Delft University of Technology

GEO1101: Synthesis Project

Building and roof type classification on 3D city models

Authors:
Sitong Li (5683688)
Chengzhi Rao (5841089)
Chi Zhang (5740568)
Qiuxian Wei (5801737)

Mentors:
Camilo León-Sánchez (PhD Candidate from TUD 3Dgeoinfo)
Gina Stavropoulou (Data Engineer from TUD 3Dgeoinfo)
Jantien Stoter (Professor from TUD 3Dgeoinfo)
Rob Wijnhoven (Leader of Research and Development from SPOTR)

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1 Introduction

In a rapidly evolving digital landscape, 3D city models have become more accurate and complex with advancements in data acquisition techniques over the past year. Where data and technology converge, a profound opportunity emerges: to harness the power and potential of 3D building models and geospatial data for numerous practical applications. This vision is the driving force behind the 3D BAG, an up-to-date data set containing 3D building models of the Netherlands, that aims to keep the 3D building models current with the latest building stock, roof shapes, and elevation information available. When compared to using satellite images or raw point cloud data [Shajahan et al., 2020, Castagno and Atkins, 2018] to achieve classification objectives, utilizing the 3D building model offers a greater possibility of capturing the complexity of real-world building characteristics [Labetski et al., 2022]. Moreover, the feature extraction workflow is more direct and convenient than using raw point cloud data.

Our client, **Spotr**, leveraging AI-powered building inspection technology, offers an innovative approach to automatically detect properties on elements, conditions, typology, materialization, and measurements of properties, and address under-insurance by providing rebuild valuations at scale, helping their clients stay protected in the face of unforeseen circumstances. Currently, Spotr is exploring expanding the business to a worldwide range. Despite the increasing number of properties, the utilization of the available data is still confined to valuations during in-depth analysis. The possibility of utilizing 3D data to aid in the evaluation of solar panel installation suitability, energy performance analysis, and other applications remains unexplored. Our project aims to propose a novel method for classifying roof and building types by integrating machine learning and topology-based approaches and seamlessly exploring the 2D and 3D features of various buildings.

Real-world buildings can be highly intricate and challenging to classify, Spotr works mainly in the realm of inspecting buildings with open data, such as satellite images, street view images, 2D footprints, etc. To enhance the versatility of the classification method, our project extends its scope beyond residential buildings to encompass public and commercial structures, and effectively identify archetypes within complex building and roof combinations and arrangements. By utilizing 3D building data, our method focuses on feature engineering and is based on the representative characteristics of building archetypes, the selected features are aligned with the classification types we choose.

The results derived from this project are poised to unlock the huge potential of 3D building models in the classification field, the output offering a wide array of practical real-world applications, including insurance estimation, energy consumption management, solar panel installation, disaster evaluation, and post-processing applications.

As Spotr works with data from varying resources and regions, our approach can apply to the popular open data format, CityJSON, the feature computation we design is for obtaining a large training set. The output of the machine learning algorithm enriches the 3D building data as additional attributes, and can further offer a wide array of practical real-world applications.

2 Problem definition

This chapter describes and analyzes the problem outlined in the **Introduction** to provide a clear overview of the project goals and guidance for the research.

2.1 Project summary

Due to the emerging trend of high-valued 3D city models, in most cities that release 3D building data as open data, the current 3D datasets often lack detailed information on building attributes, such as the type of buildings. As much of their potential is still not taken advantage of, missing building attributes, like building types and roof types, can result in difficulty in property valuation for insurance companies. Traditional measurement is costly and may lack attributes needed for downstream analysis, such as computing reconstruction costs, the energy consumption performance based on the building typology types[**?**], etc.

Our project aims to use existing 3D city model datasets for classification. To achieve accurate results, the 3D data used should depict reality as much as possible. The Level of Detail (LoD) of a 3D model describes the amount of detail captured in the model, with higher LoDs (LoD 2 and above) consisting of semantic surfaces like ground, wall, and roof surfaces. This project uses high LoDs (LoD 2 and above) based on the improved LoD specification (LoD 2.2) in 3DBAG, as Figure 1 displays [Biljecki et al., 2016]. While other countries' 3D datasets have related LoDs of LoD 2.

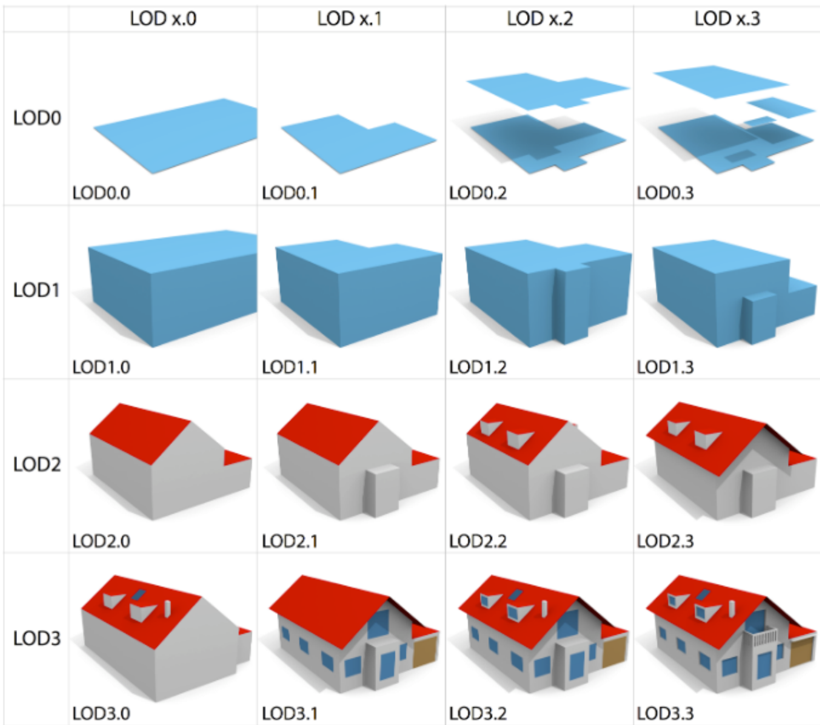

Figure 1: An improved LOD specification for 3D building models in 3DBAG [Biljecki et al., 2016]

The project goals we aim to achieve consist of two classification schemas: the building type classification and the roof type classification. To utilize the existing high LoDs 3D data to train a 3D classifier for building types and roof types, and the training set can have a high performance on 3D building classification tasks.

The innovation is that our self-defined types are based on European cities and are universal, the classification results can be applied to a wide range of regions.

2.2 Research questions and hypotheses

2.2.1 Research Problems

There are three pressing issues that need to be addressed:

1. To design a globally used building type and roof type classification schema.
2. To perform a high-accuracy classification on 3D building model. (Data pre-processing, feature design, model selection, loss function, hyperparameter tuning, etc.)
3. To efficiently and accurately establish a labeled dataset to train our models.

The research questions are as follows:

1. **Building Type and Roof Type Classification schema (Design and Universality)**:
   - What criteria and parameters should be considered when designing a globally applicable building type and roof type classification schema?
     This question focuses on the design principles of a classification schema for building types and roof types. It aims to identify the essential criteria and parameters that should be incorporated into the schema to make it universally applicable across various geographic regions and city models.
   - To what extent can the designed building type classification schema be considered universal and adaptable to different geographical regions and city models?
     This question explores the universality and adaptability of the classification schema designed in the previous one. It seeks to assess how well the schema performs across diverse geographical regions and city models, evaluating its potential for broad application.
2. **High Accuracy Classification on 3D Building Models:**
   - What are the most effective data pre-processing techniques for enhancing the accuracy of 3D building model classification?
     This question delves into the data pre-processing phase of 3D building model classification. It aims to identify the most effective techniques and methodologies for preparing the data to achieve higher accuracy in building type and roof type classification.
   - Which feature design methods contribute significantly to improving the classification accuracy of 3D building models?
     This question focuses on feature engineering, aiming to determine which methods and approaches result in the most substantial improvements in the accuracy of classifying 3D building models.
   - How does the choice of machine learning models, loss functions, and hyperparameter tuning impact the accuracy of 3D building model classification?
     This question investigates the machine-learning aspects of 3D building model classification. It examines the impact of choices related to machine learning models, loss functions, and hyperparameter tuning on the accuracy of classification outcomes.
3. **Efficient Establishment of Labelled Datasets:**
   - What strategies can be employed to efficiently and accurately create labelled datasets suitable for training building type and roof type classification models?
     This question addresses the challenge of dataset creation. It explores strategies and methodologies that can be used to efficiently and accurately label datasets, which are crucial for training

classification models.

These research questions collectively address the key challenges and objectives of the project, encompassing the design of classification schemas, accuracy improvement, dataset creation, etc.

2.2.2 Hypotheses

The current methodology depends on the following hypotheses:

1. The building type classification schema we design will demonstrate a high degree of universality and applicability across different geographic regions.
2. By employing appropriate data pre-processing, feature design, machine learning models, and hyper-parameter tuning, it is possible to achieve high accuracy in the classification of 3D building models.
3. The training dataset created for 3D building classification has global applicability due to its universal classification schemas.
4. Implementing effective data preprocessing, feature design, and machine learning techniques will significantly enhance the accuracy of building type and roof type classification.

2.3 Research methodology

Currently, several European cities share as open data semantic 3D city models in a level of detail (LoD) that allows the distinction of the surfaces that define their facade (LoD2). The classification accuracy of these data is much higher since we can use 3D features, semantic surfaces and topology information among buildings.

The approach we employ consists of two main components:

1. **Schema Design**: This part involves the design of schemas for building types and roof types, with a primary focus on an extensive literature study.
2. **Classification of Building and Roof Types**: In this phase, we perform building-type and roof-type classification using 3D city model datasets. We leverage CityJSON data for major European cities as our primary data source, calculate their 2D/3D features, and assign appropriate labels. Subsequently, a supervised classification method is applied to perform the classification.

2.3.1 Classification schema research

Building and roof type classifications have broad applications across various sectors, and several factors impact their significance. In the context of energy demand and sustainability, these classifications play a crucial role in shaping policies, promoting energy efficiency, and incorporating renewable technologies. National cadastres benefit from this data for the best use of land analysis and property management. Hence, the classification methods vary depending on the specific purposes. The mainstream approaches to building classification follow three classification criteria: function, form, and construction type. The roof classification methods follow four criteria according to various research purposes: roof shape, material composition, functional use, and cultural and architectural significance.
Our classification schemas of buildings and roofs will concentrate on examining the variations in shapes, building forms, 3D metrics, and spatial relations in order to make use of the architectural attributes from the current 3D building models. The classification schemas encompass a wide range of functional building types, and also effectively demonstrate the differences between each type based on their unique geometric arrangements and how various spatial characteristics interact to produce distinct urban textures.

2.3.2 3D data classification

The 3D city model datasets we are working with, are based on the OGC standard CityJSON (Figure 2), which allows the representation of urban areas in multiple levels of detail. They are not just good for visualization; they also let us dive into some complex analysis. Notably, its proficiency in classifying and categorizing urban elements stands out, rendering it exceptionally suitable for applications that require in-depth and precise data on geometric attributes, occupancy patterns, and topological relationships within urban areas.

```
"CityObjects": {
  "id-1": {
    "type": "Building",
    "geographicalExtent": [ 84710.1, 446846.0, -5.3, 84757.1, 446944.0, 40.9 ],
    "attributes": {
      "measuredHeight": 22.3,
      "roofType": "gable",
      "owner": "Elvis Presley"
    },
    "children": ["id-2"],
    "geometry": [{...}]
  },
  "id-2": {
    "type": "BuildingPart",
    "parents": ["id-1"],
    "children": ["id-3"],
    ...
  },
  "id-3": {
    "type": "BuildingInstallation",
    "parents": ["id-2"],
    ...
  },
  "id-4": {
    "type": "LandUse",
    ...
  }
}
```

Figure 2: Data structure of CityJSON

To approach classification, our strategy is based on Machine Learning methods. The primary challenge lies in crafting features that are easily interpretable and suitable for training purposes. Unlike deep learning, where features are automatically learned, our approach leverages user-defined features, capitalizing on a deeper understanding of the data to enhance feature quality, thereby improving overall classification results.

The choice of features varies depending on the specific classification target. In the case of building classification, we prioritize features such as building volume, area, shape characteristics, and the topological relationships it maintains with neighbouring structures. These features provide crucial insights into the nature and identity of the building. When our focus shifts to roof classification, our feature selection is tailored to capture the distinctive attributes of roof surfaces. We emphasize factors such as the number of roof surfaces, roof area, and the normal vectors associated with each surface. These features are instrumental in characterizing and distinguishing between different roof types.

By customizing our feature sets to align with the distinct requirements of each classification task, we aim to optimize the accuracy and relevance of our models for building and roof classification.

