Inferring the residential building type from 3DBAG
Master thesis P2

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1 | Introduction

The 17 Sustainable Development Goals are a universal call to action to end poverty, protect the planet and improve the lives and prospects of everyone and everywhere. These goals are adopted by all 193 Member States of the United Nations as part of the 2030 Agenda for Sustainable Development (United Nations, 2015b). From these 17 Sustainable Development Goals, Goal 11 concerns making cities and human settlements inclusive, safe, resilient, and sustainable. And, stresses the importance of cities and settlements to improve living standards and decrease energy consumption (United Nations, 2015a; Ferrando et al., 2020). One of the most pressing challenges that cities face today is the levels of urban energy consumption. Cities occupy only 3 percent of the Earth's land but account for 60 to 80 percent of all energy consumption. To decrease urban energy consumption, and to achieve Sustainable Development Goal 11, energy in cities must be better managed and the cities' design must be optimized. Many Urban Energy Modeling methodologies and tools have been developed to do so. However, if Urban Energy Modeling is not applied, cities may not have an accurate understanding of their energy use and may miss opportunities for energy savings. For example, a city may not realize that a significant portion of its energy use is coming from inefficient buildings or outdated infrastructure. This could lead to the city continuing to invest in expensive, unsustainable energy sources rather than investing in energy-efficient upgrades or renewable energy. Two main inputs required for these Urban Energy Modeling methodologies and tools are first, the building stock geometry and secondly, the thermophysical properties associated with the entities in the geometry (Ferrando et al., 2020).

The 3D BAG is an up-to-date open data set containing 3D models of the building stock of the Netherlands at multiple levels of detail. This dataset is generated by combining two open data sets: the building data from the Register of Buildings and Addresses (BAG) and the height data from the National Height Model of the Netherlands (AHN) (3D geoinformation research group, 2021). However, the 3D BAG lacks building data on thermophysical properties, which are required for Urban Energy Modelling, for example, the construction characteristics of buildings such as materials, size, and order of construction layers.

On the other hand, the IEE project TABULA developed residential building typologies for 13 European countries, where each national typology consists of a classification scheme to group buildings according to their size, age, and further parameters. The TABULA WebTool then provides an online calculation of the exemplary buildings representing the building types and displays their energy-related features (Episcope, 2012). These exemplary buildings can be used to give an estimation of the energy consumption of a building stock by classifying its buildings into residential building typologies, substituting the need for thermophysical properties of each building from the building stock.

Recent studies such as 3D Building Metrics or Global Building Morphology Indicators introduce metrics calculated from building models that could potentially be used as features for a machine learning algorithm (Labetski et al., 2022; Biljecki & Chow, 2022), for example, to classify certain building types. This master thesis aims to infer the types of residential buildings from the building stock of the Netherlands in the 3D BAG using feature engineering and machine learning, as a way to add thermophysical properties to the residential buildings, which can then be used in Urban Energy Modeling. This master thesis is divided into two main parts, firstly to calculate and evaluate the accuracy assessment of the introduced metrics from the 3D building models from the 3D BAG; secondly to implement machine learning methods to calculate the building type of residential buildings on the IEE project TABULA residential building typologies for the Netherlands.

2 | Research questions

To what extent can machine learning correctly classify the building stock of the Netherlands?

- What features are needed to infer the building types of the buildings of the 3DBAG?
- What data is required?
- Which (combination of) machine learning algorithm is the most suitable to be used for the classification of the building stock of the Netherlands, with regards to the size and nature of the data used, the availability of computational resources, the interpretability of the results and the desired level of accuracy?

3 | Related work

In order to classify a building from the 3D BAG dataset as one of the building types of residential buildings on the IEE project TABULA, we first have to investigate how the distinction of each building type of residential building is made. The IEE project TABULA (2014) classifies the residential buildings of the Netherlands into four generic building types: single-family houses, terraced houses, multi-family houses, and apartment blocks. These generic building types can then be divided into even further building types: detached single-family houses and semi-detached single-family houses (twee-onder-een-kap), middle-row terraced houses (tussenwoning) and end-house terraced houses (hoekwoning), common staircase with galleries apartment block and common staircase without galleries apartment block, and lastly maisonettes. Each of these types is also classified into their construction year class: before 1964, between 1965 and 1974, between 1975 and 1991, between 1992 and 2005, and after 2006. Each generic building type and subdivision building type has its own exemplary building for each construction year class with its energy-related features. See figure 3.1 below for the diagram of this classification made by the IEE project TABULA.

