

Formal analysis and validation of Levels of Geometry (LOG) in building information models

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Abstract. Construction projects are multidisciplinary and contractual. The collaboration among the project participants and the quality of the exchanged building information throughout the project lifecycle are prescribed in legal agreements. The Level of Development (LOD) concept is widely used for describing the building elements' maturity. Detailing models to a certain LOD is crucial for integrating the partial models as well as consumes additional time and costs. Every LOD comprises requirements for both Level of Geometry (LOG) and Level of Information (LOI). Thus far, the validation of LOD is limited to the LOI, whereas, checking the quality of the LOG is a complex and unsolved task. This paper proposes a framework for validating the LOG of building elements. In more detail, a LOG dataset is modelled, and then a formal metric is defined based on an extracted set of geometric features. Finally, a random forest model is developed for predicting the LOG.

1. Introduction

Several countries worldwide are promoting the research and development of BIM-based methodologies to facilitate their integration in the projects' life cycle. As construction projects are multi-disciplinary, a fundamental pillar for integrating BIM is describing the building elements' maturity at a particular design phase. This is crucial for the overall collaboration among the project participants as it acts as an agreement of (what) information should be available at what time (when). Based on that information, it can be decided for what the model can be used for (purpose), which makes it possible to determine what model deliverables are expected from the involved actors (who) (Betz, Borrmann and Weise, 2018). The exchange of complete BIM data within the Architecture, Engineering, and Construction (AEC) industry is crucial, as it is prescribed in legal agreements, where the information for each specific model is specified. Accordingly, a common legal framework for organizing this data is required.

Data quality is described by the compliance of its characteristics to requirements (ISO, 2015). More specifically, the quality of building information quality is expressed by the correctness and completeness of the topological relationships, geometric detailing, and semantics. Various guidelines were published to deliver a standard in which practitioners can use as a basis for a common language in their projects. A popular concept for defining the content of a model at a certain point during the design process is the Level of Development (LOD) (BIMForum, 2019). The LOD refers to the completeness and reliability of the building elements' information. A similar concept was introduced by the European Standardization Organization (CEN) (DIN, 2019), which defines the term Level of Information Needs (LOIN) comprising specifications for LOG and LOI for supporting a particular use-case.

Currently, practitioners rely on the LOD concept terminology to specify which information they need to deliver and/or to carry out their tasks (Leite *et al.*, 2011). However, as the different LOD specifications are loosely defined, each practitioner has a different interpretation of what a specific LOD means and which information should be present in the model (van Berlo and Bomhof, 2014). Such inconsistencies cause severe miscommunication and additional expenditure, which increases project risks (Leite *et al.*, 2011). For example, a structural engineer might model a highly detailed structural system in case it was understood that building elements are at high LOD, giving the impression that they are stable and less subject to change. However, the building model might be a sketch at the early design phase, which would drastically change in the subsequent phases (van Berlo and Bomhof, 2014).

Exchanging building models among the project participants requires checking the models' conformance with the defined LOD requirements, which includes semantics, a.k.a. Level of Information (LOI), and geometric information, a.k.a. Level of Geometry (LOG). While checking the completeness of the semantic information is straightforward (Abualdenien and Borrmann, 2019) and several commercial software solutions exist for this purpose, confirming that the modelled geometry fulfils the expected LOG is a complex and still unsolved task.

This paper addresses the currently existing gap of determining the LOG of building elements by investigating the major characteristics representing the increase of detailing based on a formal metric. To this end, a set of BIM elements of different family types are modelled at multiple LOGs, and the geometric information of each level is investigated. In more detail, in each LOG, the geometrical features are extracted, and their complexity is measured using a combination of various advanced geometry processing algorithms. Finally, this paper contributes with a standard criterion that facilitates inferring the LOG of any given building element.

The paper is organized as follows: Section 2 discusses the background and related work. Section 3 provides an overview of the framework developed in this paper, explaining the approach followed to generate the LOG dataset and extracting geometric features. A model for predicting the LOG of building elements is developed and evaluated in Section 4. Finally, Section 5 summarizes our progress hitherto and presents an outlook for future research.