In this context, we plan to employ Support Vector Machine (SVM) and Gradient Boosting models. One of the key advantages of SVM is its effectiveness in handling high-dimensional data and its ability to find optimal decision boundaries. SVM is particularly robust when dealing with complex, non-linear relationships within the data. However, it may be computationally intensive for large datasets. In this study, svm.NuSVC model from sklearn is used to do the supervised classification. On the other hand, Gradient Boosting is popular for its effectiveness in a variety of data-driven tasks. It belongs to the boosting family of algorithms, which aims to sequentially build a strong predictive model by combining the outputs of multiple weak learners, typically decision trees. The fundamental principle behind Gradient Boosting is to iteratively train new models to correct the errors of the preceding ones. This process results in a strong ensemble model that excels in predictive accuracy and can handle both regression and classification problems.

Gradient Boosting is highly adaptable, capable of accommodating a range of base learners, and offering options for customization through hyperparameter tuning. Notable implementations of Gradient Boosting include XGBoost, LightGBM, and CatBoost, which have become go-to choices for many data scientists due to their exceptional performance, scalability, and efficiency. With its ability to handle complex relationships in data and handle large datasets, Gradient Boosting has become a fundamental tool for solving real-world problems in fields such as machine learning, data science, and predictive analytics.

With the right design of features and classification targets, we hold the belief that classification quality can be significantly enhanced across various classification models, including Random Forest [1] and SVM [2], among others.

2.4 Scoping/Managing expectations: MoSCoW

In our professional domain, our foremost objective revolves around the intricate task of classifying building and roof types within the vast realm of 3D city model datasets. The paramount aim of our endeavours is to develop robust classifiers that exhibit a high level of proficiency in categorizing these architectural features.

In the realm of our work,

Must:

- We must propose two classification schemas, one for building types, and one for roof types;
- We must use various 3D model datasets to implement our methodology.
- we must achieve building and roof type classification for the 3D city model datasets.

Should:

- The classification schemas should strive for universality by including all buildings, regardless of their function or usage.
- We should extend the research scope to European cities.
- We should divide the buildings in high LoDs models from one into multiple parts for detecting multiple roof classification results.
- The classifiers should demonstrate proficiency in categorizing building and roof types.

Could:

1. The framework has the potential to be extended, allowing for a broader scope that can include architectural types and other relevant classification tasks.
2. Additionally, the classification result of 3D roof classification can be curated into a small 2D image dataset, as the comparison.

Won't:

1. Our focus, remains primarily on classification tasks related to 3D city models with contain the sufficient information we need, we won't extend to the regions which only release low-valued or poor-quality 3D city data.
2. Additionally, curating both the classification result of 3D building and roof classification into a large labelled 2D image dataset, used worldwide, would be suggested as future work, out of our project scope.

2.5 Overview of relevant theory/concepts

2.5.1 Classification methods on building and roof types

Previous research primarily focused on classifying buildings and roofs using either 2D datasets, such as orthoimages and street view images, or 3D datasets derived from LiDAR scans and photogrammetry. Despite achieving high accuracy in specific classification tasks, both approaches have their limitations.

In the realm of 2D classification, algorithms like ResNet have demonstrated impressive accuracy and have delivered promising results in downstream tasks like object detection (e.g., YOLO) [Jiang et al., 2022]. The adoption of transformer architectures [Dosovitskiy et al., 2020] and UNET [Ronneberger et al., 2015] has also exhibited efficient processing capabilities for image classification and segmentation tasks. Nevertheless, obtaining 3D information about buildings, such as height, volume, and rectangularity, remains a considerable challenge, leading to less reliable classification results. Additionally, the absence of registration information makes it nearly impossible to extract administrative boundaries that separate buildings.

When it comes to point cloud datasets, pioneering techniques like PointNet [Qi et al., 2017a] and PointNet++[Qi et al., 2 have paved the way for using neural networks in point cloud classification. Dynamic Graph Convolution has also demonstrated promising performance in 3D classification tasks [Wang et al., 2019]. Utilizing multi-view models for classification [Kang et al., 2018] is another promising approach. However, these methods demand substantial storage space for datasets and impose high computational requirements, rendering them less suitable for large-scale training and testing scenarios.

Currently, in the world of open-source 3D city model datasets, despite their widespread availability, these invaluable resources remain underutilized. Our core mission is to unlock their full potential. Most of the past studies on CityGML only focus on enrichment and visualization and its utilization is still in the very first stage. This studysubsection 3.3 marks the first foray into 3D urban morphology, setting the stage for a new research paradigm. Unlike previous research that often relied on 2D or basic 3D approximations of buildings, this study introduces comprehensive 3D metrics, offering a more detailed view of building shapes and attributes.

The reasons for this phenomenon may be because:

1. 3D models already have many more potential features that can be directly used for 3D classification such as the number of polygons, volume of models, or incident angle of planes. There is no need to design another black box tool for 3D vector model classification
2. The topology validation of large scale CityGML data is still to be evaluated.
3. It is hard to label a dataset large enough for supervised classification on a continental scale

2.5.2 Building types classification schema

Existing classification schemas predominantly revolve around categorizing buildings based on their primary functions or usage. With the emergence of open data, such as the building footprints and points of interest

(POIs) revealing the potential of deriving building function information from open data[Hecht et al., 2015] [Xiao and et al., 2022] [Huang and et al., 2022], function-based building classification helps in understanding the purpose and role of buildings within the urban fabric.

Within the domain of residential buildings, a more nuanced classification strategy has emerged, taking into account various factors such as the combination or arrangement of house units and the time period in which the buildings were constructed. This approach is particularly evident in research conducted in European countries [Loga and et al., 2016] [Tab,], where the historical and architectural diversity of residential structures necessitates a more nuanced categorization.

In addition to function-based and residential-specific typologies, research interests in exploring building forms and urban morphology [Ratti and et al., 2003] are on the rise. Some researchers analyze the effect of building geometry and shapes on energy and thermal performance [Zhang and et al., 2017]. The typology-based approach is continuously developing with more and more 3D city models being released, which not only provides insights into the architectural and urban form but also contributes to sustainable design practices by considering the energy performance and environmental implications of different building types. 3D city model data plays a pivotal role in exploring the building's geometric features.

In summary, building classification schemas primarily revolve around function-based categorization, with residential buildings further differentiated by factors like unit arrangement and construction period, a trend notably observed in European research. Additionally, there is a growing body of work that integrates typology with urban morphology, focusing on the impact of building geometry on energy and environmental aspects. These multifaceted approaches collectively enhance our understanding of building typologies, their relationships with the urban environment, and their implications for sustainability and architectural design.

2.5.3 Roof types classification schema

Roof design and classification offer a wide range of shapes and angles, from flat or shed to gabled, hipped, arched, domed, and more. The angles range from almost flat to steeply pitched and are crucial to a roof's aesthetics and function. One notable aspect of roof types is that the terminology associated with roofs is not rigidly defined. Roofs can vary by location, climate, building materials, customs, and preferences, adding complexity to classification. To systematize this complexity, roof classification schemas consider several factors in the classification process:

Roof Shape: The primary criterion for categorizing roofs is their shape, with common categories being gable, hipped, and flat roofs, based on their geometrical configuration.

Material Composition: Roofs can also be classified based on the materials used, such as shingles, tiles, thatch, or metal.

Functional Use: Some roofs are categorized based on their intended function, such as green roofs for environmental benefits, solar roofs for energy production, or garden roofs for aesthetic and recreational purposes. These classifications emphasize sustainability and energy efficiency.

Cultural and Architectural Significance: Roof designs are recognized for their historical, cultural, and architectural significance in defining the identity of a structure or region by many classification schemas.

When it comes to classifying different types of roofs based on the emerging geo-information datasets, the mainstream method involves using the roof shape as the main criterion for the schema design. Innovative machine-learning approaches are now being employed to LoD2 models which include roof shapes [Biljecki and Dehbi, 2019], as well as aerial images [Mohajeri et al., 2018] and Lidar point cloud data which offer rich information about roof structures [Shajahan et al., 2020] [Ölçer et al., 2023] [Aissou et al., 2021].

3 System design

3.1 Workflow

In this research, There are three main steps.
The first step involves designing a classification schema that is not only representative but also universally applicable. The classification results can be effectively used in the previously mentioned applications. To achieve this, we have conducted literature research on building morphology and building metrics. The second phase involves extracting and selecting valuable features of 3D building models. What's more, the 3D city model we have may not be watertight and needs to be fixed. During this step, the clustering algorithm will also be used to see if the current classification schema fits the actual world. The final step will be using the machine-learning method to do the classification.

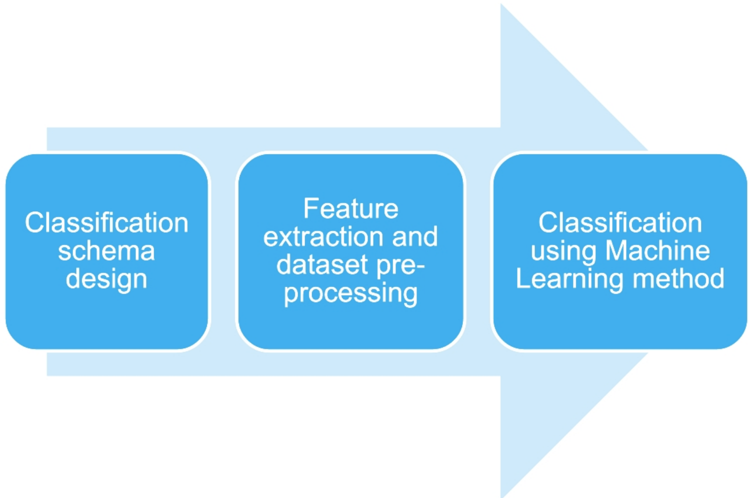

Figure 3: Pipeline

The experiment is mainly carried out with the CityJSON datasets of the Hague, Rotterdam, Delft, Berlin, Munich and Montreal, the **LoD**(level of detail) is above 2.

In the context of roof type classification, it is essential to perform a segmentation process for buildings with roofs composed of multiple simple roof structures, in order to align them with our schema. We utilized datasets from both LOD 1.3 and LOD 2.2 for the buildings. As depicted in Figure 4, it's evident that in comparison to the intricate structures found in LOD 2.2, the roofs within the LOD 1.3 model have been simplified into flat surfaces at varying heights. To address this difference, we projected the roof surfaces from LOD 2.2 onto the LOD 1.3 model and performed an intersection operation, which enabled us to divide these roof surfaces based on their semantic distribution.

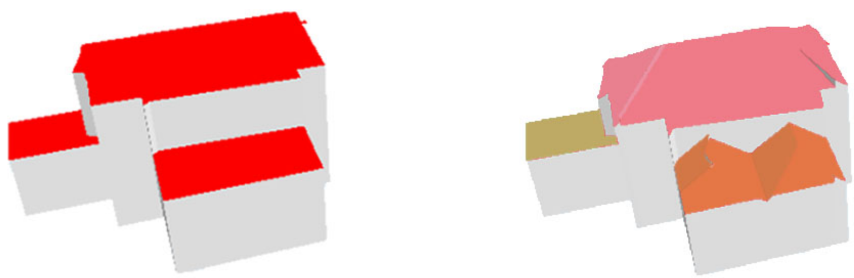

Figure 4: Roof Segmentation

3.2 Classification schema design

3.2.1 Building type classification

Considerations for designing a classification schema for building To decide the classification schema, four factors as followed are taken into account:

1. Classification encompasses all the buildings;
2. Functional or usage of buildings existing in PDOK;
3. Typologies and geometric characteristics;
4. The neighbourhood relation in spatial.

The schema is designed to classify buildings based on their characteristics and features. It aims to differentiate between different types of buildings using various factors:

- **For residential houses:** To distinguish the different arrangements (mainly the footprint combination and neighbourhood relations) of residential houses, we introduce four types, detached, semi-detached, terraced and multi-family houses.
- **For all types of buildings:** To encompass all types of buildings and classify them without using their usage, the shapes of the footprint are considered as the crucial factor and employed in the schema. I-shaped, O-shaped, L-shaped, U-shaped, and Circular buildings represent the most common building form shapes in modern cities, and Complex buildings are the representation of buildings with irregular shapes or facade changes.
- **For capturing the characteristics of special buildings:** With the development of urban planning and architecture designing, some typical construction methods are applied for the specific usage of buildings, for example, the tall apartment buildings, tall structure of modern skyscrapers, and the flat structure in industry buildings. To classify those special buildings, height, volume and more related 3D traits are used in the schema design.

In the end, we carried out 15 building types. The comprehensive building type scheme is rooted in the principles of urban morphology. This scheme serves as a foundational framework for categorizing and understanding the diverse array of building structures within urban areas[Labetski et al., 2022].