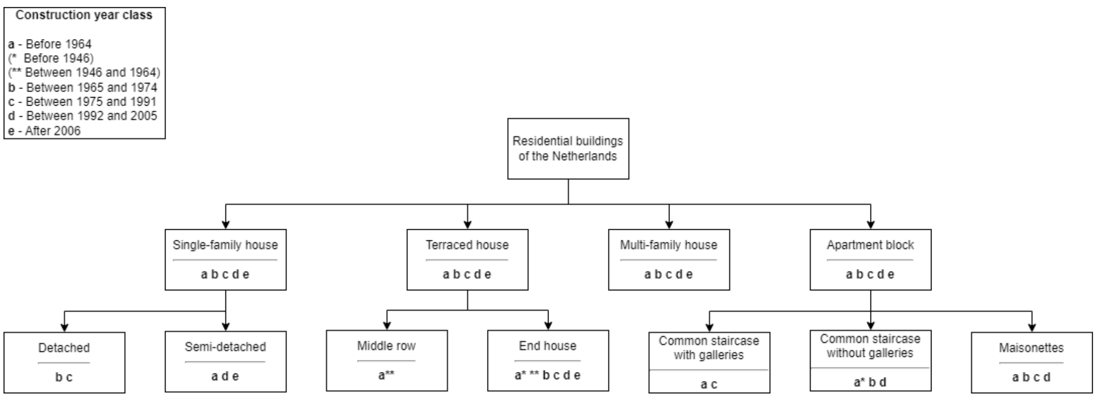

Figure 3.1: TABULA classification diagram.

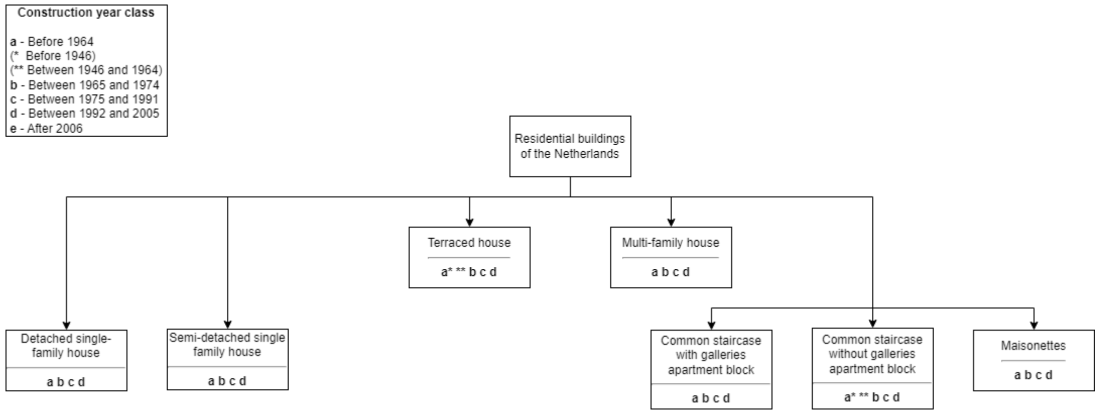

Figure 3.2: Voorbeeldwoningen 2011 classification diagram.

Voorbeeldwoningen 2011	**IEE project TABULA**
Vrijstaande woning	Detached
2 onder 1 kap woning	Semi-detached
Rijwoning	Terraced house
Maisonettewoning	Maisonettes
Galerijwoning	Common staircase with galleries
Portiekwoning	Common staircase without galleries
(Overig) flatwoning	Multi-family house

Table 3.1: Same building types between Voorbeeldwoningen and IEE project TABULA.

