A 3D INDOOR-OUTDOOR BENCHMARK DATASET FOR LoD3 BUILDING POINT CLOUD SEMANTIC SEGMENTATION

Y. Cao, M. Scaioni *

Department of Architecture, Built Environment and Construction Engineering, Politecnico di Milano, via Ponzio 31, 20133, Milano
Italy - (yuwei.cao, marco.scaioni)@polimi.it

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ABSTRACT:

Deep learning (DL) algorithms require high quality training samples as well as accurate and thorough annotations to work effectively. Up until now a limited number of datasets are available to train DL techniques for semantic segmentation of 3D building point clouds, except a few ones focusing on specific categories of constructions (e.g., cultural heritage buildings). This paper presents a new 3D Indoor/Outdoor building dataset (BIO dataset), which is aimed to provide a highly accurate, detailed, and comprehensive dataset to be used for applications related to sematic classification of buildings based on point clouds and meshes. This benchmark dataset contains 100 building models generated from existing polygonal models and belonging to different categories. These include commercial buildings, residential houses, industrial and institutional buildings. Structural elements of buildings are annotated into 11 semantic categories, following standards from IFC and CityGML. To verify the applicability of the BIO dataset for the semantic segmentation task, it has been successfully tested by using one machine learning technique and four different DL algorithms.

1. INTRODUCTION

Applications for semantic segmentation of building point clouds play a very important role, due to the relevance of these objects, especially in urban areas (Czerniawski and Leite, 2020). 3D building models can be classified into different Level-of-Details (LoD) (Kutzner et al., 2020). In recent years, high LoD 3D building point cloud representations, such as LoD3, have enabled and promoted various applications. These applications of this technology include indoor navigation (Isikdag et al., 2013), energy efficiency (O'Donnell et al., 2019), disaster response (Nikoohemat et al., 2020), and sustainable urban planning (Schrotter et al., 2020).

However, these applications are still at an early stage, with most of them focusing on the representation of the whole building (LoD0 and LoD1) or a few types of semantic subsurface (LoD2), and a few applications applying to the more detailed subsurface of the building (LoD3) (Czerniawski and Leite, 2020; Wen et al., 2019). To enhance such applications, it is essential to acquire LoD3 representations that contain fine-grained semantic information.

Recent developments in deep learning (DL) techniques for the semantic segmentation of 3D point clouds have resulted in impressive progress and opened new challenges in the building field (Cao and Scaioni, 2022). On the other hand, DL techniques need to be trained to work effectively. Despite the fact research has recently focused on methods to reduce the amount of training data, it is essential to have access to high-quality, rigorously annotated datasets (Géron, 2022).

Obtaining real-world 3D scene datasets of buildings typically requires a quite time-consuming data acquisition stage. Static or mobile ranging and/or imaging sensors should be operated through the 3D environment to collect point clouds directly (e.g., using laser scanning) or indirectly (e.g., using photogrammetry). To be used for training DL networks, the data must be segmented and classified before they can be applied to this purpose. This time-consuming process can limit the number of building scenes that can be surveyed and classified. For this reason, the coverage, diversity, and accuracy of existing 3D datasets of buildings is quite limited. In addition, the most of them only alternatively cover indoor or outdoor environments. As a result, it becomes difficult to develop novel artificial intelligence (AI) applications that require a thorough understanding of complex indoor and outdoor built environments. For instance, the ArCH dataset (Matrone et al., 2019) only focuses on the cultural heritage (CH) domain, and the S3DIS dataset (Armeni et al., 2016) contains more than 200 rooms but does not include the exterior elements of buildings.

Online 3D models are much more prevalent today than they were a decade ago. Millions of polygonal 3D models covering a variety of objects and scene categories, including commercial, residential, industrial, and institutional buildings, are now available through services such as the 3D Warehouse (Trimble, 2023). Models may come from 3D modelling process of existing building previously surveyed, or they may be artificially created from scratches (e.g., based on procedural modelling). This large amount of 3D data about buildings could be exploited to create dataset for training DL network. The main goal of this research is to develop a complete and accurate dataset of typical buildings in modern cities to support emerging building-related AI applications, which require a deep understanding of complex indoor and outdoor environments.