Here is the building type classification schema we developed:

1. Detached House: A single-family home not connected to any other structures, standing alone on its own land.
2. Semi-detached House: A residential building divided into two separate units, with one unit sharing a common wall with another.
3. Terraced House: A row of interconnected houses, each sharing walls with adjacent houses on both sides.
4. Multi-family house(clustering): A type of housing structure that accommodates multiple individual housing units within a single building.
5. Block: A general term often used to describe a larger building or structure, which can include residential, commercial, or mixed-use buildings.
6. I-shape: A building or structure with an "I"-shaped straightforward layout.
7. O-shape: A building or structure with a circular or oval-shaped layout.
8. L-shape: A building or structure designed in the form of the letter "L," with two connected wings forming the shape.
9. U-shape: A building resembles the letter "U" when viewed from above. It consists of a central section or courtyard with two wings extending outward.
10. Circular: A building with a circular or cylindrical shape, often chosen for its unique architectural design.
11. Tall Slab: A tall, slender building with a minimal footprint, typically found in urban environments.
12. Thin Slab: A building characterized by its thin, flat horizontal structure, often used in modern architecture.
13. Tower: A very tall and often slender structure, much taller than it is wide, often by a significant factor. Usually designed for various purposes, including residential, office, or observation.
14. Tower with Podium: A tower building with an elevated platform or podium, or multiple towers connected with a podium to form a complete structure.
15. Complex Building: A multifaceted building or group of interconnected structures, typically serving multiple functions and purposes.

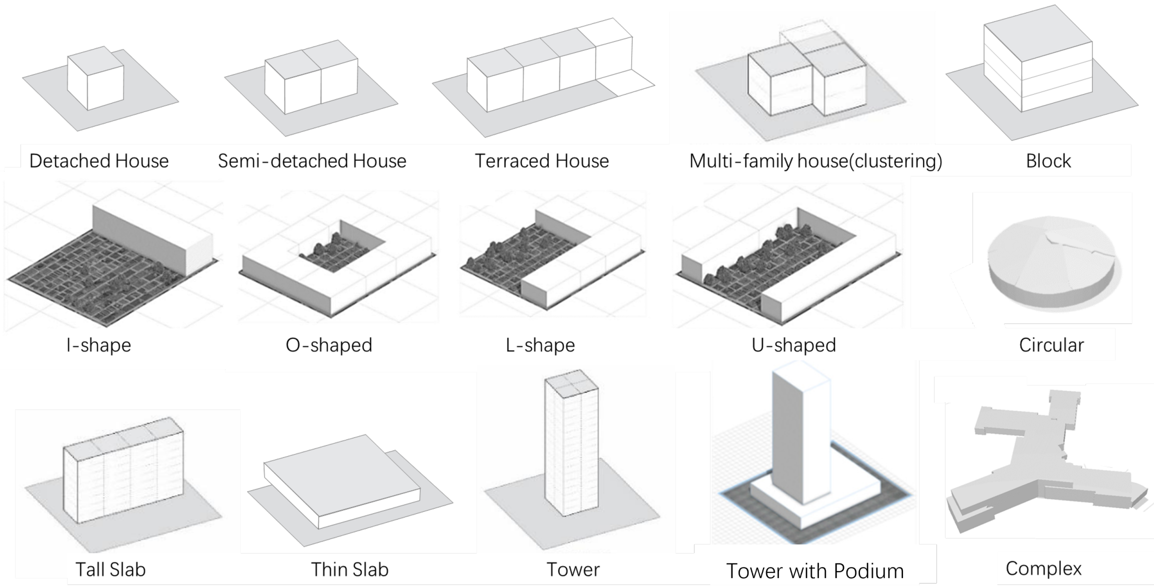

Figure 5: Building type

3.2.2 Roof type classification

Considerations for designing a classification schema for roof To decide the classification schema, four factors as followed are taken into account:

- Classification encompasses all the buildings;
- The existing 3D models depict the various roofs by their typologies and geometric characteristics;
- Roof types should be simplified as archetypes which can detect the multiple classes in one single building roof;
- Dormers or other attached structures should not influence the basic type of roofs.

In the end, we carried out 7 roof types. Here is the roof type classification schema we developed that can further help the customer to do the value evaluation of buildings. Our schema is specifically designed to accurately identify and merge different types of roofs present in a building. It focuses primarily on the most common roof types found in urban structures, which can serve as templates for other roof components within a building.

1. Flat Roof: A flat roof is nearly level with a slight slope for water drainage.
2. Shed Roof: A sloping roof surface with a steeper pitch on one side and a shallower slope on the other.
3. Gable Roof: A traditional triangular-shaped roof with two sloping sides meeting at a ridge.
4. Clerestory Roof: Features a row of vertical windows along the top section of the roof.
5. Simple Hip Roof: Has four sloping sides, each of equal length, forming a pyramid-like shape.
6. Mansard Roof: Features a steeply sloping roof on all sides, often with dormer windows.
7. Complex Roof: A complex roof design combines different roof shapes and designs into a single structure. Although a building's potential roof segments may be divided into different parts, the combination of various roof shapes, including the six types mentioned above, is still common in real-world models. A complex roof is a type that consists of at least two basic types (types 1-6) and cannot be classified into any of these six classes.

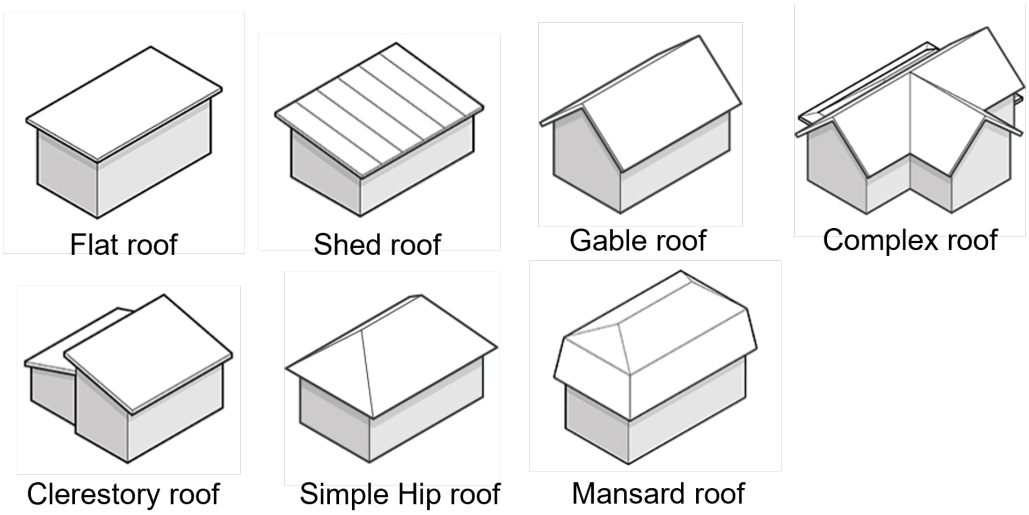

Figure 6: 7 Roof Types. Source: https://jtcroofing.co.uk/

3.3 Feature extraction

3.3.1 Building Types and determined features

3D building metrics for urban morphology The 3D building metrics are a number of metrics that are related to the 3D characteristics of the buildings. The metrics have four categories based on the methodological similarities of their computation [Labetski et al., 2022]:

- **Geometric properties:** These are mostly statistics that refer to the properties of the model of a building.
- **Derived properties:** Metrics that require some form of analysis and calculations, but whose meaning is mostly direct and deterministic. They represent generic notions related. to the size and proportions of a building.
- **Spatial distribution** Metrics that focus on the relationship between a building and its neighbors.
- **Space indices** Complex metrics that highlight more details about the shape of the building.

Geometric properties	Number of vertices, Number of surfaces, Number of vertices by semantic type (i.e. ground, roof, wall), Number of surfaces by semantic type (i.e. ground, roof, wall), Min/Max/Range/Mean/Median/Std/Mode height
Derived properties	Footprint perimeter, Volume, Volume of convex hull, Volume of Object-Oriented Bounding Box, Volume of Axis-Oriented Bounding Box, Volume of voxelised building, Length and width of the Object-Oriented Bounding Box, Surface area, Surface area by semantic surface, Horizontal elongation, Min/Max vertical elongation, Form factor
Spatial distribution	Shared walls, Nearest neighbour
Space indices (see Table 3)	Circularity/Hemisphericality*, Convexity 2D/3D*, Fractality 2D/3D*, Rectangularity/Cuboidness*, Squareness/Cubeness*, Cohesion 2D/3D*, Proximity 2D/3D^{+}, Exchange 2D/3D^{+}, Spin 2D/3D^{+}, Perimeter/Circumference*, Depth 2D/3D^{+}, Girth 2D/3D^{+}, Dispersion 2D/3D^{x}, Range 2D/3D*, Equivalent Rectangular/Cuboid*, Roughness^{x}

*Formula-based index, size-independent by definition.
$^{+}$Index based on interior grid points (discretised), normalised.
^{x}Index based on surface grid points (discretised), normalised.

Figure 7: Computed metrics

Neighbor number To capture the features of neighboring structures, the number of neighboring buildings plays a crucial role. We begin by extracting the ground surface for each building and generating a 0.05-meter buffer around it. Subsequently, we perform intersections with other ground surfaces, forming clusters for the overlapping areas. Ultimately, we compute the count of buildings directly or indirectly connected to the target structure. Additionally, we determine the number of adjacent buildings and calculate the intersected area for these adjacent structures.

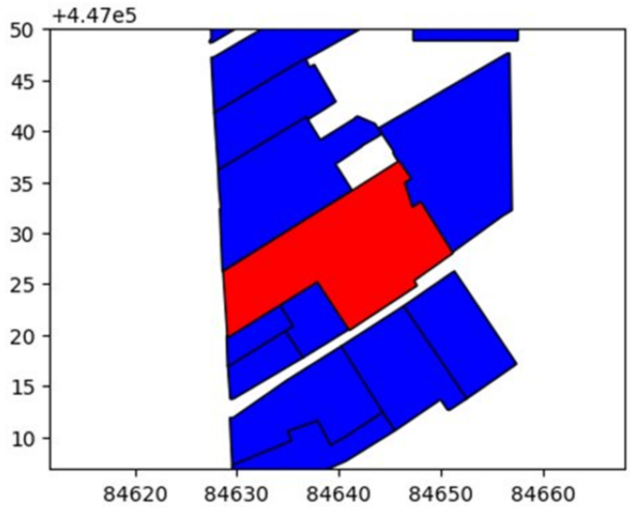

Figure 8: Neighbor number

Features table The final features table contains features calculated from 3D building metrics and features calculated from neighbors.

- **N_count:** The number of connecting neighboring buildings.
- **I_count :** The number of directly connecting neighboring buildings.
- **N_direct_area** The area of the directly connecting neighboring buildings.
- **Area_Height** Ratio of ground area and height of a building.

Representative building types in 3DBAG Figure 9 shows the typical classes of buildings in 3DBAG to visualize the representative traits of each type.

Table 1: Building Features

point_count	unique_point_count	surface_count	actual_volume
convex_hull_volume	obb_volume	aabb_volume	footprint_perimeter
obb_width	obb_length	surface_area	ground_area
wall_area	roof_area	ground_point_count	wall_point_count
roof_point_count	ground_surface_count	wall_surface_count	roof_surface_count
max_Z	min_Z	height_range	mean_Z
median_Z	std_Z	mode_Z	ground_Z
orientation_values	orientation_edges	valid	hole_count
geometry_x	2d_grid_point_count	3d_grid_point_count	circularity_2d
hemisphericality_3d	convexity_2d	convexity_3d	fractality_2d
fractality_3d	rectangularity_2d	rectangularity_3d	squareness_2d
cubeness_3d	horizontal_elongation	min_vertical_elongation	max_vertical_elongation
form_factor_3D	equivalent_rectangularity_index_2d	equivalent_prism_index_3d	proximity_index_2d_
proximity_index_3d	exchange_index_2d	exchange_index_3d	spin_index_2d
spin_index_3d	perimeter_index_2d	circumference_index_3d	depth_index_2d
depth_index_3d	girth_index_2d	girth_index_3d	dispersion_index_2d
dispersion_index_3d	range_index_2d	range_index_3d	roughness_index_2d
roughness_index_3d	shared_walls_area	closest_distance	geometry_y
buffered_geometry	N_count	I_count	N_direct_area
Area_Height			