2. Background and Related Work

2.1 3D Shapes

The 3D representation of objects is a fundamental aspect for numerous domains, starting from computer graphics to building information modelling. A popular approach to represent shapes in various applications is the polygonal mesh representation, which explicitly captures a shape's surface characteristics and topology (Botsch *et al.*, 2010; Garland, 1999; Shikhare, 2001). Polygonal meshes require only a small number of polygons to represent simple shapes (regardless of their size). Additionally, it has the necessary capability to comprehensively represent complex shapes with high resolution, capturing the salient surface features. Accordingly, simple shapes are represented by few large polygons, while detailed and complex shapes are represented by many small polygons. The mesh polygons comprise a set of vertices, which are interpolated through a connectivity graph to approximate the desired surface.

2.2 Shape Complexity

As detailed below, there are strong indicators that there is a correlation between LOG and shape complexity. The meaning and measurement of a shape complexity can vary according to different aspects. Processing geometric models can be as simple as iterating over a mesh's vertices, faces, and edges, or as complex as performing different calculations to extract information about the curvature or shape topology. Numerous researchers have developed algorithms to retrieve the most dominant features (Botsch *et al.*, 2010), including detecting sharp edges, deducing surface patches, and decomposing the shape into smaller and meaningful shapes, a.k.a segmentation (Shapira, Shamir and Cohen-Or, 2008). Dominant features provide an essential description of the geometrical objects' resolution and detailing. In the same context, Hanocka *et al.* (2019) and Nikhila *et al.* (2020) have developed MeshCNN and PyTorch3D by employing deep-learning approaches to analyze, process, and extract features from 3D shapes.

A popular classification for shape complexity was firstly introduced by Forrest, where it defines three main types (Forrest, 1974): (1) geometric, describes the shapes' basic features, such as lines, curves, faces...etc., (2) combinatorial, refers to the topology of the shape, i.e. the number of components that comprise it, and (3) dimensional, which classifies the shape as 2D, 2.5D or 3D. Other researchers have interpreted shapes as a set of rules through shape grammars (Heisserman, 1994). Shape grammars describe the shape decomposition as a set of rules and series of transformations, including addition, subtraction, rotation, etc.

Accordingly, defining what a shape complexity means in the AEC industry requires the specification of which geometric features are essential for capturing the degree of maturity of building elements at the different LOGs.

2.3 Level of Development (LOD)

As a response to the need of having a consensus about what information should exist during the development of building elements, various guidelines were published to deliver a standard, which practitioners can use as a basis for a common language in their projects. Prior to the LOD concept, a relatively similar concept, a.k.a Level of Detail (LoD), was already common in computer graphics. The LoD is used to bridge the graphical complexity and rendering performance by regulating the amount of detail used to represent the virtual world. In computer graphics, the LoD concept is mainly concerned with the geometrical detailing (Luebke *et al.*, 2003). In Geographic Information System (GIS), the LoD represents different levels of geometric and semantic complexity of a city model (Kolbe, Gröger and Plümer, 2005).

In the AEC industry, the LOD represents the completeness and reliability of the geometrical and semantical information associated with building elements (BIMForum, 2019). The first initiative was by VicoSoftware® (Trimble, 2013; VicoSoftware, 2005), where the Level of Detail (LoD) was introduced. The LoD concept has then been adopted and refined by the American Institute of Architects (AIA) to become the Level of Development (LOD) (AIA, 2008). The AIA introduced a definition of the LOD that comprises five levels, starting from LOD 100 and reaching LOD 500. The BIMForum working group developed LOD 350 and published the Level of Development Specification based on the AIA definitions (BIMForum, 2019). At the same time, Trimble's Project Progression Planning (Trimble, 2013) was published and is widely used in practice.

2.4 LOG Analysis and Validation

The process of adopting a LOD specification in a particular country (or even internally in the individual firms) requires a comprehensive analysis and understanding of which geometric and semantic information should be present at each LOD. However, practitioners have an inconsistent understanding of the information necessary at each LOD (Abualdenien and Borrmann, 2019; van Berlo and Bomhof, 2014). This is because although the specification of semantics is usually simplified to a list of properties, defining the geometrical complexity is highly vague and systematically checking it is an unresolved task.