In this study, we present the indoor-outdoor building dataset (BIO dataset), which at the current initial stage contains 100 building models that have been carefully labelled in point cloud and mesh formats. Data have been derived from the online repository 3D Warehouse.

Figure 1 reports some examples of building models in mesh and point cloud formats. Through the use of automated mesh repair, point cloud sampling, thorough manual labelling, and

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* Corresponding author

verification, the dataset has an exceptional level of detail, accuracy, and consistency.

Along with the creation of the labelled BIO dataset, we additionally propose a thorough pipeline that makes use of cutting-edge AI methods to assess its usefulness and practical applicability for training networks. These entail either Machine Learning (ML) method: Random Forest (RF) and DL methods: PointNet (Qi et al., 2017a), PointNet++ (Qi et al., 2017b), DGCNN (Wang et al., 2019), and RandLA-Net (Hu et al., 2020).

We divided the BIO dataset into distinct training, validation, and test subsets to ensure a robust evaluation. The DL models were then trained on the training split, and extensive testing was performed on the dedicated test split. This thorough evaluation allowed us to evaluate the pipeline's efficiency and performance in handling the complex indoor-outdoor environments contained in the dataset.

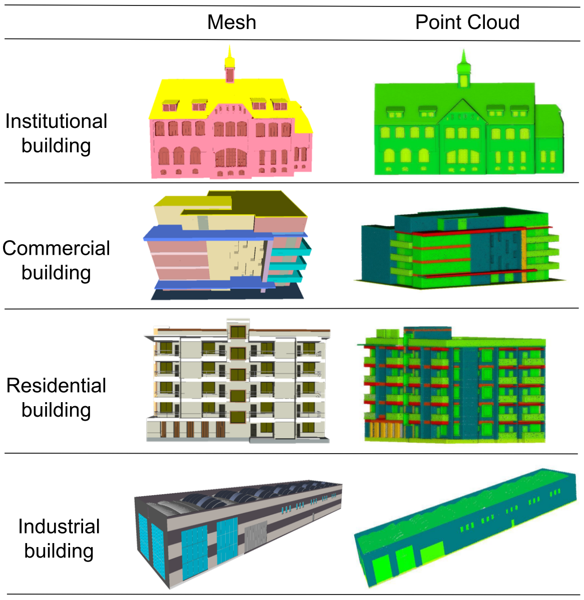

Figure 1. Examples of some buildings from the indoor-outdoor building dataset (BIO dataset): labelled meshes and point clouds of four different buildings.

The results confirm the potential of using the dataset to improve DL algorithms, opening up opportunities for better performance in various real-world applications that demand a thorough comprehension of complex indoor-outdoor environments. Thus, the proposed pipeline offers a promising route for the development of DL in building-related applications.

2. LITERATURE REVIEW

Buildings in urban scenes, indoor scene datasets, and building exterior datasets are some different types of 3D building datasets that are frequently used for AI applications. The following list includes several types of commonly used datasets:

- Indoor datasets: For instance, the Stanford Large-Scale 3D Indoor Spaces (S3DIS) dataset (Armeni et al., 2016) contains labelled point cloud data for 271 rooms in six indoor spaces. The ScanNet dataset consists of 1,500 labelled 3D scans of indoor environments and textured meshes, as well as pointwise semantic labels and 3D object instance labels.
- Street/City datasets: The Semantic3D (Hackel et al., 2017) dataset has semantic labels for outdoor urban scenes in LoD1 for building objects with insufficient geometric and semantic detail. DublinCity is the first labelled dataset of high-density aerial laser scanning (ALS) point clouds at the city scale (SM Iman Zolanvari et al., 2019), but the generated building objects are only at LoD0 and LoD1.
- LoD3 building dataset: The ArCH dataset (Matrone et al., 2019) at LoD3 has 10 semantic labels, but it focuses on the architectural cultural heritage dataset.