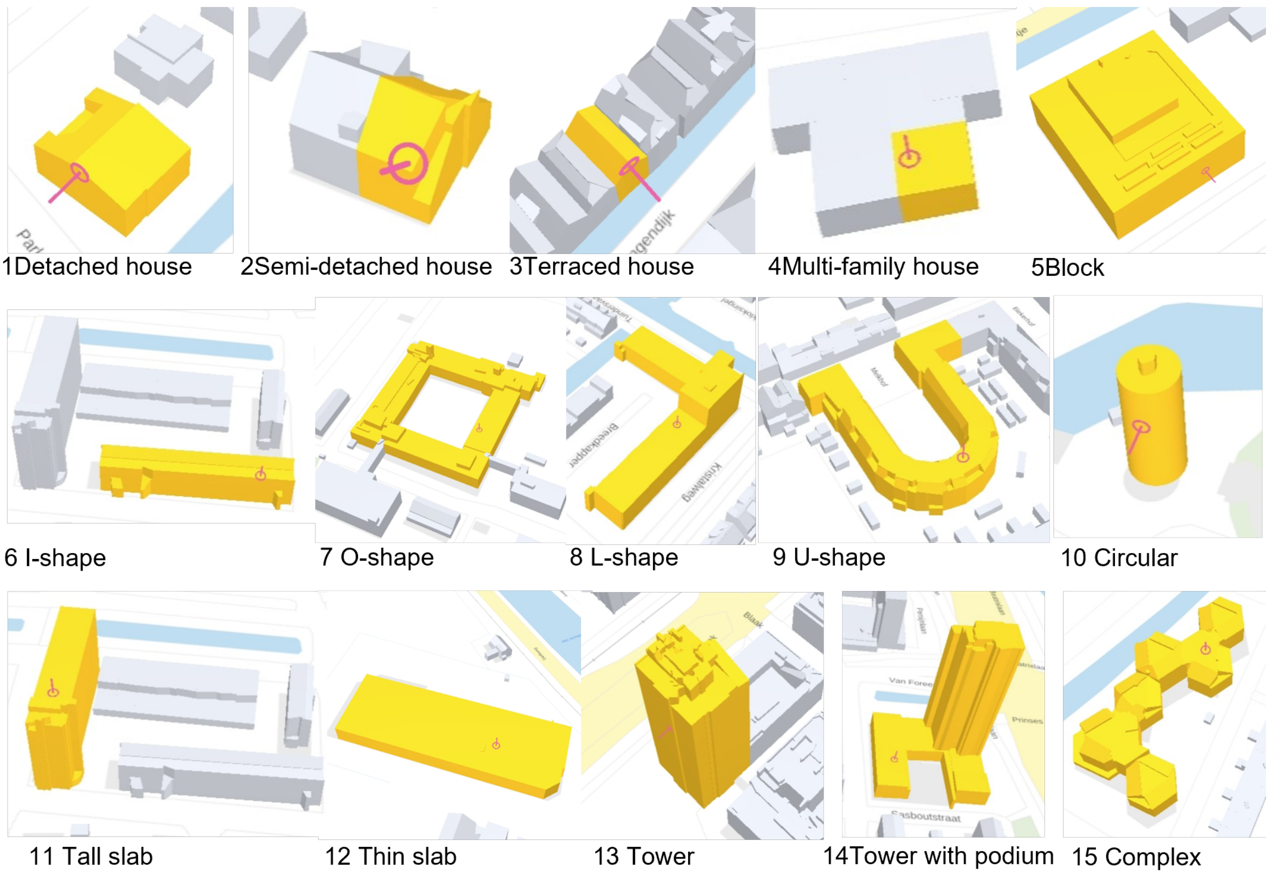

Figure 9: Representative building types in 3DBAG

3.3.2 Roof Types and determined features

The schema we design for roof classification is mainly focused on the roof shape, based on the 3D geometrical configuration.

Feature calculation includes the following five categories:

1. **Area**: Calculate the area and area ratio of roof polygons.
   (a) The total area of the roof polygons;
   (b) Area of largest, second-largest, and minimum polygons (if roof contains multiple polygons) and their proportions;
   (c) Threshold for detecting dormers, attached structures or the artefacts on the roof and the area ratio of these structures, the "small roof parts".
2. **Angle**: Calculate intersection angles of roof polygons with ground surface and main roof polygons.
   (a) Maximum roof polygon-ground intersection angle;
   (b) Minimum roof polygon intersection angle with the ground surface;
   (c) Largest and second-largest roof polygons' intersection angle;
   (d) Average, median and standard deviation of all the intersection angles between roof polygons and the ground surface.
3. **Number**: Calculate the number of roof polygon(s).
   (a) The number of roof polygons in the roof segment;
   (b) The number of horizontal roof polygon(s) in the roof segments;
   (c) The number of "small roof parts" in the roof segments.
4. **Height**: Calculate the height values of roof polygons, using the centroid of roof polygons.
   (a) Maximum absolute height, the height difference from roof to ground;
   (b) Maximum relative height, the height difference between roof polygons;
   (c) Average, median, and standard deviation of roof polygon height differences from the ground surface.
5. **Squareness**: Calculate the squareness of each roof polygon and the average, median, and standard deviation of squareness values.

Representative roof types in 3DBAG Figure 10 shows the typical classes of roofs in 3DBAG to visualize the representative traits of each type.

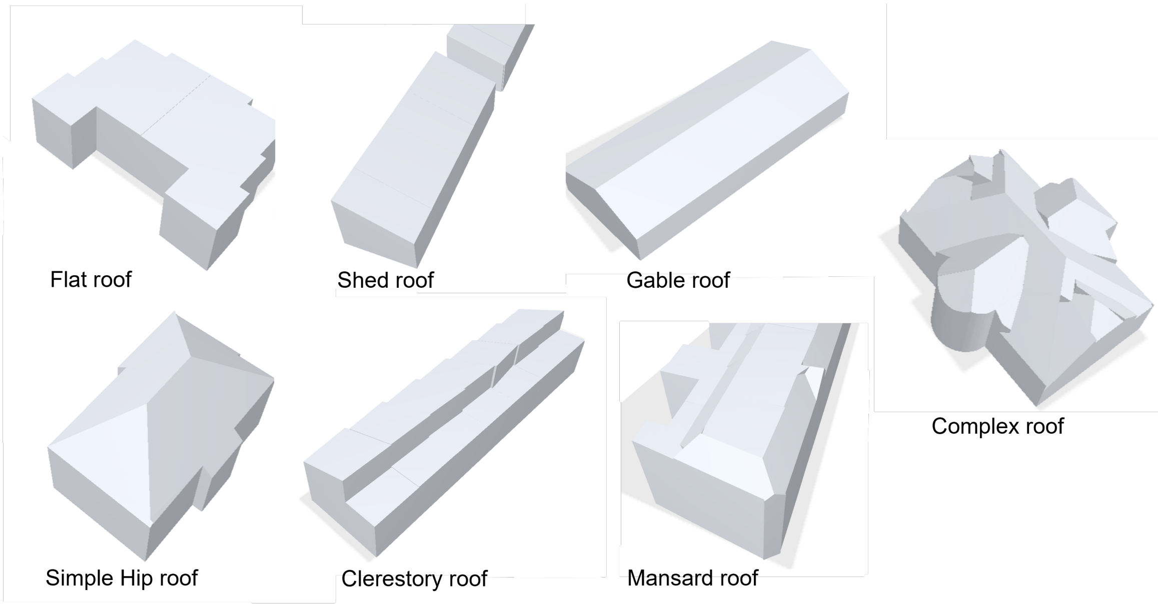

Figure 10: Representative roof types in 3DBAG

3.4 Label system and pre-labelling

3.4.1 Visualization system

In the need to label the sample data for further machine learning process, we implement a code to visualize the 3D data and features, thus we can manually label the training data. Figure 11 is the building type labelling window, and Figure 12 is the roof type labelling window.

3.4.2 Pre-labelling

Pre-labelling for building and roof types In addition to the features extracted in the section 3.3 on feature extraction, we employ the most prominent features in the manual pre-labelling process to address the complexity and ambiguity of different buildings and roofs. The mindmap (Fig. 13) depicts the priorities of building types in the pre-labelling process:

- **Residential or non-residential:** Use "area" and "neighbor numbers" along with surrounding building attributes to identify residential houses. They typically have a low height, small volume, and footprint area, which makes them easily recognizable through our label visualization system. If the building is classified as a "house", it will be categorized into 1-4 classes based on spatial relations. If not, it will be considered as belonging to other classes, with priority given to the shape of the footprint, followed by height.
- **The constraints of specific types:** In pre-labelling, consider the difference and typical traits by setting constraints for valid labelling. For example, "height" is used to distinguish I-shaped, tall slab, thin slab and tower buildings.

Furthermore, Tables 2 and 3 present the features considered during the pre-labelling process, all the features we used in this step are calculated. Some certain characteristics are discernible to humans, but high-dimensional data is required for the machine-learning approach.