In this regard, Leite *et al.* (2011) evaluated the modelling effort associated with generating BIM models at different LODs. The authors have shown the need for an increased modelling time ranging from doubling the modelling effort to eleven folding it, to detail models further to reach a higher LOD. Additionally, van Berlo and Bomhof (2014) has analysed 35 building models (where each comprises multiple building elements) taking into account different ratios between volume, triangles, space areas, and the number of properties, in an attempt to find a standard or relationship between the different LODs. However, the authors did not find any standard or pattern of increasing the complexity across the LODs. The main reason for not detecting any standard for increasing the complexity is because of the inconsistencies and different interpretations of the LOD specifications (Gigante-Barrera *et al.*, 2018). More specifically, using the LOD concept for describing the maturity of the overall building model versus the individual elements. Van Berlo and Bomhof (2014) performed their experiments on the overall building models rather than the individual elements. In this regard, the LOD specifications provided by the AIA (AIA, 2008), BIMForum (BIMForum, 2019), and Trimble (Trimble, 2013) describe the geometric and semantic information of the individual elements rather than the overall building model. On a wider scale, Wong and Ellul (2016) analysed the geometry of 3D city models for fit-for-purpose by looking into the ratios between the number of buildings, geographic area, geometrical details, and disk size.

3. Methodology

The hypothesis in this paper is that the geometric complexity of the individual elements can be represented by multiple features, forming the basis for a metric allowing to formally assess the geometric complexity of a given model. Through analysing the changes of the extracted features across the LOGs, the detailing pattern can be recognised, which in turn provides the means for the LOG classification of building elements.

As depicted in Figure 1, the proposed approach consists of two steps. First, a LOG dataset is modelled according to the most common LOD specifications. The dataset generation took into account modelling the different kinds of building elements as well as additional cases for including openings and reinforcement. Afterwards, multiple geometry processing algorithms are performed to extract the most prominent features representing the shape complexity of each building element. The result is a dataset of geometric features for diverse building elements on the LOGs 200 - 400. The second step describes the process of predicting the LOG of a new element. The geometric features of the new element are extracted in a similar way to the dataset generation, and then the individual features are compared for similarity to the features available in the dataset to predict the new element's LOG. The complete framework is discussed in detail in the next subsections.

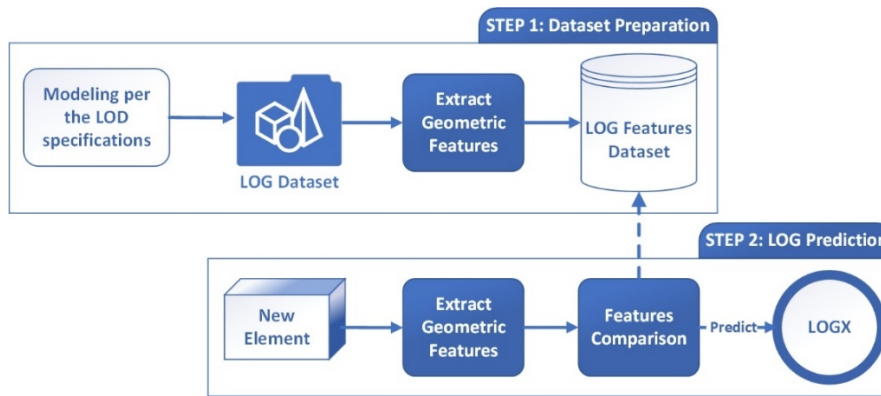


Figure 1: The proposed framework for LOG prediction

3.1 Modelling per the LOD Specifications

In this study, the BIMForum’s LOD specification (BIMForum, 2019) and Trimble’s Project Progression Planning (Trimble, 2013) were comprehensively reviewed and followed during modelling different families on multiple LODs. We followed the combination of multiple specifications because although the BIMForum’s definitions are descriptive for many building elements, they are in many cases, vague in describing the progression of the geometric detailing. Despite the fact that the specification is prepared in a way that visualizes the newly added parts in every LOD, the graphical illustrations for many elements are inconsistent and ambiguous. For example, when modelling a stair, information regarding the riser count and height should be available starting from LOD 300 (per the text description). However, the graphical illustration at LOD 200 already includes them.

Based on the LOD specifications, LOG 100 (conceptual model), is limited to a generic representation of the building, meaning no shape information or geometric representation. At LOG 200 (approximate geometry), elements are represented by generic placeholders, depicting the overall area reserved by their volume. At LOG 300 (precise geometry), the elements’ main shape is refined, showing the fundamental detailing required for describing the element type. Next, at LOG 350 (construction documentation), any parts that are necessary for depicting the connections with other elements, that are attached or nearby, are additionally modelled. Modelling these parts, like supports and connections, is crucial for the coordination with different domain experts. Finally, at LOG 400, elements are fully detailed, providing the accuracy required for fabrication, assembly, and installation. LOG 500 represents the field verified model state, which means in terms of design and detailing, it is the same as LOG 400.