For researchers working on building-related AI applications, these datasets collectively provide a useful resource. However, these datasets have a few coverage areas. To be more precise, many existing 3D building datasets include only a small number of buildings or only include interior or exterior scenes, which may not accurately represent the entire range of building types and environments. As shown in Table 1, the ScanNet is an indoor dataset. The Semantic3D is an urban-level dataset that contains only coarse buildings. The ArCH dataset is focusing on cultural heritage and only 17 labelled scenes.

Dataset	Training	Testing	Number
ScanNet	1513	312	1825
Semantic3D	15	15	30
ArCH	15	2	17
Ours	85	15	100

Table 1. The scene numbers in different datasets

Furthermore, we have also analysed the semantic categories contained in these datasets. We counted the number of occurrences of each category and presented them in a word cloud, the results of which are shown in Figure 2. We can see that the most frequent category is 'building', which means that the objects belonging to this category are at the LoD0 or LoD1 level. Other categories related to the structural elements of buildings are walls, floors, stairs, doors, and windows, which are often presented in interior scenes. However, elements such as beams, slabs, balconies, etc., which are important in the exterior and interior of a building, are rarely present in these datasets.

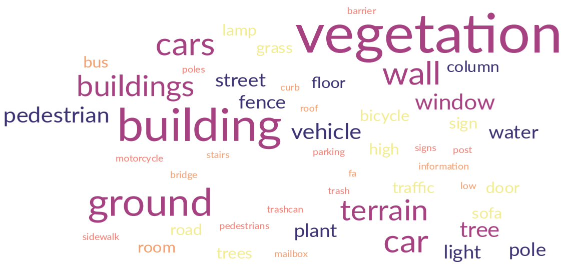

Figure 2. Word cloud of semantic labels from building-related datasets.

3. METHOD

In this section, we outline the process used to create the annotation pipeline for defining, collecting, processing, labelling, and evaluating the dataset (see Figure 3).

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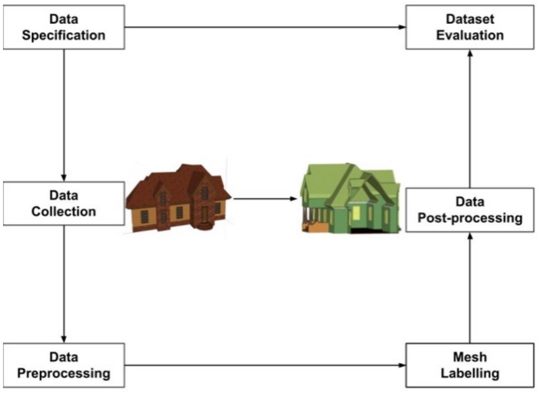

Figure 3. Pipeline of the dataset creation.

3.1 Dataset Specifications

We started the process by defining the specifications of the dataset. The building types, building numbers, and annotation types are defined in this step.

Specifically, four building types are selected in this study:

- Residential building
- Commercial building
- Industrial building
- Institutional building

As seen in Figure 4, these four types of buildings exhibit different characteristics, such as different geometric shapes and scales. At last, for each type, we will collect 25 building models; a total of 100 building models will be contained in our dataset.

Although semantic annotation can be applied to all different kinds of architectural elements, at this point we specifically focus on the enrichment of structural elements. A common semantic information model for the representation of 3D urban objects is defined by the CityGML Conceptual Model Standard and can be used by various applications. Furthermore, IFC (ISO 16739-1:2018) is a standardised, digital description of the built environment, including buildings and civil infrastructure. It is an open, global standard that is intended to be vendor-neutral, or agnostic, and usable across a wide range of hardware devices, software platforms, and interfaces for many different use cases, enabling faster and more effective utilisation. The semantic annotations in our dataset are identified in accordance with CityGML 3.0 (Kutzner et al., 2020) and IFC standards (ISO, 2018) to emphasise the reusability of information within lifecycle thinking. In addition, the classes included in the ArCH dataset (Matrone et al., 2020) and the indoor S3DIS dataset (Armeni et al., 2016) were taken into account to identify the semantic annotations in our study. As a result, 11 classes — wall, roof, window, door, balcony, floor, stairs, column, ceiling, beam, and slab — have been selected.

