points, does not accomplish. Emunds et al. [18] compared three diverse DL neural networks: MeshNet, Multi-view Convolutional Neural Networks (MVCNN), and Dynamic Graph Convolutional Neural Network (DGCNN) were evaluated for their efficacy in classifying IFC elements. MeshNet's focus on directly leveraging mesh data allows it to understand geometric and topological relationships, providing an edge in accurately modelling the detailed structure of BIM elements [19]. MVCNN's strategy of utilizing multiple 2D views offers a comprehensive perspective of 3D shapes, blending the ease of 2D image analysis with the complexity of 3D forms [20]. Finally, the DGCNN distinguishes itself by dynamically updating the graph connections between points in a cloud, enabling a more nuanced capture of 3D object structures through point relationships [21].

The main purpose of all discussed frameworks is to classify an element based on its geometry. However, most data validation tools require selected property sets, not only information about an element class [12–14]. Therefore, the efficient validation of existing properties and generation of missing properties remains an unsolved issue, a significant step to a more integrated AEC workflow [2].

III. METHOD OVERVIEW

A. *Data selection and labelling*

In preparation for training the neural network, a selection process was carried out wherein 100 elements each from the ifcSlab, ifcWall, and ifcStair categories with correctly defined and valid property sets. Elements were randomly chosen from publicly accessible models [22]. These selected elements were then converted into the Wavefront Object (OBJ) format for compatibility with the training process.

Next, these mesh elements were labelled manually using the Blender software. The result of the labelling process is illustrated in Fig. 1, where each mesh face was assigned to one of several predetermined categories based on its characteristic features for further validation. The stair elements were divided into five distinct categories, each marked by a different color: the *top area* was colored blue, the *risers* red, the *side areas* pink, the *bottom area* in a sand color, and the *connection point to the upper landing* was indicated in yellow. The categorization for ifcSlab elements consisted of four groups: *top*, *bottom*, *openings*, and *side areas*. The ifcWall elements were also systematically categorized into five sections: the *top area*, *openings*, the *bottom area*, the *cross-section*, and the *side areas*.

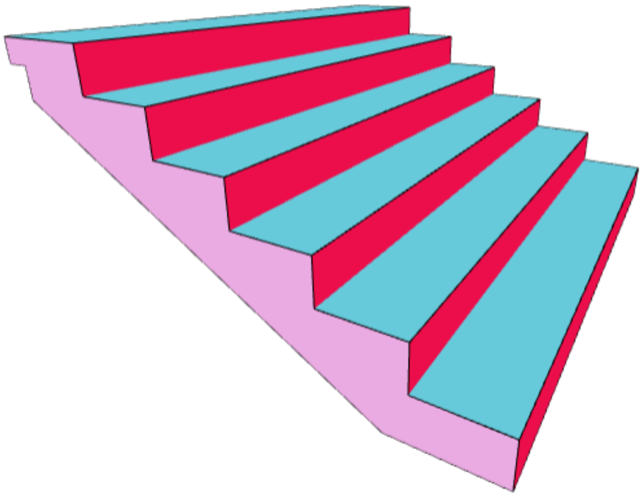

Fig. 1. An example of a labeled ifcStair object

A corresponding JSON file was generated for each of the labelled OBJ files, including the information about ground truth labels for each face. The number of elements in the JSON file matched the number of faces within the OBJ file. Each mesh face is associated with a unique label to facilitate the subsequent phases of neural network training.

B. *Dataset preparation*

After labelling, the data was divided into three parts. 80% of the elements were used for training the neural network. Another 10% was dedicated to monitoring the progress of the neural network training by a constant time interval set for 16 epochs. The last 10% was used for the final check to see how well the network had learned.

Every element was randomly spun around the vertical (Z) axis, within the range of -179 and +179 degrees, to provide a more diverse dataset. The goal of this step was to prevent the data from being all in one direction, which could make the network too specialized on that orientation and not perform well on different ones.

C. *Element features*

Using the methodology of Tang et al. [23], this study adopted mesh faces as the primary analytical units, transforming each into a graph node within a graph structure. This transformation enabled the derivation of a detailed feature set for each node, consisting of 57 attributes encompassing both spatial and structural aspects. These attributes include the angles between a mesh face and its adjacent faces, the normal vectors of the face and its neighbours, and details within a 1d-ring neighbourhood. The attributes are enhanced with additional descriptors, such as point normal and Gaussian curvature on the mesh surface, providing a rich, multidimensional data structure for neural network training.