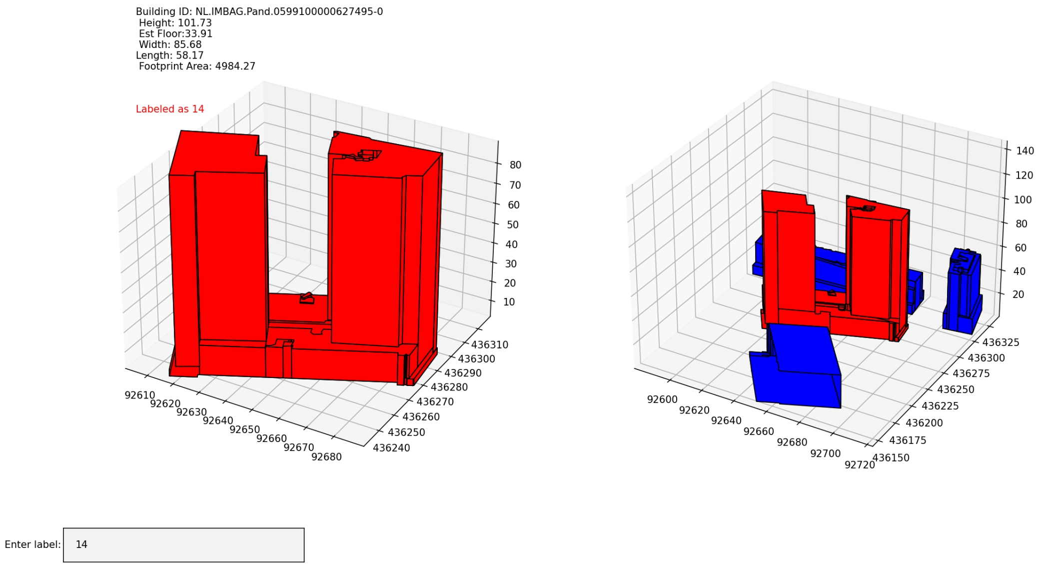

Figure 11: Building Label System

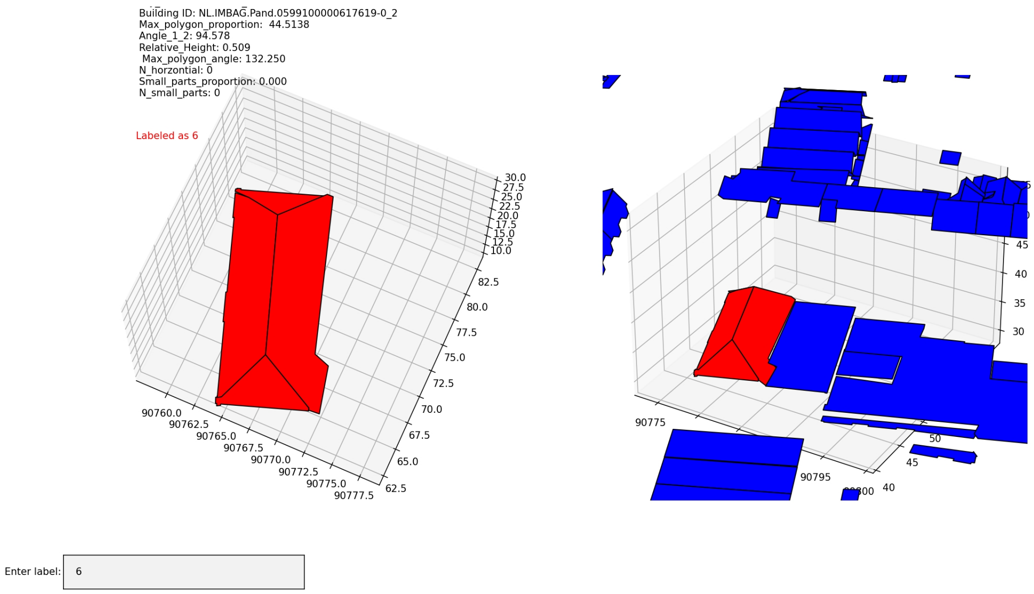

Figure 12: Roof Label System

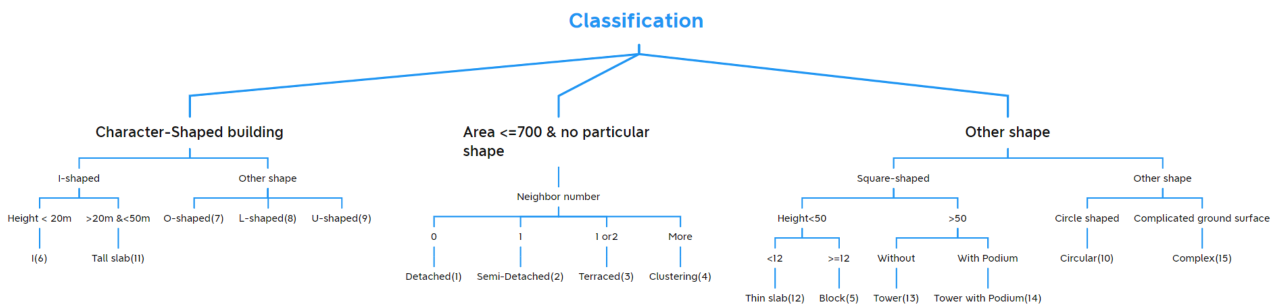

Figure 13: Building classification pipeline in pre-labelling

No.	Neighbour	Footprint	Area of ground surface	Height and other
1 Detached	0	basic rectangular or multiple rectangular shapes	< 700	-
2 Semi-detached	1 and its neighbour only has one neighbour	basic rectangular or multiple rectangular shapes	< 700	-
3 Terraced	2 or the neighbour has 2 neighbours	basic rectangular or multiple rectangular shapes	< 700	-
4 Multi-family	2 or the neighbour has 2 neighbours	basic rectangular or multiple rectangular shapes	< 700	-
5 Block	0	basic rectangular	> 700	-
6 I-shaped	0	long rectangular	-	Height<20 m
7 Tall slab	0	long rectangular	-	20m < Height < 50 m
8 Thin slab	0	ratio of ground surface and height	-	Height < 12m
9 Tower	-	ratio of ground surface and height	-	Height > 50 m
10 Tower with podium	-	-	the ratio of highest surface and the 2D footprint, highest height	Height > 50 m
11 L-shape	-	L-shape	-	-
12 O-shape	-	O-shape	-	-
13 U-shape	-	U-shape	-	-
14 Circular	-	basic circular	-	-
15 Irregular/-Complex	-	irregular	-	-

Table 2: Building type features in pre-labelling

No.	Number	Angle	Area of roof surface	Height and squareness
1 Flat	Total number of roof surface equals to the number of horizontal roof surface(ignore the small roof surface)	parallel to ground surface (angle threshold is 4)	area ratio of horizontal surface > 0.9	-
2 Shed	No horizontal roof surface (ignore the small roof surface)	not parallel to ground surface (angle threshold is 4)	area ratio of slanted surface > 0.9	-
3 Gable	number of slanted roof surface > 2, no horizontal surface (ignore the small roof surface)	not parallel to ground surface	the area of largest and second-largest surface are similar	each roof surface is basic rectangular
4 Clerestory	number of slanted roof surface > 1	-	-	each roof surface is basic rectangular
5 Simple Hip	number of slanted roof surface => 3, no horizontal surface (ignore the small roof surface)	not parallel to ground surface	the area of largest and second-largest surface are similar	roof surface shape is trapezoid or triangle
6 Mansard	number of slanted roof surface > 1, number of horizontal surface =1 (ignore the small roof surface)	-	-	each roof surface is basic rectangular
7 Complex	total surface > 2, number of slanted roof surface > 1		-	irregular surfaces are usually seen in this type

Table 3: Roof type features in pre-labelling

3.5 Classification Models

3.5.1 Explanation of classification models

Scikit-learn (sklearn) provides support for different types of Support Vector Machine (SVM) algorithms, including: SVC (C-Support Vector Classification), the standard SVM algorithm for classification, which allows you to control the margin and trade-off between maximizing the margin and minimizing classification errors through the parameter C, and NuSVC (Nu-Support Vector Classification) which uses a different parameter, "nu," instead of "C." The "nu" parameter represents an upper bound on the fraction of margin errors and a lower bound on the fraction of support vectors.

In this project, nuSVM is used because NuSVC handles the trade-off between margin errors and support vectors differently. NuSVC uses "nu" to directly control this trade-off, which can be seen as a more intuitive way to specify the margin and support vectors compared to the "C" parameter used in other SVM classifiers.

Another algorithm we used is "HistGradientBoosting". It's based on decision tree. In "HistGradientBoosting", decision trees are constructed in a way that makes use of histograms to efficiently represent and process the data.

This approach is centered around the quantization of feature values, effectively transforming continuous numerical attributes into discrete bins, each representing a specific range of values. For every feature, "HistGradientBoosting" constructs histograms that tally the occurrences of data points falling into these bins, encapsulating the distribution of that feature's values. Unlike classical Gradient Boosting, where decision trees explore all potential splits on all features at each node, "HistGradientBoosting" strategically selects the most informative features and optimal bin boundaries for making splits in the tree. By leveraging these histograms and carefully chosen splits, the algorithm aims to minimize the impurity or loss function at each node during tree construction. The process is iterative, where new trees are added to the ensemble in each boosting iteration, and the histograms are continually updated based on the residuals from previous iterations. Ultimately, the model becomes an ensemble of decision trees, each constructed using this histogram-based technique, resulting in a highly efficient and scalable method capable of handling large datasets, while still capturing intricate data relationships. This histogram-based approach helps improve the algorithm's efficiency, especially for large datasets, by reducing the memory and computational requirements compared to traditional Gradient Boosting.

3.5.2 Strength and weakness of classification models

One of the strengths of the Nu-Support Vector Classification (NuSVC) algorithm is its flexibility in managing the trade-off between margin errors and support vectors. Unlike the traditional Support Vector Classification (SVC), which uses the "C" parameter to control this balance, NuSVC employs the "nu" parameter, allowing for a more intuitive way to specify the fraction of margin errors and support vectors. This can be particularly advantageous when dealing with imbalanced datasets, as "nu" directly relates to the number of support vectors and provides more control over the model's complexity. However, a potential weakness of NuSVC is that it requires proper tuning of the "nu" parameter, which might be less intuitive for users accustomed to "C" in SVC. If the "nu" parameter is not chosen carefully, it can lead to overfitting or underfitting, making hyperparameter optimization a critical aspect of effectively using NuSVC in practice.

As for HistGradientBoosting, its strength lies in its exceptional efficiency and scalability when dealing with large datasets. By employing a histogram-based approach to represent and process the data, it significantly reduces memory and computational demands, making it particularly well-suited for substantial data volumes. Moreover, this algorithm efficiently handles categorical variables without the need for one-hot encoding, which simplifies the data preparation process. However, a potential weakness is that the histogram-based binning, while efficient, may introduce some loss of information due to the discretization of feature values. Additionally, the algorithm may require more careful hyperparameter tuning compared to traditional Gradient Boosting methods to achieve optimal performance. Overall, HistGradientBoosting is a robust choice for big data applications where computational efficiency is critical, but it may require careful configuration to strike the right balance between speed and predictive accuracy.

4 Results

The code is on: *https://github.com/StoneLee0917/Building_roof_classification_on_3D_building_model.git*

4.1 Training dataset

In total, we have 6599 building labels from 5 main cities (Rotterdam, Den Haag, Delft, Munich, and Berlin) and 2551 roof labels from Rotterdam and Den Haag. The distribution from between classes is still uneven. RandomOverSampler() function from imbalanced learn library is used to generates synthetic sample for the minority class in the training data by randomly duplicating existing samples.

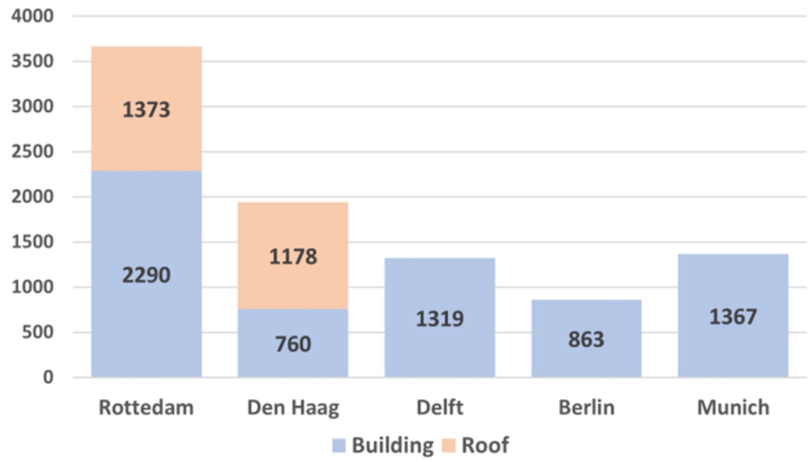

Figure 14: Labelled building and roof number

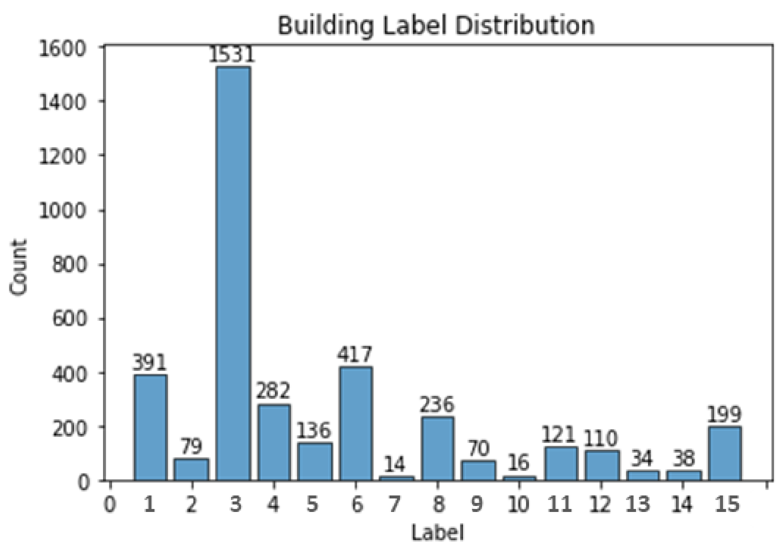

Figure 15: building label distribution

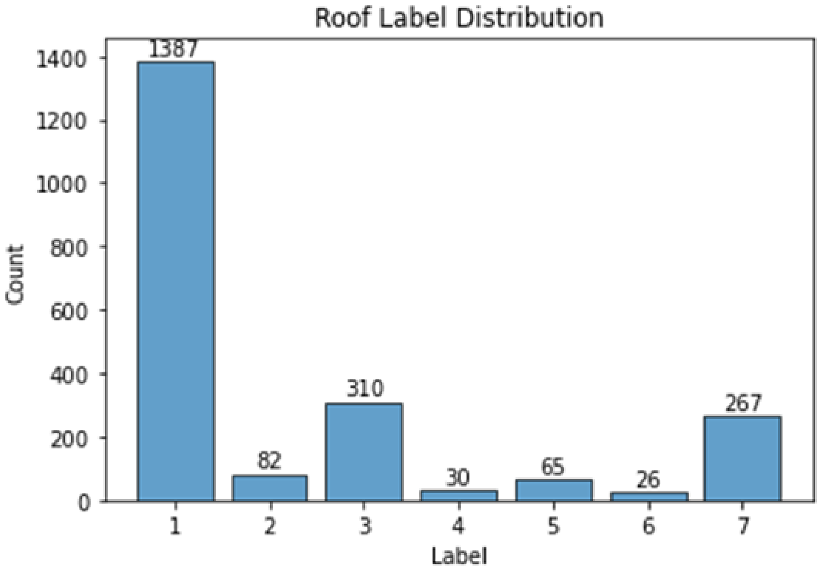

Figure 16: roof label distribution

4.1.1 City scale visualization for building types

Here is an overview of labeled buildings:

Figure 17: Rotterdam building label result

4.1.2 City scale visualization for roof types

Here is an overview of labeled roofs:

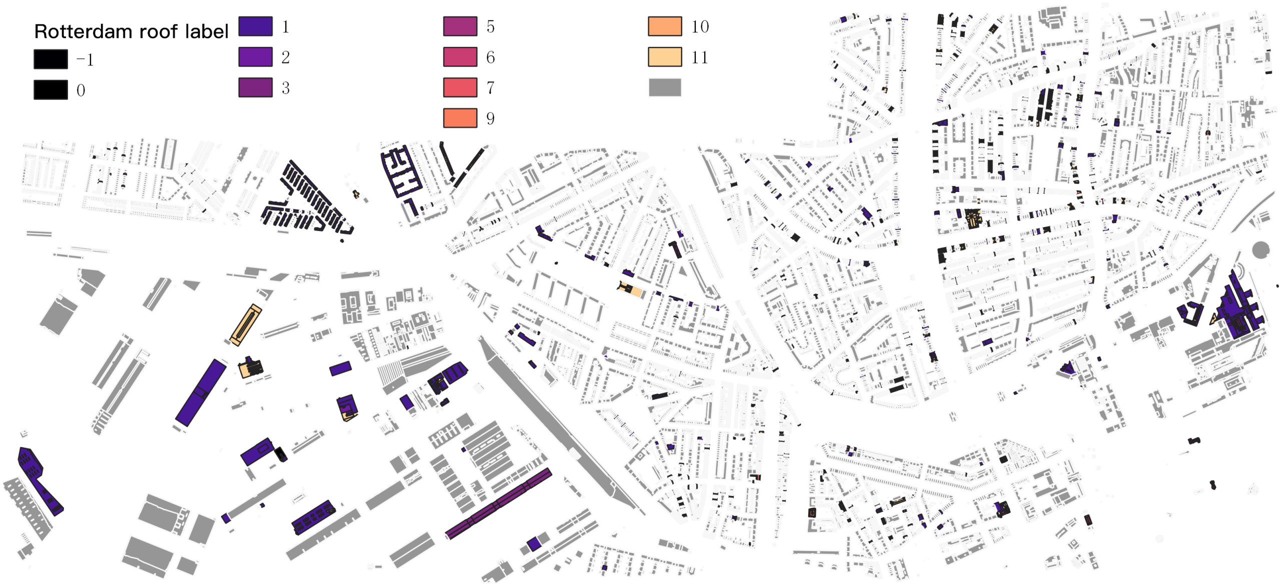

Figure 18: Rotterdam roof label

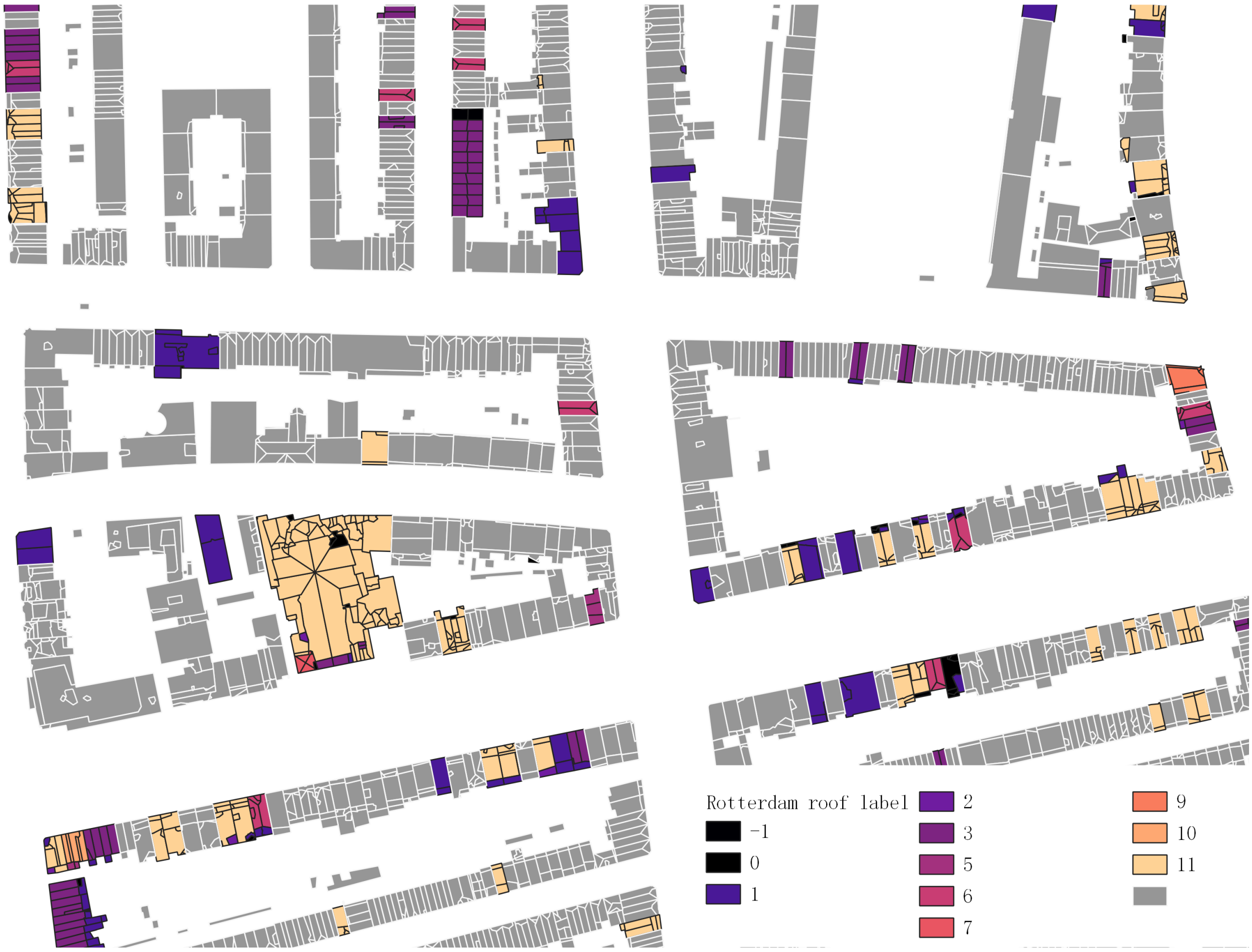

Figure 19: Part of Rotterdam roof label

4.2 Data augmentation

Data augmentation, specifically oversampling, as a technique to address class imbalance in a classification problem. Class imbalance occurs when one class in the dataset has significantly fewer samples than another, which can lead to poor model performance as the model may not adequately learn the minority class. To mitigate this issue, the code first prepares the data by extracting target labels and features. It then standardizes the features using the StandardScaler to ensure that they have a mean of 0 and a standard deviation of 1, making them suitable for modeling.

The data is then split into training and testing sets, with 33% of the data reserved for testing, ensuring the model's performance can be evaluated effectively. To address class imbalance, Random Over-Sampling is employed. This technique generates synthetic samples for the minority class in the training data by randomly duplicating existing samples. This approach helps balance the class distribution and ensures that the model doesn't favor the majority class. Data augmentation, in this context, enhances the representation of the minority class, thereby promoting better generalization and more accurate classification by the machine learning model.

4.3 Feature selection(permutation importance)

The main workflow of our training process is that in the first round, the model is trained using all features, and permutation_importance function from sklearn.inspection gives us an overview of the importance of each feature. Then, only features with a mean importance of more than zero will be used. The permutation importance function offers a systematic and model-agnostic approach to quantifying the impact of individual features on a model's predictive performance. This technique works by evaluating how shuffling or permuting the values of a particular feature affects the model's accuracy or other chosen evaluation metric. By comparing the model's performance before and after permuting a feature, one can determine the feature's contribution to the model's predictive power. From the result of permutation importance, the features with positive importance, which means a positive effect on classification.

4.3.1 Building feature importance

For building classification, the most important top five features are 2D equivalent rectangularity index, 2D convexity, horizontal elongation, 3D rectangularity, and height standard deviation.
Form factor 3D: A measure of the compactness of a 3D object which attempts to remove the bias introduced by the size of an object.
Direct neighbor area: The intersected area of one building's buffered footprint and its neighbours.
Horizontal elongation: Refers to the measurement of how a polyhedron's minimum bounding extends or elongates along its horizontal axis.
2D range index: It focuses attention on the distance between the furthest edges of a given polygon
3D fractality: It measures the surface roughness or smoothness.
Elongation: Assess the polyhedron's departure from regular or symmetrical shape, particularly in its horizontal dimensions.
Range index: evaluate the influence of small patches that are part of the polygon but far away from the rest of the polygon.

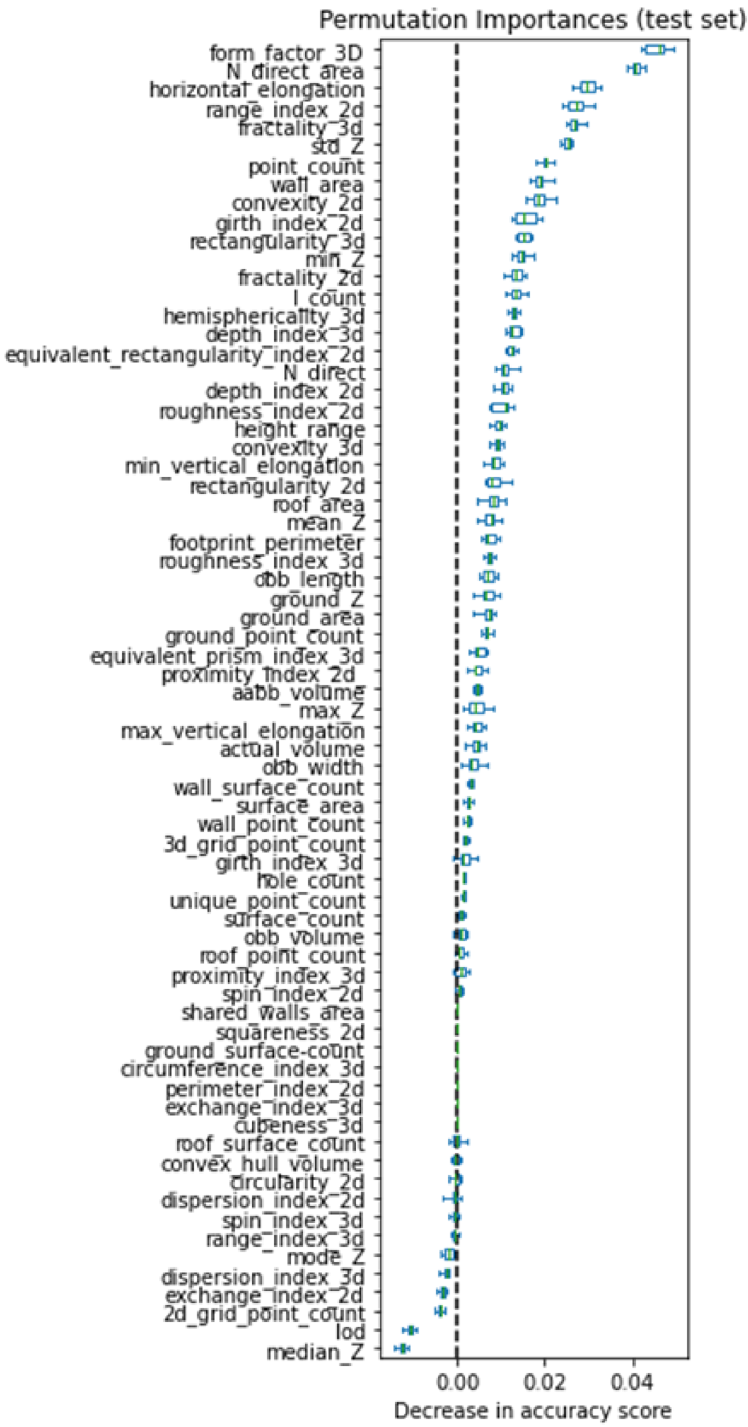

Figure 20: Permutation importance of building features

4.3.2 Roof feature importance

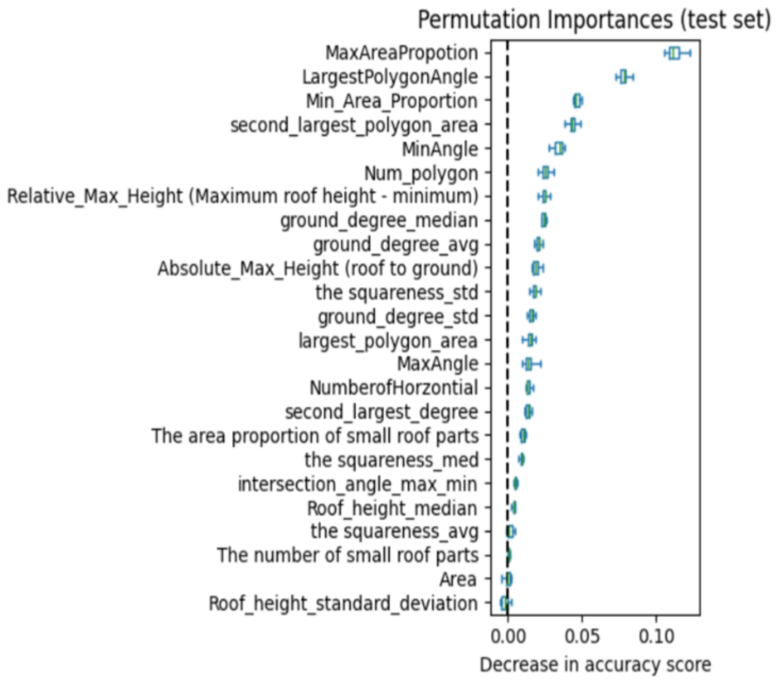

Figure 21: permutation importance of roof features

For roof:

1. **Area**: The area and area ratio of roof polygons.
   (a) Area: The total area of the roof polygons;
   (b) Area of largest polygon and its proportion, second largest polygon area, minimum polygon area portion;
   (c) Threshold for detecting dormers, attached structures, or the artifacts on the roof and the area ratio of these structures, the "The area proportion of small roof parts".
2. **Angle**: Intersection angles of roof polygons with ground surface and main roof polygons.
   (a) Maximum and minimum roof polygon-ground intersection angle;
   (b) Largest polygon angle;
   (c) Average, range, and standard deviation of all the intersection angles between roof polygons and the ground surface.
3. **Number**: Calculate the number of roof polygon(s).
   (a) The number of roof polygons in the roof segment;
   (b) The number of horizontal roof polygon(s) in the roof segments;
4. **Height**: Calculate the height values of roof polygons, using the centroid of roof polygons.
   (a) Height range, median, and standard deviation;
5. **Squareness**: Calculate the squareness of each roof polygon and the average, median, and standard deviation of squareness values.