In addition, to enable those who require semantic building models at a coarser level for use in specific applications, a multi-level definition is also provided. Figure 5 illustrates how LoD3 can be hierarchically abstracted into LoD2 and LoD1.

3.2 Models Collection

We then collected 3D building models from online repositories such as 3D Warehouse to create our indoor-outdoor labelled building dataset. Specifically, we first searched for models according to the building types we defined in Section 3.1, restricting the models to geometry models and tagged them as architectures. In addition, in this study, we focus on the structural elements of buildings. Therefore, we excluded building models that contained too many furniture objects when collecting models.

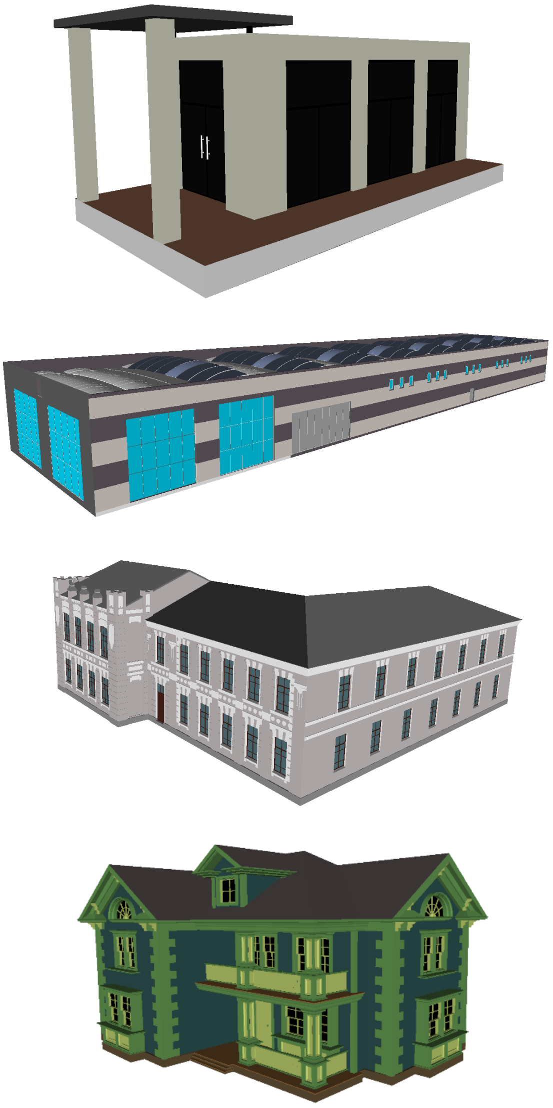

Figure 4. Four different building types. From top to bottom: commercial building, industrial building, institutional building, and residential building.

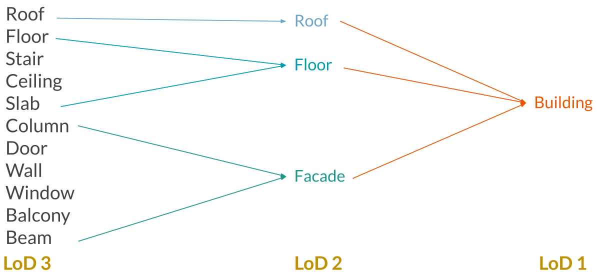

Figure 5. The definition of a multi-level building dataset. From left to right: LoD3, Lod2, and LoD1.

3.3 Pre-processing

Then, through an automated pipeline, these models were put through a series of pre-processing steps: 1) data format conversion to convert the SketchUp models into the ply format models to be readable in CloudCompare software; and 2) employing the pymeshlab library (Muntoni and Cignoni, 2021), mesh repair functions are automatic to remove the geometric errors (e.g., duplicated vertices) in these models.