Additionally, the brochure Voorbeeldwoningen 2011 published by Agentschap NL (2011) describes reference dwellings with their energy-related features and the impact of refurbishment measures with the same building types as the IEE project TABULA (see table 3.1), but with less hierarchical distinction (see figure 3.2). For example, there are no generic building types, and the distinction between a middle row and end house terraced house is not made, but specific building properties are given: front-back facade and side facade. Also, for some of the building types, the number of floors is given and the floor area for each building type is given, whereas in the TABULA the number of floors is not given and some of the referenced floor areas are estimated (Episcope, 2013).

Furthermore, Kadaster (2015) makes somewhat the same distinction as the Voorbeeldwoningen 2011 and IEE project TABULA. Like the IEE project TABULA, Kadaster also makes the distinction between a middle-row and end house terraced house. But, it does not make the distinction between a multi-family house, maisonette, common staircase with galleries apartment block, and common staircase without galleries apartment block. Instead, these are all classified as apartments. However, the Kadaster does elaborate on the classification process of the building types through a flowchart, this classification process classifies a building by linking its address to an exemplary building type or reference dwelling type. This flowchart has been expanded to include the specific classification of apartments by IEE project TABULA, see figure 3.3, using additional information gathered from Voorbeeldwoningen 2011.

According to Kadaster (2015), using their classification process in 2014 there were less than 1 million classified as non-residential from the 8.5 million addresses in the Netherlands. And less than 3000 addresses that were not classified. The reasons for these unclassified addresses are overlapping buildings in the BAG dataset, (neighboring) buildings with the same addresses, and buildings that were not in use (e.g. buildings for sale). There were also errors propagated from errors in the BAG, for example, a building missing data on their dwelling will lead to incorrectly classifying its type, and a small space between buildings can lead to classifying a building as an end house instead of a middle-row house or semi-detached single-family house. On closer inspection, it seems that these errors have been corrected in the BAG, but it is good to keep these special cases of unclassified buildings and errors in mind when designing the classification method for this thesis.