The modelling process followed to generate the dataset was focused on the LOGs 200 - 400. In order to have confidence in how to model the families, we have modelled first most of the families existing in the specifications, taking guidance from the text description as well as the visual illustrations. Afterwards, we have expanded the dataset size by making use of the available BIM objects libraries¹, where the families were downloaded and adjusted to match the different LOGs. Figure 2 shows a window on multiple LOGs from the modelled dataset. In total, the modelled dataset included 216 objects (54 families at four LODs). Figure 3 shows an example of an elevator, stairs, brick wall, and wall frame on multiple LODs.

¹ <https://www.bimobject.com/> | <https://www.nationalbimlibrary.com/> | <https://market.bimsmith.com/> | <https://www.revitcity.com/> | <http://www.familit.com/> | <https://www.arcad.com/>

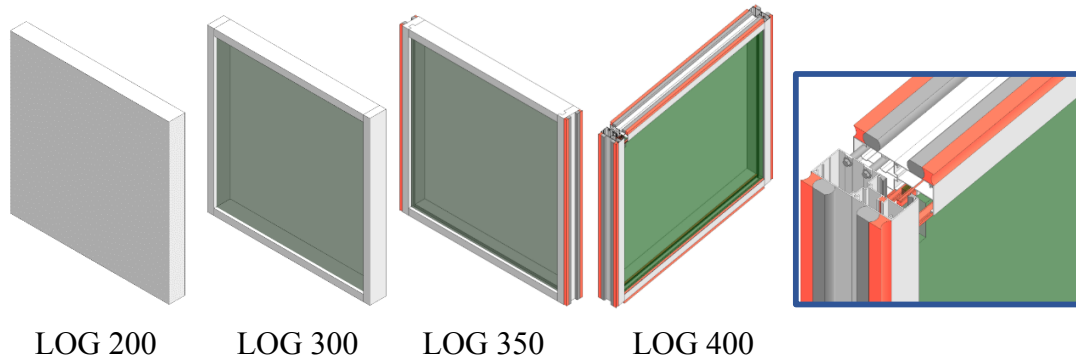


Figure 2: Dataset sample: window at LOGs 200 - 400

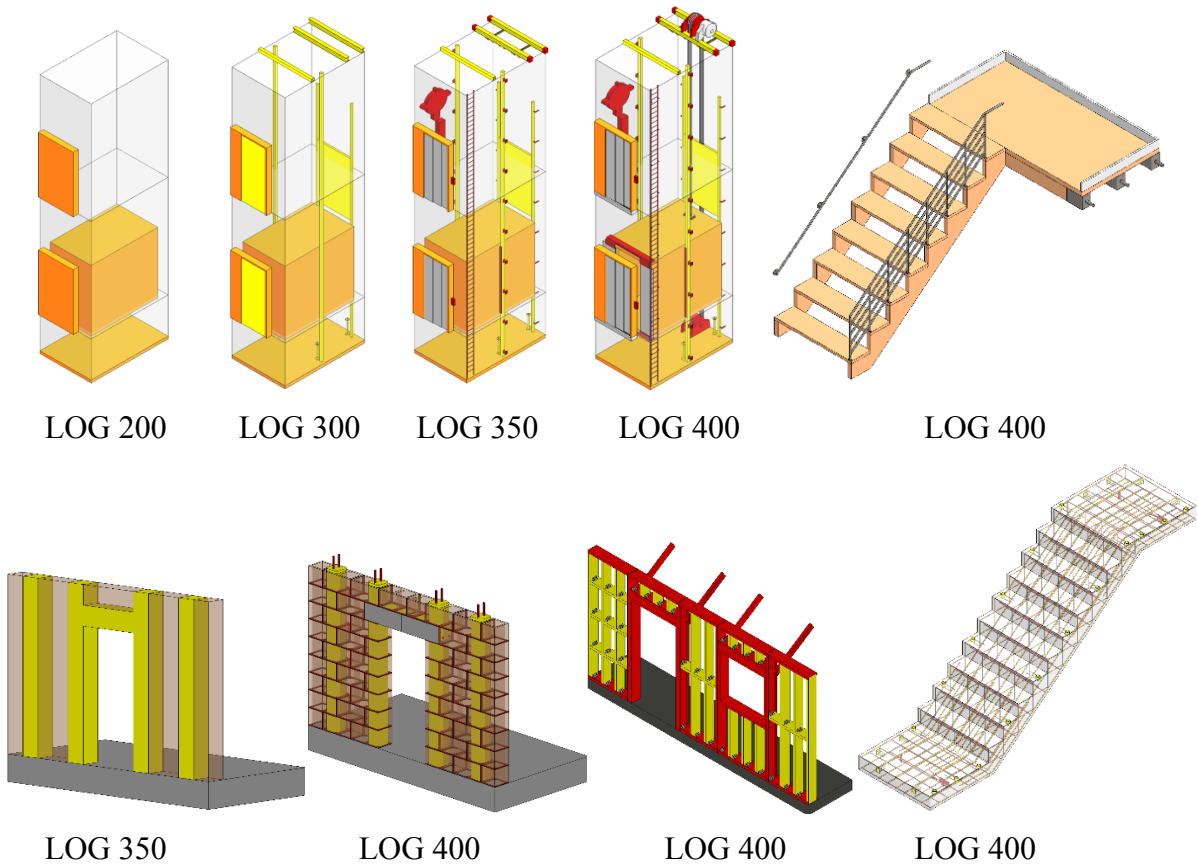


Figure 3: Dataset sample: selected models at different LOGs

3.2 Analysis and Extraction of LOG Features

Typically, shapes having more numerous or smaller features can be viewed as more detailed. The challenge in identifying the LOG through analysing geometric features lies in deducing a standard pattern that describes the individual LOGs. The simplest geometric metrics can be based on the total number of vertices, faces, and edges. However, an increased number of these features does not necessarily mean an increased detailing or higher LOG. For example, a window at LOG 200 (rectangular shape) consists of 30 vertices, 16 faces, and 78 edges, while a cylindrical column or heating tank at LOG 200 is formed by 2358 vertices, 4268 faces, and 13244 edges. Thus, the sole consideration of vertices, faces and edges does not provide a suitable metric. To measure the geometric detailing (i.e. LOG) of elements, the applicable features need to be capable of representing the geometric detailing of elements taking into account the overall shape.

In the proposed approach, we combine the extracted results of multiple geometric features to observe various aspects of the shape detailing. In total, we investigated the effect of detailing across the LOGs through four main aspects, resulting in 14 geometric features, as follows:

1. **Basic Geometric Features:** The increase of vertices, faces, and edges. Here, the ratio of vertices to faces provided an additional indicator for the shape complexity (this ratio indicates the required points for capturing the shape details). In more detail, a shape with just rectangular parts always has a ratio of 2, adding more complex parts, like screws or reinforcement, substantially reduces the ratio.
2. **Edges Length:** Count and length of edges can provide a strong description of the shape complexity. Numerous short edges reflect more detailing and additional complex parts. In this regard, we measured the length of 50%, 62.5%, and 75% of edges, and compared it to the total edges' length. Similarly, the mean edge length is also calculated and compared.
3. **Sharp Edges:** Sharp edges represent the most prominent surface characteristics of a geometric shape. Therefore, sharp edges are extracted and counted by measuring the change in curvature as well as counting the number of surface patches bounded by those edges.
4. **Diameter-based Segmentation:** In this process, the shape is segmented into smaller meaningful pieces based on the change in diameter (Shapira, Shamir and Cohen-Or, 2008). This segmentation provides additional insights into the complexity of the parts comprising building elements on each LOG. Accordingly, we count the segments, measure their area, and evaluate their shape (flat surfaces, cubic, or cylindrical). In this aspect, the segments with similar shapes are grouped, and the ratio of the count and area of each shape to the overall segments can characterize the overall shape (differentiating a window from a tube system).

The discussed geometric features above were extracted for the complete dataset presented in Section 3.1. Additionally, multiple ratios were calculated to capture different positive or negative correlations among the features, including average area per surface patch and segment, as well as average vertices per face, patch, and segment. Finally, the extracted features were normalized to make the features correspond to the elements' geometric complexity regardless of their total area or total edges length.