3.4 Dataset Annotating

These models were then manually labelled after the pre-processing phase, where their accuracy was carefully checked. We used a well-known annotation platform (Gao et al., 2022) specifically designed for annotating urban datasets to ensure accurate and consistent labelling across the dataset. We adapt it to our building scenes by inputting models without the over-segmentation step. Instead, we directly use the original polygon mesh as input to the annotation platform to reduce the labelling time required.

Then, we created point cloud samples from the labelled meshes using a uniform sampling technique to improve the usability of the dataset in AI applications. This allowed us to better represent the complex geometry of the buildings. We employed a method of sampling point clouds in accordance with the size of each mesh face in a mesh to produce a uniform point cloud on each building, yielding 3,500,000 points per building. The point densities between various buildings vary depending on the scale of the buildings. The semantic labels and colour information on each mesh face were converted into points within the corresponding face during the sampling process, in addition to maintaining the geometric information.

3.5 Classification

To use the dataset for deep learning training, we randomly divided the dataset into three parts: the training set, the validation set, and the test set, which contain 70, 15, and 15 building models, respectively (see Figure 6).

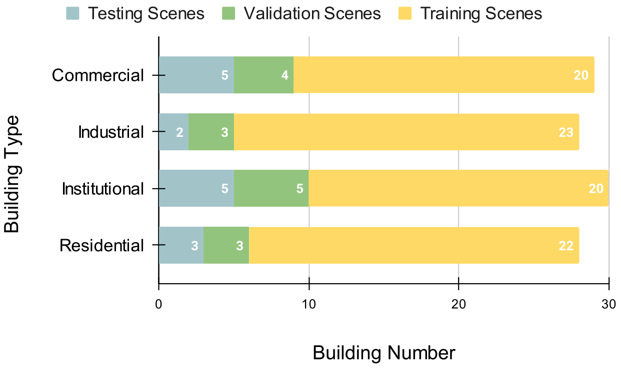

Figure 6. The number of each type of building model in the training, validation, and testing splits of the dataset.

Finally, to establish a benchmark for the dataset and ensure the accessibility of our dataset, these DL networks have been selected in our study for their potential in handling the dataset effectively:

- PointNet (Qi et al., 2017a): PointNet is a ground-breaking dataset that is designed to process point clouds directly. It uses a multi-layer perceptron to learn features effectively from points.
- PointNet++ (Qi et al., 2017b): Building upon PointNet, PointNet++ enhances the performance by utilising hierarchical structures to capture intricate features in point clouds.
- DGCNN (Wang et al., 2019): By dynamically constructing graphs within larger scales and employing graph convolutional networks, DGCNN enables the establishment of relationships between neighbouring points in point clouds.
- RandLANet (Hu et al., 2020): RandLANet leverages a random sampling strategy to efficiently downsample large-scale point clouds to ensure the whole point cloud can be processed in the network.

We used the training data (see Figure 6) and these four different DL models to train the classifiers. To be more precise, we first divided each building into $1m \times 1m$ blocks and then randomly sampled 4,096 points from each block. We then trained three networks, PointNet (Qi et al., 2017a), PointNet++ (Qi et al., 2017b), and DGCNN (Wang et al., 2019), on the generated blocks. For RandLA-Net (Hu et al., 2020), each training scene was downsampled into 40,960 points before the whole building scene was fed into the network. The pretrained models were then tested on the test data using the pre-trained classifiers.

As a comparison and to check the availability of our dataset, we also employ a machine learning method, Random Forest, as our classification methods. Following earlier research (Weinmann et al., 2017), we first chose a set of features that are relevant to the classification problem. These features (see Figure 7) place a strong emphasis on the point cloud's structure within the predetermined radius of the points.