This detailed approach to feature extraction facilitates a nuanced understanding of the mesh structure, which is crucial for training the neural network effectively. The comprehensive feature set forms the foundation for the subsequent training of the neural network, enabling it to recognize and classify 3D objects with high accuracy.

D. *Neural Network architecture*

Following the neural network architecture proposed by Tang et al., this research integrates Multi Densely Connected Graph Convolutional Networks (MDC-GCNs) specifically tailored for handling 3D mesh data. The core of this architecture lies in its ability to manage the geometric complexities of 3D objects without the constraints of shape normalization or uniform input face numbers, distinguishing it from predecessors like PointNet.

The MDC-GCN architecture is characterized by its use of densely connected layers, a strategic choice enabling the network to aggregate and refine features across the mesh structure effectively. Each layer within the network is designed to receive input from all preceding layers, fostering a rich, cumulative feature set that enhances the model's learning capability. This dense connectivity ensures that even deep in the network, layers have access to the initial input features, preventing information loss and ensuring a more accurate prediction mechanism.

E. *Training*

This section outlines the segmentation of mesh elements through the hyperparameters detailed in TABLE I.

TABLE I HYPERPARAMETERS USED FOR MDC-GCN TRAINING

Hyperparameter name	***Value***
Dropout probability	40%
Hidden layers	1024
Epochs	512

For the training process, the learning rate (LR) is initially set at 0.0004. This rate undergoes a multiplication by a gamma factor of 0.8 every 128 epochs. This adjustment strategy leads to a final learning rate of 0.00016 by the conclusion of the training period. The network employs the Rectified Linear Unit (ReLU) as its activation function. This choice is pivotal for uncovering nonlinear patterns within the dataset. Moreover, the model's performance is evaluated based on the cross-entropy loss function during the training, validation, and testing phases. This function is widely recognized for its effectiveness in multicategory classification tasks.

F. *Usage of segmentation results for IFC validation*

The process depicted in Figure 2 begins with selecting an IFC file. Based on the input file, all geometrical elements are converted to a mesh object and proceed to the segmentation stage. This stage returns the number of labels reflecting the number of mesh faces.

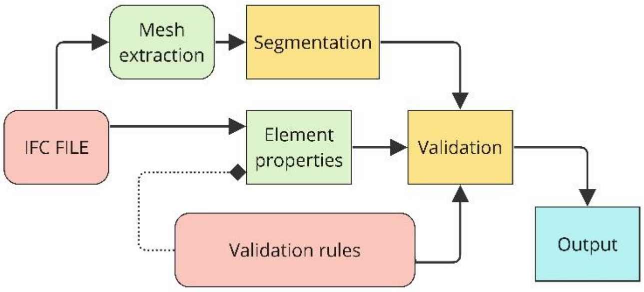

Fig. 2. The IFC project validation workflow

In the workflow, properties for each segmented element are extracted simultaneously. This process is refined for efficiency by selectively extracting only those properties that require validation, as determined by the specifications within the validation rules container, as presented in Figure 2.

The validation rules container presented in Figure 2 contains information about the validated parameter type, the expected segmentation label for this property and the data type. The methodology incorporates two types of data parameters. The first type is dedicated to identifying and quantifying elements describing repetitive patterns within the object. In the IFC schema, this property is defined as IfcCountMeasure datatype. The second kind of parameter validation uses the segmentation results to verify the area measurement defined in property sets of the IFC schema. The IFC schema classifies these measurements as IfcQuantityArea data type.

IV. RESULTS

A. *Model training process results*

The training process was conducted on selected datasets for three types of ifcClasses separately using an Ubuntu system with 128Gb of RAM and Nvidia A4500 GPU with CUDA acceleration. The accuracy and epoch diagram for ifcSlab, ifcStair, and ifcWall elements is shown in Figure 5. The accuracy is calculated based on the percentage of correctly predicted faces. It was found that the ifcStair class achieved high accuracy more quickly than the ifcWall and ifcSlab elements.

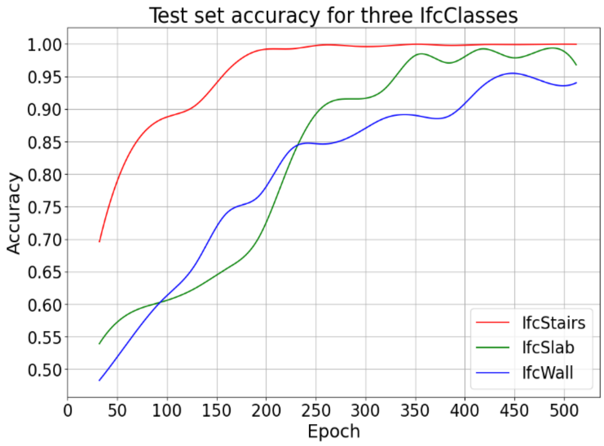

Fig. 3. Diagram of test accuracy for three ifc classes

Despite the high accuracy, the visual interpretation of the segmentation results leads to the conclusion that the most confusing elements to be recognized by the neural network are locations related to the openings, as shown in Figure 4.