4.4 Result visualization

Overall, using HistGradientBoosing algorithm can get better result. The final result is as below:

Class	Precision	Recall	F1-Score	Support
1	0.87	0.68	0.76	612
2	0.48	0.85	0.61	273
3	0.9	0.45	0.6	966
4	0.48	0.56	0.52	412
5	0.61	0.57	0.59	514
6	0.76	0.55	0.64	663
7	0.58	0.89	0.7	314
8	0.7	0.54	0.61	623
9	0.42	0.86	0.56	233
10	0.87	0.92	0.89	456
11	0.55	0.72	0.62	368
12	0.51	0.63	0.56	392
13	0.67	0.86	0.75	372
14	0.6	0.8	0.69	366
15	0.75	0.55	0.64	651
Accuracy			0.65	7215
Macro Avg	0.65	0.7	0.65	7215
Weighted Avg	0.7	0.65	0.65	7215

Table 4: Building Classification Metrics

Class	Precision	Recall	F1-Score	Support
1	0.93	0.46	0.62	942
2	0.57	0.92	0.7	289
3	0.87	0.46	0.6	888
4	0	0	0	15
5	0.49	0.93	0.64	246
6	0.25	0.9	0.39	131
7	0.61	0.37	0.46	758
Accuracy			0.53	3269
Macro Avg	0.53	0.58	0.49	3269
Weighted Avg	0.74	0.53	0.58	3269

Table 5: Roof Classification Metrics

4.4.1 Confusion Matrix

It can be noticed from the matrix that building of class 2,4 are easily misclassified as class 3, and also U-shape can be easily classified as L-shape.

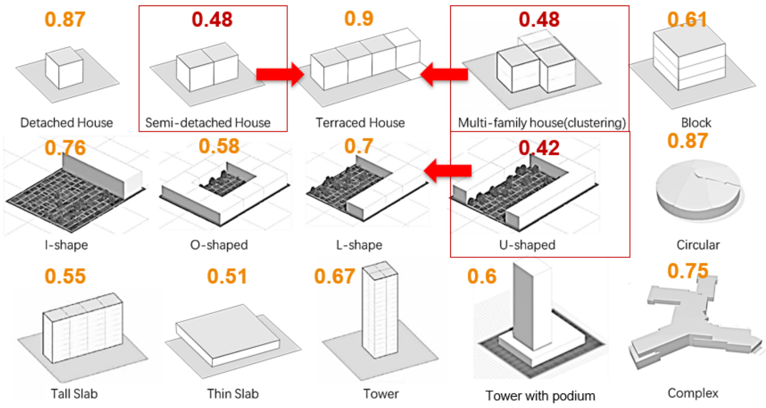

Figure 22: Building classification accuracy

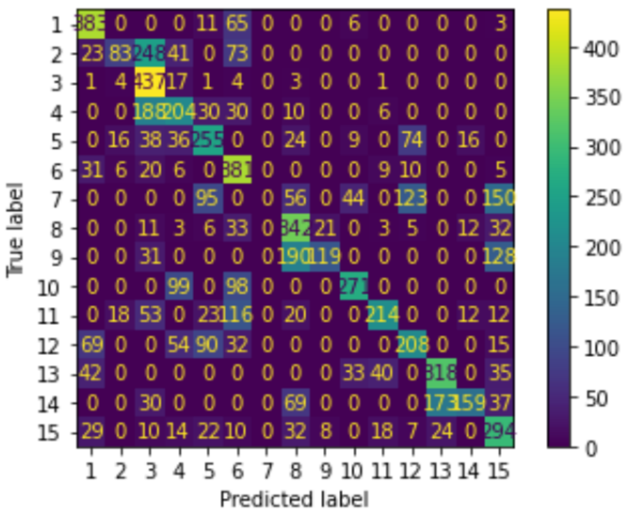

Figure 23: Building before feature selection

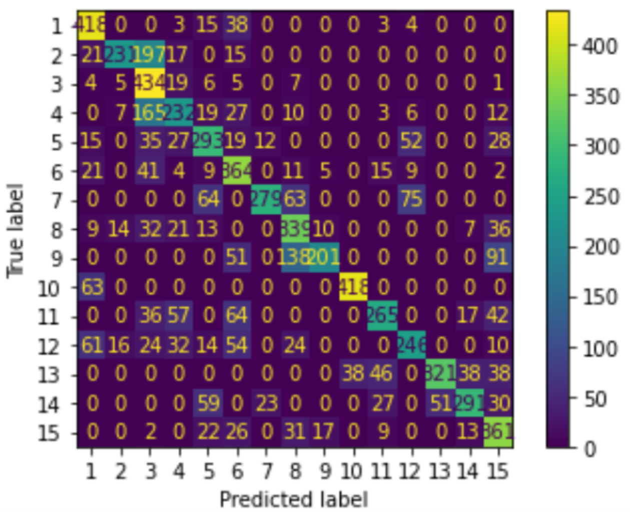

Figure 24: Building after feature selection

None of the class 4 roof is classified correctly and only 25 percent of class 6 roof is correct. Possible reasons as follows:

1. Geometry similarity between classes and more features are needed;
2. Low train number due to time limitation;
3. Roof segmentation limitation;
4. Quality of 3D model;

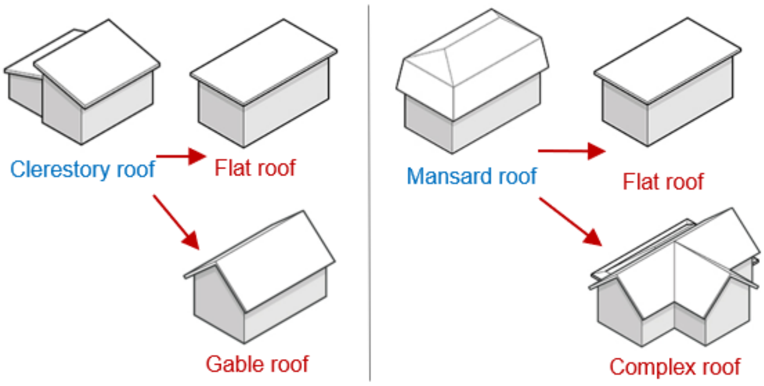

Figure 25: Misclassification of roof

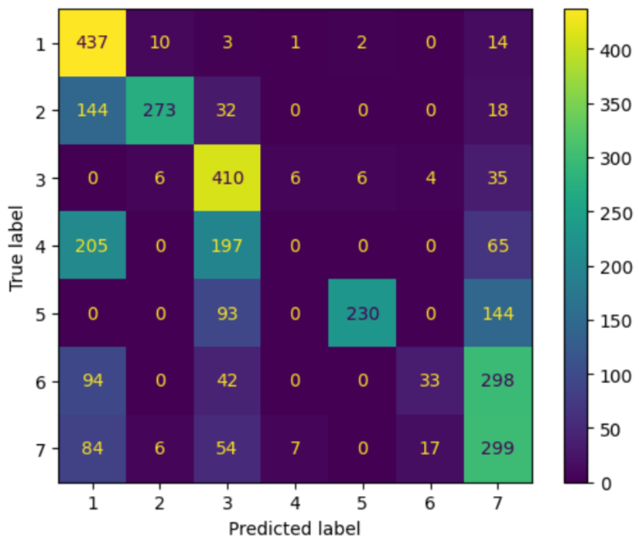

Figure 26: Roof before feature selection

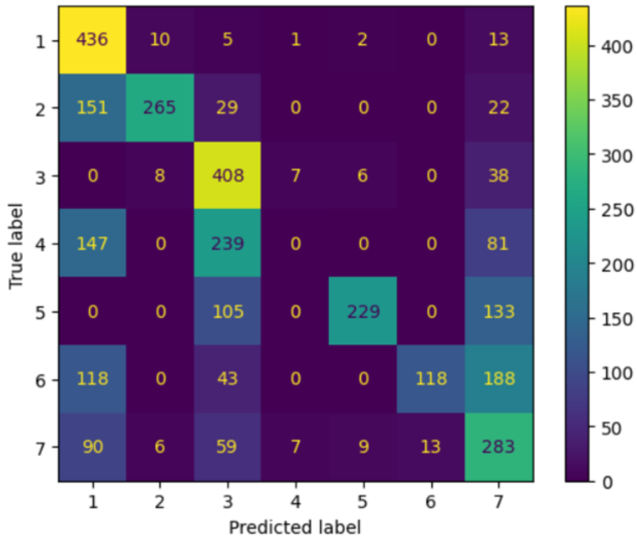

Figure 27: Roof after feature selection

4.4.2 SHAP

To explain the predictions of a machine learning model, SHAP (SHapley Additive exPlanations) library is used. SHAP is a popular tool for understanding the importance of different features in a model's predictions. It is based on the principles of cooperative game theory and provides a mathematically grounded approach to understanding how individual features contribute to a model's predictions. Two kinds of plot is made: First, a summary plot is made to evaluate each feature's impact on classes, this can be used as a reference for weight-setting.

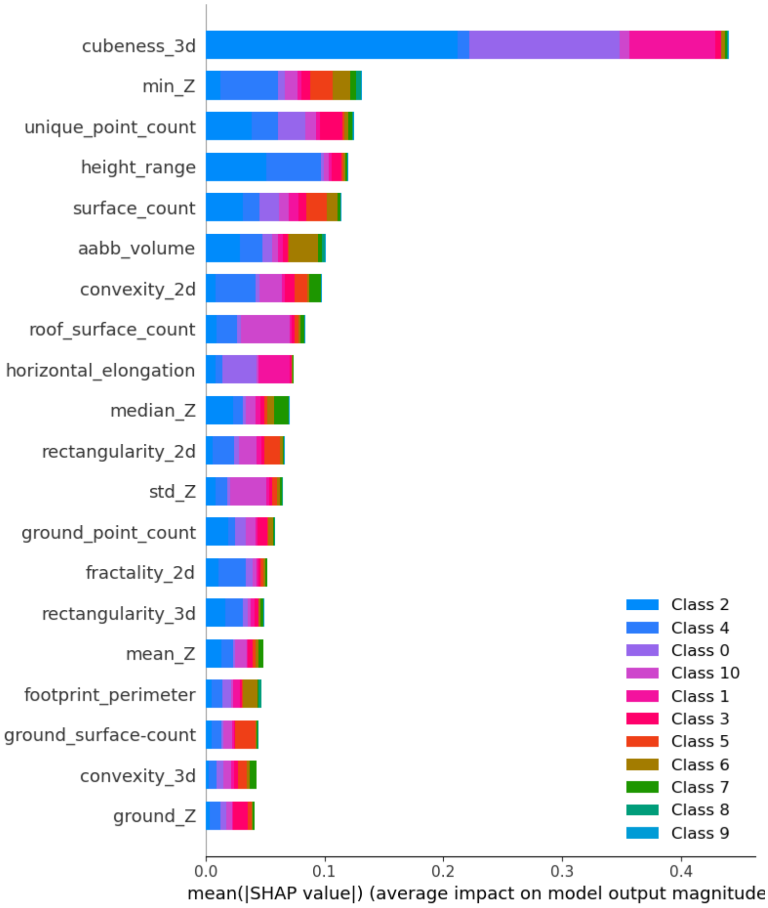

Figure 28: Impact of building features on each class

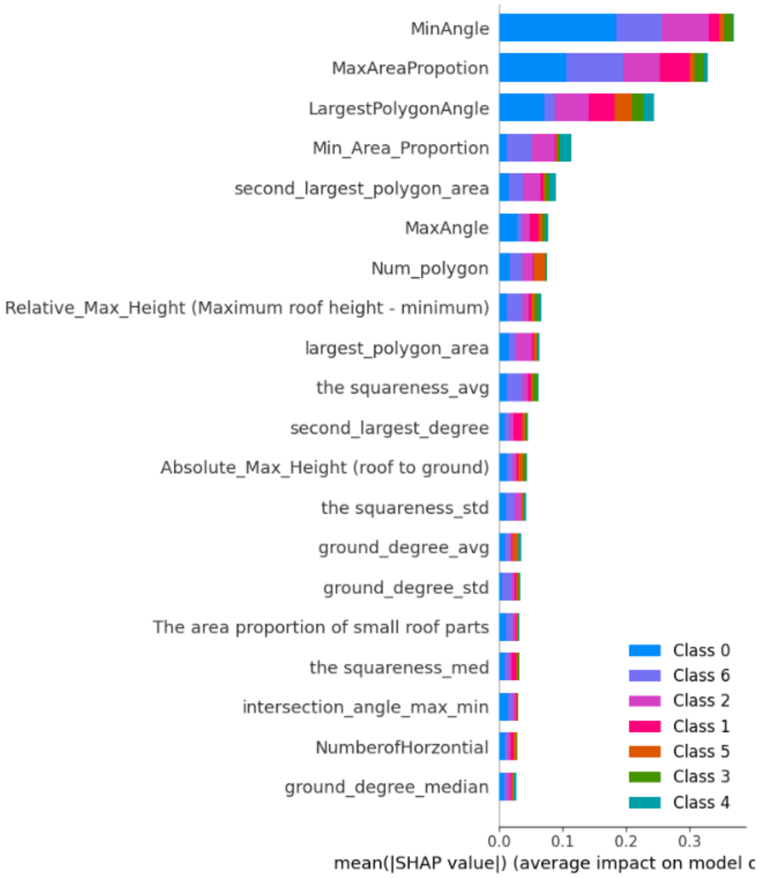

Figure 29: Impact of roof features on each class

The second plot generates individual summary plots showing the impact of features on each class separately. This helps understand how different features influence the model's predictions for each class, making your model interpretation more class-specific. Here is an example:

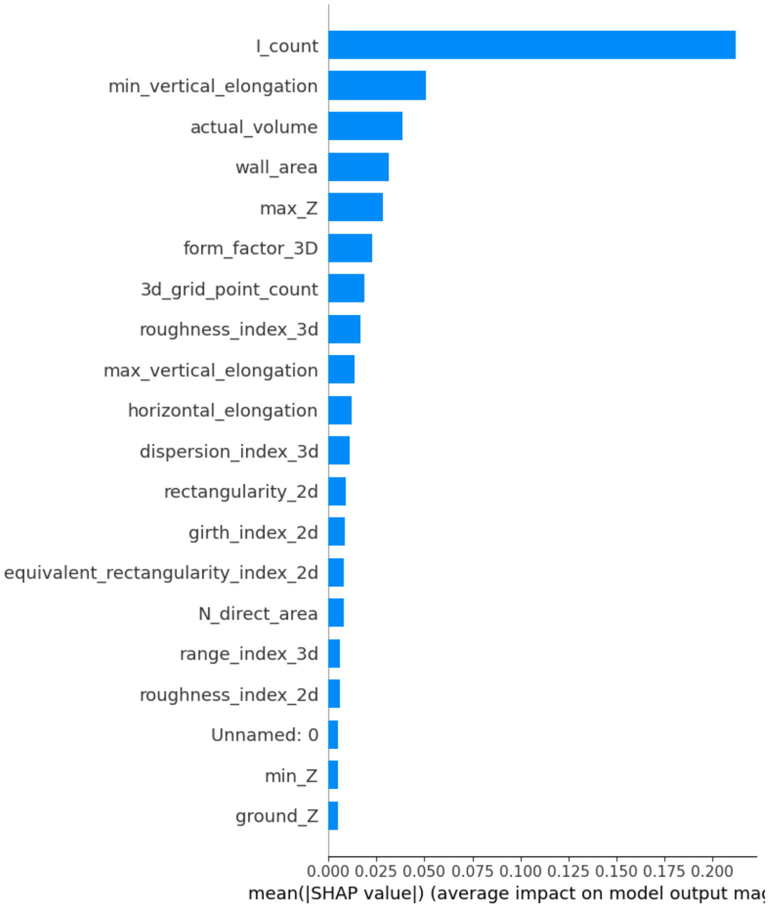

Figure 30: Impact of building features on class 5

5 Discussion and future work

5.1 Research limitations

Developing universal classification schemas and applying them to the many regions that release enough 3D city datasets is the goal of this project, however, certain limitations impact the goals. The following are the main areas of limitation:

1. **Limitation of classification schema design:** There are many variables taken into account in the schemas, non-exclusive classes may exist, and it's possible that some buildings have more than one representative trait. This can lead to ambiguity and make labelling more difficult, which in turn affects the classification results. Even with the highest importance that we assign to labelling, there are still situations in which these objects cannot be categorised into a single category and cannot, thus, be classed.
2. **Unbalanced class:** To cover all building kinds, classification schemas include both common and uncommon types. As a result, the distribution of labelled classes remains highly unbalanced even when numerous datasets are used. The most prevalent types are the focus of structural classes.
3. **Limited training set size:** Due to the time limitation, the training set size is limited, and the data we used is also limited to the Netherlands and Germany.
4. **Quality of 3D data:** Because the entire workflow and technique depend on the 3D datasets, the quality of the source data is essential. When we use the 3D classifier's results as labels during training, the faults in the 3D model are magnified, which has an impact on the final outcome, even on relatively small defects. The primary limitations we came across in the process are:
   - The incorrect hierarchy between "Building" and "Buildingpart" causes certain entire buildings to be split up into multiple connected pieces, which goes against the building classification schema's rule of separation based on randomness.
   - The correctness of the roof classification results cannot be guaranteed by the feature calculation results because the current 3D data in 3DBAG are reconstructed from the Lidar point cloud, and there are significant gaps between the roof surfaces and the actual roof shapes. In certain places, like Zurich, the roof surfaces are reconstructed by photogrammetry which has higher quality, nonetheless, there is a hierarchy of "Building" and "Buildingpart" issues, which makes the 3D data useless for classifying roofs.
5. **The incompatibility of 2D and 3D data:** In our workflow, we divide the roofs rather than taking them into consideration as a single unit. The bounding box of the 3D models is what determines the 2D image classification coordinates, meaning that the accuracy of the 3D model determines the upper bound of the model. In our research, we discovered that after dividing building roofs and connecting them with 2D satellite images appropriately, the segmentation may not match. Possible reasons for inaccurate identification of roof parts could be imprecise 3D data, or mistakes arising from integrating the bounding box of divided roof pieces with 2D images containing neighbouring pixels that don't belong to the roof parts.
6. **Lack of enough validation:** Besides, time constraints have limited our time period to just two months. The research needs more validation and the extension from 3D to 2D may only be carried out on a sample city. More following research should be conducted to explore this issue.

5.2 Future work

The future of this work can be furthered on:

1. **Data processing and labelling:** Our labelled dataset is currently limited to regions within the Netherlands and Germany. Consequently, certain building types and roof variations may not be adequately represented in our dataset. Additionally, the accuracy of the 3D data utilized for roof classification poses some limitations, which may affect the overall confidence in the classification results.
2. **2D images for roof classification:** We have noticed that there is a discrepancy between the 3D roof data and the roofs present in 2D images. In the future, we can improve the 3D training set using various methods:
   - Choosing the high-quality 3D datasets which can construct the roof shapes accurately;
   - Adapting the approach of splitting buildings, for example, instance segregation for roof parts on 2D images.

6 Project organisation

6.1 Competences, experience and complementarity of the participants

6.1.1 Team members

- **Sitong Li** BSc. Remote Sensing Wuhan University
  Tel: +31 0644569718; E-mail: lisitong0917@outlook.com
  Study field: Photogrammetry, Remote Sensing

- **Chengzhi Rao** MSc. Landscape Architecture
  Tel: +31 0647201128; E-mail: rchengzhi@gmail.com
  Study field: Landscape Architecture and planning, GIS, 3D modelling

- **Chi Zhang** BSc. Geography The Chinese University of Hong Kong
  Tel: 13530541690/+31 0644191633; E-mail: 1155124276@link.cuhk.edu.hk
  Study field: machine learning models, Hybrid Model, LLM, Remote Sensing

- **Qiuxian Wei** BSc. Urban Planning Harbin Institute of Technology
  Tel: +31 0647073919; E-mail: wqiuxian@student.tudelft.nl
  Study field: GIS, 3D modelling, Map develop.

6.1.2 Supervisory team

- Camilo León-Sánchez
  PhD Candidate from TUD 3Dgeoinfo

- Gina Stavropoulou
  Data Engineer from TUD 3Dgeoinfo

- Jantien Stoter
  Professor from TUD 3Dgeoinfo

- Rob Wijnhoven
  Lead Research and Development from SPOTR

6.2 Responsibilities within the project

6.2.1 Responsibilities of team members

- Chi Zhang
  Technical Manager: Deals with technical aspects, and defines algorithms in *image segmentation*.

- Sitong Li
  Technical Manager: Defines algorithms and methodology of *point clouds*.

- Chengzhi Rao
  Quality Manager and Report Manager: Reviews the quality of delivered work and classifies the

technological route and classification types.

- Qiuxian Wei
  Data Manager and Report Manager: Prepare and transform the data format for analysis, organize the result for the report and visualize the data.

6.2.2 Responsibilities of supervisory team

- Camilo León-Sánchez
  Coordinate Manager and Technical Manager: Leads the meeting and instruct technological route.

- Gina Stavropoulou
  Coordinate Manager and Technical Manager: Defines the agenda and guides the project methodology, does the communication between Spotr and the team.

- Jantien Stoter
  Coordinator: Defines the agenda and leads the meeting.

- Rob Wijnhoven
  Data Manger: Provides available data and guides the program.

6.3 Project Team Meetings

- **Group meeting**: Three times per week.
- **Meeting with all supervisors**: Every Monday for 1 hour.
- **Q and A**: Every day.

6.4 Dissemination and communication

6.4.1 Dissemination of the research results

- **Collaboration with Other Researchers**: The result will be discussed about collaboration efforts with SPOTR and TU Delft 3D groups for joint publications.
- **Social Media and Website**: Result could be used for TU Delft 3D groups' and SPOTR's promotion on website.

6.4.2 Exploitation of results and intellectual property

- **Protection of Intellectual Property**: The data used in this research are all open-source, the result will belong to the research team.
- **Collaboration with Industry**: Findings from this research may contribute to SPOTR on building evaluation, insurance classification and energy consumption.

6.4.3 Proposed measures to communicate the activities to different target audiences

- **Identify Target Audiences**: The target client will be real estate companies, insurance companies and energy organizations, etc. that have interest in building evaluation.
- **Feedback Mechanisms**: The feedback from clients will be mainly based on the evaluation and annual report.

6.5 Deliverables

No.	Deliverable Title	WP	Lead Team Member	Dissemination level	Due date
D1	PID	WP1	All	Private	2023/09/18
D2	Midterm presentation	WP2	All	Public	2023/09/26
D3	Final report	WP3	All	Public	2023/11/03
D4	Presentation	WP4	All	Public	2023/11/09

Table 6: Table Deliverable list

6.6 Gantt chart

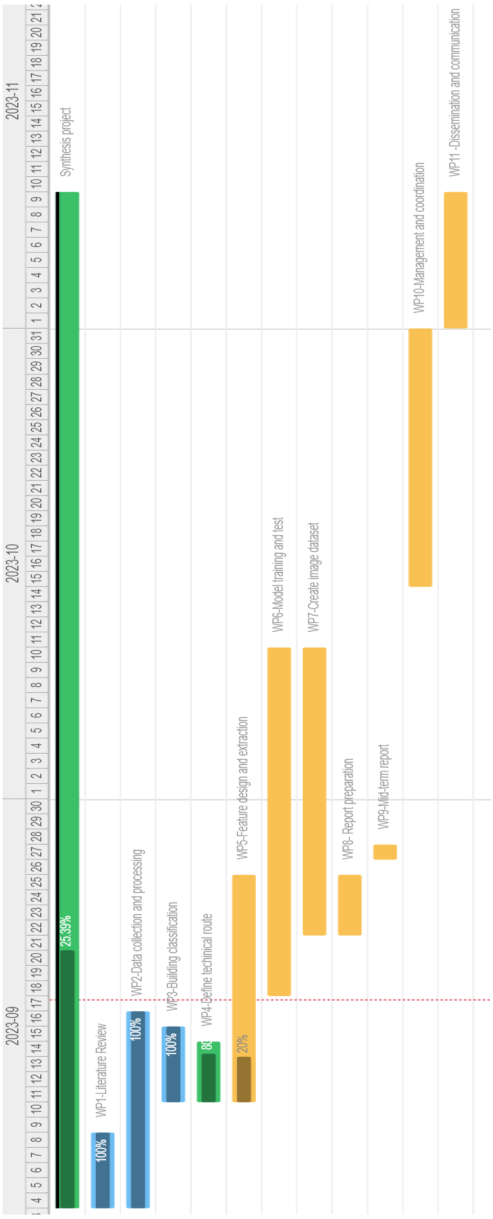

Figure 31: Ghatt chart

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