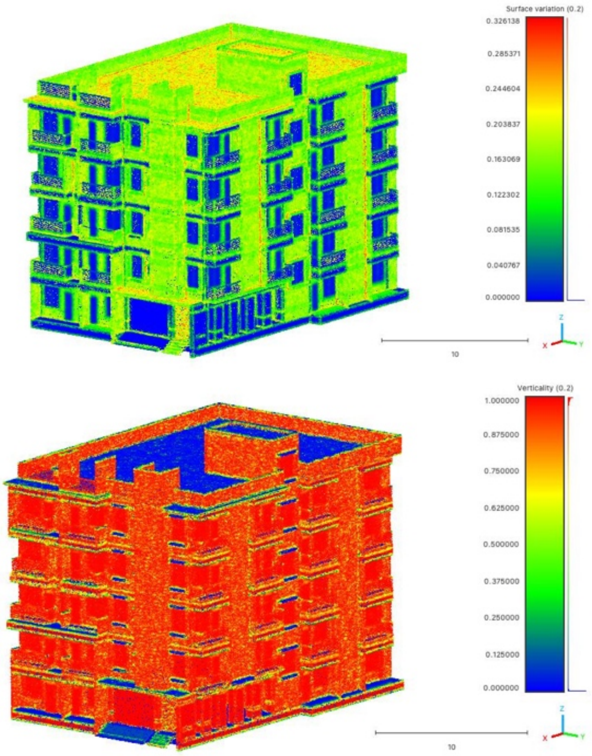

Figure 7. Examples of geometric features. Top: surface_variation_0.2m, bottom: verticality_0.2m.

Method	OA	mIoU	wall	roof	window	door	balcony	floor	stairs	column	ceiling	beam	slab
PointNet	0.656	0.188	0.430	0.735	0.000	0.000	0.002	0.712	0.000	0.000	0.188	0.000	0.000
PointNet++	0.662	0.198	0.586	0.275	0.000	0.000	0.000	0.974	0.040	0.000	0.003	0.000	0.300
DGCNN	0.835	0.294	0.578	0.787	0.025	0.000	0.003	0.915	0.012	0.000	0.407	0.000	0.509
RandLA	0.518	0.336	0.584	0.229	0.167	0.216	0.505	0.622	0.053	0.355	0.097	0.572	0.584

Table 2. The semantic segmentation results of deep learning methods.

We then rank the significance of each feature in predicting the target variable using the random forest feature importance method. Finally, 16 features are used in our experiment, including x, y, z, r, g, b, normalised colour, verticality_0.1m, verticality_0.2m, anisotropy_0.2m, surface_variation_0.2m, omnivariance_0.2m, verticality_0.4m, linearity_0.4m, and planarity_0.4m. The search radii used when calculating geometric covariance features are indicated by the numbers that come after the name of the geometric features. We used randomly selected 1% and 10% portions of each building as training data and tested the outcomes with the remaining portions.

We used the two commonly used metrics, Intersection-over-Union (IoU) score, the mean IoU (mIoU) and the Overall Accuracy (OA), as performance metrics of deep learning methods to evaluate the quality of the semantic segmentation results. Besides, the Weighted_F1 and OA are used as metrics in the machine learning methods.

4. RESULTS

4.1 Dataset

As can be seen in Figure 8, the point clouds are densely and uniformly sampled on the labelled meshes. We used a method of sampling point clouds according to the size of each mesh face in a mesh to produce a uniform point cloud on each building, resulting in 3,500,000 points per building.

Figure 9 highlights the size and complexity of our dataset by showing the number of points for each class, giving an understanding of the dataset's size and the difficulties it poses.

4.2 Classification Result

Table 2 summarises the performance of different DL models on our test dataset. In particular, using 70 buildings as training data, our semantic segmentation achieves an OA of 0.835. This indicates a high level of accuracy in the semantic segmentation of building elements. It is important to note that the choice of DL model has a significant impact on certain aspects of semantic segmentation performance. For example, DGCNN emerges as the top performer in terms of OA, demonstrating its effectiveness in achieving high overall accuracy. While PointNet and PointNet++ can make accurate predictions to some extent, they struggle with capturing fine-grained details, leading to a relatively lower mean IoU. Conversely, RandLA-Net achieves the highest performance in terms of mIoU, indicating its superior ability to handle class-imbalanced scenarios. Figure 10 shows the prediction result using the DGCNN network as the classifier.

Overall, our results demonstrate the feasibility of using our dataset in DL models, as evidenced by the impressive OA of 0.835. This indicates that DL techniques are highly effective in segmenting building elements.