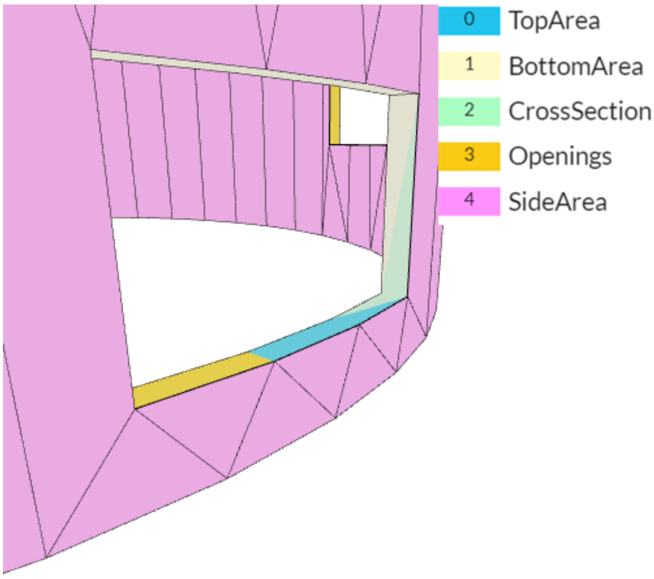

Fig. 4. Example of misclassification, based on the complex ifcWall element

Figure 4 demonstrates that a single opening can be labelled using multiple wrong classes, leading to challenging postprocessing of the results. On the other hand, the results for elements with less complex geometry ensure the high quality of the segmented object and less challenging postprocessing, as shown in Figure 5.

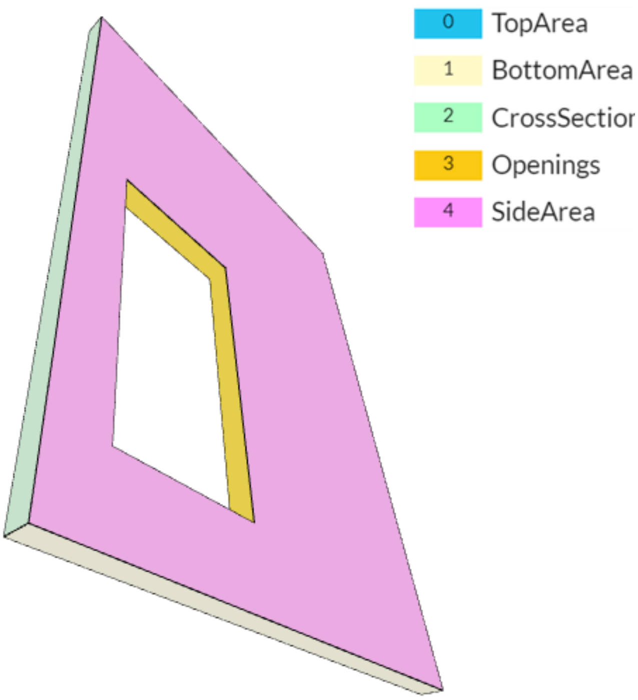

Fig. 5. Example of correctly segmented simple ifcWall element

The same behaviour is observed for stairs segmentation, which exhibits accuracy higher than 99% for all testing elements. The most often occurring discrepancies are meshes faces related to the part where the ifcStair object is connected to the stairs landing, as shown in Figure 6. The figure shows the segmentation results of a single object, with marked correct labels (green) and incorrectly predicted labels (red).