After the extraction of features, their change across the LOGs was analysed. Figure 4 shows three features for three different elements, wall, column, and a stair. Those three different elements are selected to show the difference in their pattern throughout the LOGs. Interestingly, we have noticed relatively similar patterns among rectangular shapes (e.g. walls, doors, windows), cylindrical shapes (e.g. columns, heating tanks, tube systems), and complex shapes (e.g. stairs, escalators, elevators). In the same context, we observed that in case the count of the cylindrical segments is low and represents more than ~50% of the overall area, then the overall shape has a high probability of having a cylindrical overall shape (a pipe as an example).

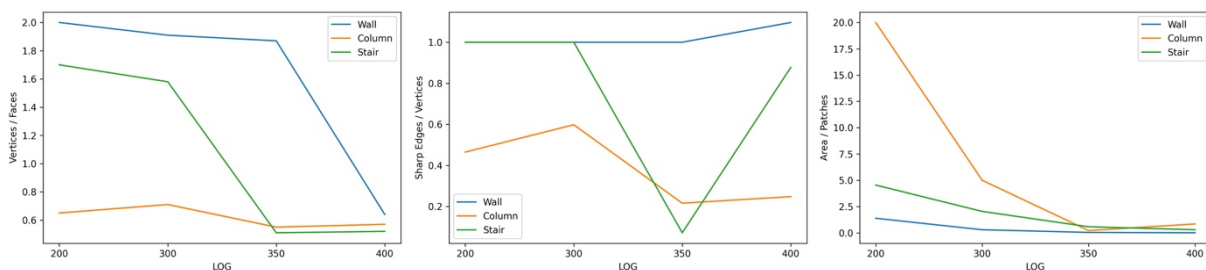


Figure 4: Three geometric features of three building elements on different LOGs

Additionally, rectangular and complex shapes at LOG 350 and 400, are composed of a high number of cylindrical segments while representing less than ~40% of the overall area. When reinforcement is modelled, then the number of cylindrical segments is relatively high (~50 – 80%), while their aggregated area is less than ~40% of the overall area.

4. Prediction of LOG

The analysis of the extracted features (presented in the previous section) showed multiple patterns that are present in the dataset. Predicting the LOG of a new building element is a classification problem, i.e. detecting which class (LOG) an observation (the set of extracted features) belongs to. The simplest way to classify new observations is to consecutively try to split the dataset observations (based on feature values) in a way that groups similar observations as much as possible. This is exactly what a decision tree (Breiman, 2001) performs while following a certain route yielding a specific result. However, as decision trees are based on a greedy model, meaning it tries to find the most optimal decision at each step and does not consider the global optimum, we decided to build a random forest model (Breiman, 2001). A random forest consists of numerous decision trees that operate as an ensemble; each decision tree selects features randomly and predicts a class; the class that receives the highest number of votes becomes the final prediction.

In order to develop the random forest model, the modelled elements presented in Section 3.1 were randomly split into training and test datasets with a ratio of 80% (172 elements) and 20% (44 elements) respectively. The resultant model is composed out of 22 trees, where the max depth of each is four. Figure 5 shows one decision tree of the developed random forest using the training dataset. In this tree, the average area of surface patches is the first metric splitting the dataset to LOG 200 and 400. The Gini Impurity represents the likelihood of classifying a new instance incorrectly (Raileanu and Stoffel, 2004). Then, the metrics of the average vertices per faces, as well as the average area of surface patches, are used to split the dataset further. Going deeper in the right branch, the tree is completely confident about predicting LOG 300 for two samples while 94% confident of LOG 200 of 32 samples. On the other hand, the left branch has lower confidence at the first level, but it increases in the next levels. It is important to emphasize here that this is one decision tree of the complete forest. The other trees randomly employ a different set of geometric metrics to reach a final decision.