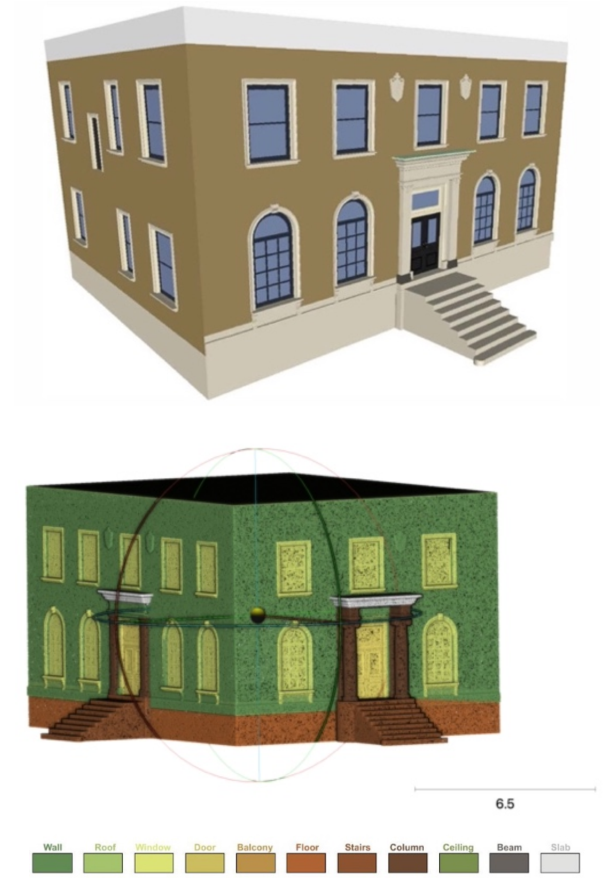

Figure 8. Example of a point cloud (bottom) sampled on a textured mesh model (top). Different colours represent different categories in the dataset.

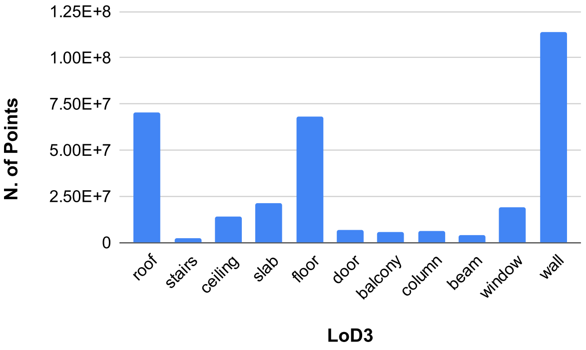

Figure 9. Number of points in each category in the dataset.

Nevertheless, our analysis of DL methods highlights several challenges specific to the domain of the built environment. In particular, we observe a class imbalance problem in building models, as shown in the accompanying figure. The distinction between window/door objects from wall objects is still a particular challenge. In addition, the accurate semantic segmentation of ceiling regions poses difficulties due to their geometric similarities with ceilings and floors.

Table 3 summarises the performance of the RF model with different settings on our test dataset. In particular, using 1% randomly selected blocks in each building as training data, our semantic segmentation achieves an OA of 0.878. While using 10% as training data for each building, the average OA reaches 0.969 on the rest of the blocks of each building. Figure 11 shows the prediction errors using RF as the classifier.

	Weighted_F1	OA
1%	0.860	0.878
10%	0.966	0.969

Table 3. The semantic segmentation results of Random Forest (RF) method.

As we can see, the RF method demonstrates notable strong performance compared to the DL-based methods, especially with a larger portion of each building (10%). DGCNN, being the best-performing DL method, shows a competitive OA compared to the RF classifier with 10% of the data. However, the RF needs training data from each building, so the test data is coming from the same buildings, which leads to its stronger performance. The choice of method may ultimately depend on the specific task at hand. Further fine-tuning may be needed to optimise each method.