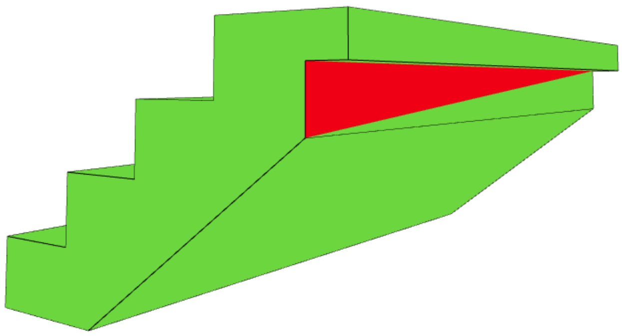

Fig. 6. Results of stairs segmentation

B. *Usage of the segmentation results to validate IFC data*

The methodology employs the methodology introduced in section III.F to validate the IFC properties defined in TABLE II. The table contains three columns, including the ifcClass, the name of its validated parameters, and the 'Type' column indicating the applied validation mode. 'CM' represents IfcCountMeasure, which is specifically used to represent discrete quantities, such as a count of items or the number of particular elements within the models' scope, such as the number of risers. The 'QA' designation pertains to 'Quality Area' for area measurements, ensuring that the area detailed in the IFC property is correct.

TABLE II IFCCLASS AND IFCCOMMON PROPERTIES USED FOR METHODOLOGY VALIDATION

Class	***Parameters***	***Type***
IfcStair	NumberOfRiser, NumberOfTreads	CM CM
IfcSlab	NetArea	QA
IfcWall	NetFootprintArea, NetSideArea	QA QA

These properties were validated using Python programming language and trimesh library, capable of operating on 3D meshes. The validation of ifcStair properties demonstrates a 100% success rate. IfcSlab and ifcWall's success rate is lower, resulting in 88% for ifcSlab and 91% for ifcWall, respectively.

V. DISCUSSION

A. *Properties validation using deep neural network*

The proposed methodology has effectively validated numerical properties derived from segmentation results, addressing the first research question. It proves capable of validating two main types of parameters: those based on area measurements and those counting occurrences within an element, as exemplified by the parameters of the ifcStair.

The observed difference in accuracy between ifcStair objects and those of ifcWall and ifcSlab can be attributed to the greater geometric diversity found in the latter two. Unlike stairs, which typically consist of a single stair run characterized by variations in width, height, and step count, walls and slabs exhibit a wide range of openings and significant size differences.

Upon manually reviewing the outcomes, it becomes apparent that an automated approach to generating datasets for ifcSlab and ifcWall might benefit from transitioning to a more meticulous manual segmentation into more balanced datasets, enhancing their correlation. Additionally, the initial dataset comprising 100 elements is deemed inadequate for capturing the full complexity of construction elements. Expanding the dataset is advised to enhance the methodology further, aiming for several thousand elements. This expansion is crucial for capturing the vast diversity of construction elements and ensuring a more robust and comprehensive analysis.

B. *Neural network*

The main advantage of employing the mesh-based graph convolutional neural network is the direct connection between the result and the 3D object geometry. Moreover, compared to the PointNet or MVCNN, it does not require data postprocessing and projection of the result to the original mesh [16,20].

The next advantage is the ability to operate using any number of mesh faces. This feature ensures that the geometry is always represented with the minimal required number of faces instead of artificial mesh splitting to reach the required input vector shape. Additionally, it enables the inclusion of additional properties in the input features. Therefore, the graph-based convolutional neural networks best handle 3D mesh segmentation tasks, answering research question 2.

C. *Conversion of segmentation results to IFC properties*

The segmentation results are validated against ifc element properties using predefined rules. The validation rules contain two types: count measurement and area quantity measurements. GCN network characteristics result in the direction connection between mesh results and the predicted segmentation labels. For the validation of results, postprocessing is required. It involves counting similar subobjects (e.g., stair steps) within the scope of the mesh or the summation of the area of all connected geometrical labels. These totals are then compared with a predefined IFC property value, addressing research question 3.

VI. CONCLUSION AND FURTHER WORK

The research presented in this paper introduces a novel approach to the validation of Building Information Modelling (BIM) data using deep graph convolutional neural networks (GCNNs), addressing the significant challenge of data validation within the Architecture, Engineering, and Construction (AEC) industry. Through meticulous training and testing of neural networks on segmented 3D mesh data from various IFC model elements, the methodology demonstrated high accuracy in validating and correcting IFC properties, particularly for elements with less complex geometries, such as stairs, which achieved over 99% accuracy.

Despite the challenges raised by the geometrical diversity of wall and slab elements, the proposed method still achieved notable success rates, highlighting its potential for broader application. This study contributes to advancing the accuracy and reliability of BIM data validation and paves the way for future research into integrating AI in enhancing BIM processes.

VII. Further work

Future efforts will be directed towards broadening the approach’s applicability to encompass various complex element types. This will be achieved by refining the neural network model to enhance validation accuracy across an expanded range of IFC elements. The dataset will be extended, and a more robust and versatile framework for validating IFC properties will be developed. Furthermore, more extensive labels will be created and tested for effectiveness across more IFC classes.

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