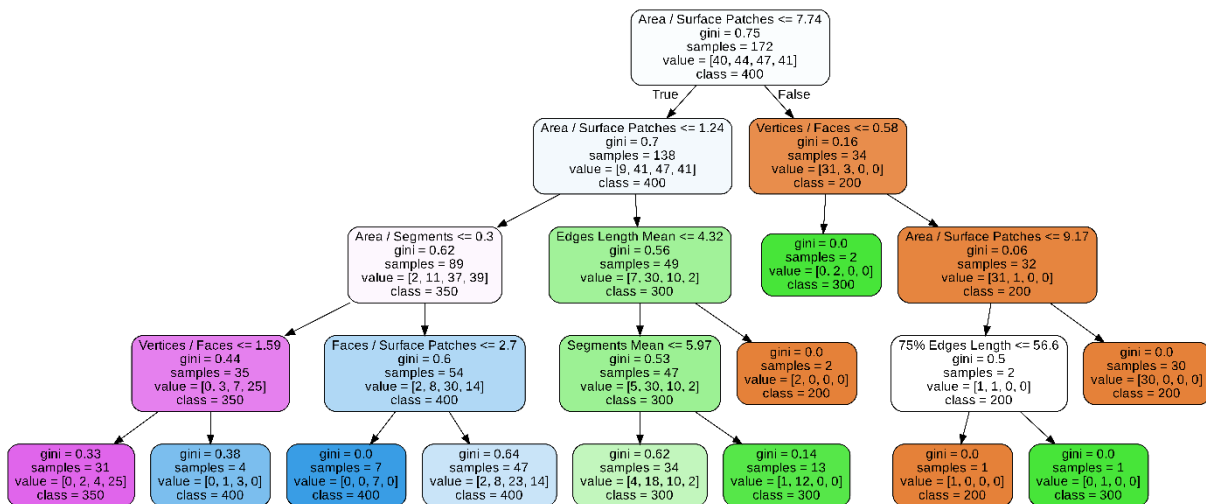


Figure 5: Random forest model: showing the selected features of one decision tree

The evaluation of the performance of the developed random forest model for predicting the LOG was conducted on a completely new set of elements (test dataset - 44 elements). The performance metrics is described as precision, recall, and F-Score, as presented in Table 1. Precision describes the model performance in positive predictions while considering false positives. Recall incorporates false negatives instead of false positives, and F1-score provides a balance between precision and recall. Table 1 shows the confusion metrics, depicting the difference between the actual and predicted LOG. In total, 35 out of 44 elements were predicted correctly. Additionally, investigating the incorrect predictions further, we can notice that the classes were confused with the its close neighbours, e.g. LOG 200 with 300. This is mainly because, in this specific case, the number of changes modelled to detail the model further from LOG 200 to 300 are not necessarily increasing the shape complexity enough to be differentiated. Moreover, this approach heavily relies on the dataset size (finding similar observations). Therefore, increasing the dataset size would substantially improve the model performance.

Table 1: Performance metrics, precision, recall, F1-score, and accuracy for each LOG. On the right side, the prediction confusion metrics depicts the ratio between the actual and predicted LOGs.

LOG	Precision	Recall	F1-score
200	0.90	0.82	0.86
300	0.80	0.86	0.83
350	0.67	0.80	0.73
400	0.86	0.67	0.75
Accuracy			
Macro Avg.	0.81	0.79	0.79
Weighted Avg.	0.81	0.80	0.80

Predicted \ Actual	200	300	350	400
200	9	1	0	0
300	2	12	1	0
350	0	1	8	3
400	0	0	1	6

5. Conclusions and Future Research

Building models consist of numerous and diverse kinds of information to fulfil multiple use-cases, including fire-safety regulations, structural and energy analysis, as well as pedestrian simulations. Hence, practitioners need a common ground to communicate the content of their requirements and deliverables across the design phases. The LOD concept brings multiple benefits for describing and managing the expected information in the individual design phases. The geometric representation of building elements is crucial for the collaboration among domain experts as it forms the basis for integrating the partial models and carrying out the different kinds of simulations. However, the currently available tools are only capable of checking the completeness of semantic information; validating the conformance of the modelled geometry to the required LOG is currently manual and prone to multiple interpretations.

This paper has proposed a framework for predicting the LOG of building elements. The prediction is based on a formal metric of a LOG dataset that includes 216 elements. The elements were modelled according to the most common LOD specifications. The metric is formed out of four main aspects, basic geometric details, edges length, sharp edges, and

diameter-based segmentation. Finally, a random forest model was developed and evaluated, showing the ability to predict the LOG of 44 new building elements. As a next step, additional building elements should be modelled to improve prediction accuracy. Additionally, the state-of-the-art acritical neural networks will be evaluated for extracting geometric features and predicting the LOG.

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