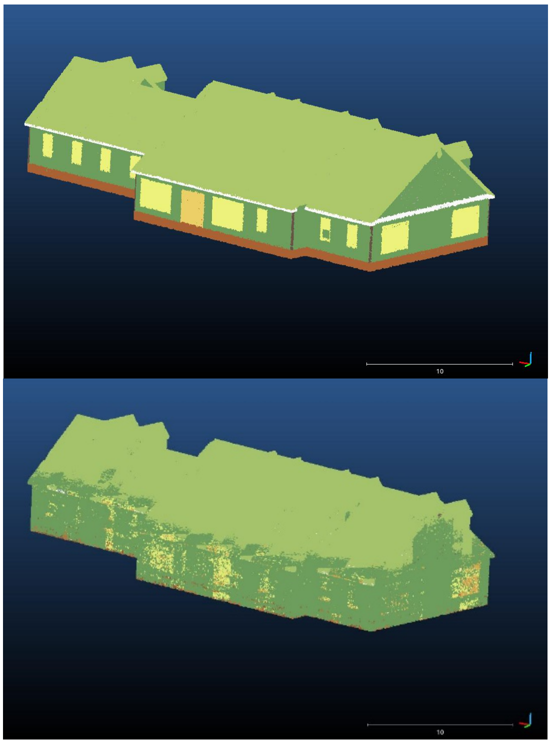

Figure 10. Prediction result of a residential building using DGCNN, top: ground truth, bottom: prediction result.

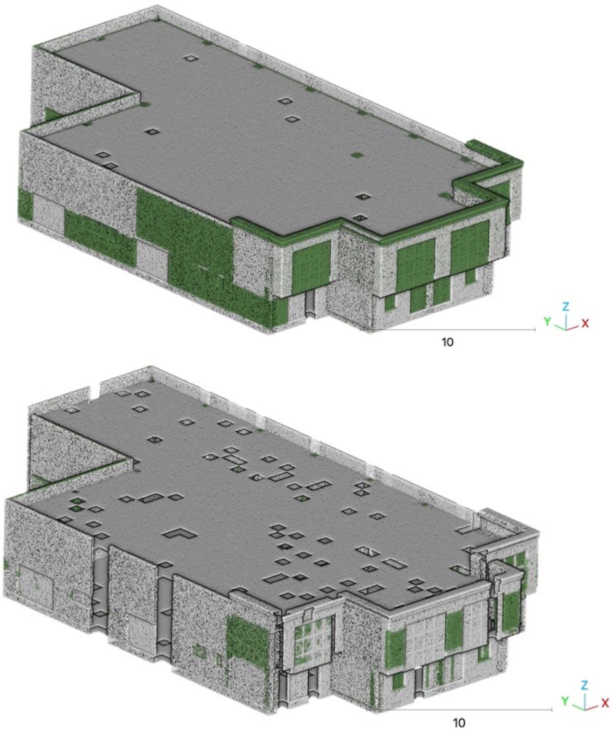

Figure 11. Example of prediction errors with two different settings using Random Forest (RF) classifier (1% - top / 10% bottom)

5. CONCLUSION

In conclusion, our newly created indoor-outdoor labelled building dataset and pipeline can support brand-new indoor-outdoor AI applications that require accurate and deep understanding of complex environments. We can also support a broad class of recently resurrected deep neural networks (DNNs) and machine learning methods for applications dealing with geometric data by providing a large-scale, richly annotated dataset. Our semantic segmentation results validate the utility of our dataset for training and evaluating DL models for built environment analysis. However, challenges remain, particularly in dealing with class imbalances and accurately delineating objects with similar geometric features. These challenges present exciting opportunities for future DL models to improve and address, thereby advancing the state of the art in semantic segmentation for the built environment. Additionally, we introduced the Random Forest method and observed its robust performance, showcasing the effectiveness of traditional machine learning approaches.

More powerful deep learning (DL) algorithms will be tested on the dataset in the future. In addition, the possibility of using this dataset to improve the performance of real-world datasets will be investigated. In order to define and develop the dataset as an important one with lasting impact, we would like to involve the wider research community.

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