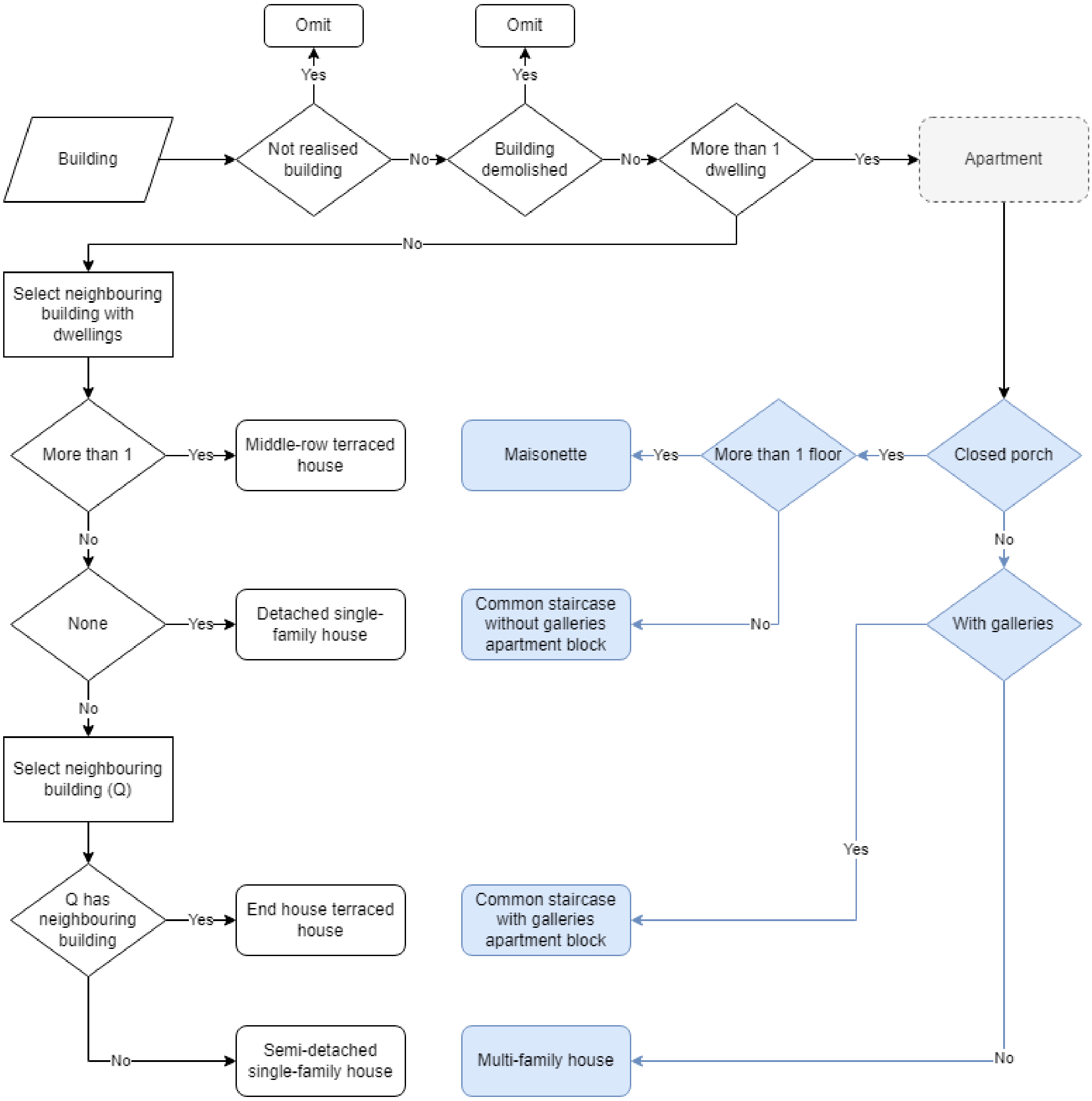

Figure 3.3: Flowchart of Kadaster's classification process of residential buildings, expanded to include the specific classifications of apartments (in blue).

Furthermore, Kadaster's classification process groups the multi-family houses, maisonettes, common staircase with galleries apartment blocks, and common staircase without galleries apartment blocks into a single type: apartments. The elimination of the subdivision of apartments is also made in the Referentiewoningen nieuwbouw 2013 published by Agentschap NL (2013), a brochure giving exemplary buildings to be used as a reference for new residential buildings, but still, they divide the apartments into gallery buildings and apartment buildings. While admitting that the diversity within these types is big and therefore the energy-related values given are an average of the diverse subtypes.

However, it is still important to include the subdivision of the apartments in this thesis, although the buildings from this subdivision will not be referenced anymore, the building stock now includes these buildings, so it is still important to classify them, to get a more precise estimation on the energy consumption of a building.

The Global Building Morphology Indicators (GBMI) (Biljecki & Chow, 2022) is a comprehensive list of hundreds of building form multi-scale measures derived through a systematic literature review, and also a methodology and tool for the computation of these metrics in a database suited for big data and comparative studies. The list of these indicators at the building level for both the independent and contextual instances can be found in figure 3.4.

At the same time, the 3D building metrics for urban morphology (3DBM) (Labetski et al., 2022) provide a comprehensive set of 3D metrics elevating building metrics into full/true 3D, uncovering the use of higher levels of detail, and taking into account the detailed shape of a building. These metrics are computed per building (see figure 3.5) and are available as a software package that ingests 3D city models and computes these metrics and stores them in a structured manner to enable data analyses. These indicators and metrics that characterize buildings are fundamental to studying the urban form and are used in many large-scale studies and analyses (Biljecki & Chow, 2022; Labetski et al., 2022). In this master thesis, these indicators and metrics can be used as features together with machine learning to classify the building stock of the Netherlands in the 3D BAG to their residential building types, but also to classify the generalized type of apartments, defined by the Kadaster (2015), to their subdivisions from IEE project TABULA (2014) and in the Voorbeeldwoningen brochure from Agentschap NL (2013).

Indicator	Data type	Unit
Footprint area	Decimal	m^2
Perimeter	Decimal	m
Height	Decimal	m
Height to footprint area ratio	Decimal	m^{-1}
Volume	Decimal	m^3
Wall area	Decimal	m^2
Envelope area	Decimal	m^2
Number of vertices	Integer	
Complexity	Decimal	
Compactness	Decimal	
Equivalent rectangular index	Decimal	
MBR[a] Length	Decimal	m
MBR[a] Width	Decimal	m
MBR[a] Area	Decimal	m^2
Orientation (azimuth)	Decimal	degree
Number of storeys	Integer	
Floor area	Decimal	m^2
Number of neighbours[b]	Integer	
Site coverage in the buffer[b]	Integer	
Distance to neighbours[b]		
– Minimum	Decimal	m
– Median	Decimal	m
– Mean	Decimal	m
– Maximum	Decimal	m
– Sum	Decimal	m
– Standard deviation (SD)	Decimal	m
– Index of dispersion (D)	Decimal	m
– Coefficient of variation (CV)	Decimal	
Neighbour footprint area[b]		
– Same 8 descriptive statistics as above		
Ratio neighbour height to distance[b,c]		
– Same 8 descriptive statistics as above		

[a] MBR – Minimum Bounding Rectangle.
[b] The size of the buffer varies in literature. In our implementation, we create three buffers using the following values: 25, 50, and 100 m.
[c] The last contextual indicator measures the ratio between the average height of buildings in a buffer and the distance among them.

Figure 3.4: List of indicators at the building level from the GBMI (Biljecki & Chow, 2022).

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 3.5: Metrics, from the 3D building metrics for urban morphology (Labetski et al., 2022), computed per building based on category.

Finally, the master thesis Inferring the number of floors of building footprint in the Netherlands by Roy et al. (2022) has been used as inspiration and recommended by the supervisors for its clear structure and the similarities to this master thesis. Roy et al's (2022) master thesis focus on inferring the number of floors of the buildings from also the 3D BAG by using supervised machine learning techniques, which requires labeled data (data including the desired solutions). The labels, in this case, are the building floor count and the features are the building properties. Three machine learning algorithms were used in this thesis: Random Forest Regression, Gradient Boosting Regression, and Support Vector Regression. And, it was identified that inferring the number of floors is a regression problem since classification would require the training data to include all possible floor counts that exist in reality, which would be difficult to find in practice.

However, in this master thesis, the problem is classification, since the building needs to be inferred to discrete residential building types and the training data can include all the possible residential building types of the Netherlands. Nonetheless, the classification counterparts of the three introduced machine learning algorithms can be used as a basis for the research for the most suitable machine learning algorithm for this master thesis, namely, Random Forest Classification, Gradient Boosting Classification, and Support Vector Machine. But more machine learning classification algorithms will also be explored.

Furthermore, the features considered in Roy et al's (2022) master thesis should be relevant to this master thesis as well. The number of floors, the result of the thesis, itself can be considered a feature in inferring the residential building type. The features can be subdivided into cadastral, geometric, and census features. The cadastral features were obtained from the BAG. The geometric features are split into 2D and 3D features, where the 2D features were extracted from the BAG and the 3D features from the 3D BAG. Last, the census features were obtained from the Centraal Bureau voor de Statiek (CBS), a government agency responsible for collecting statistical information about the Netherlands. All these features can be found in figure 3.6 through 3.9, with their details and relevance. The relevances are described for the number of floors but should be relevant for the residential building type as well.

	Feature	Details and relevance
1	Construction year	Construction period is often related to storey height. For instance, after 2003, the Dutch building code increased the required storey height of new buildings from 2.4 to 2.6 meters [Ministry of the Interior and Kingdom Relations, 2012]. This means that construction year could be used to distinguish buildings with the same number of floors but different heights.
2	Building function	A distinction is made between residential and mixed-residential, as mixed-residential buildings have been found to exhibit different properties than purely residential buildings [Biljecki et al., 2017].
3	Net internal area	Previous research has found that taller buildings (with more storeys) generally have a higher net internal area [Biljecki et al., 2017].
4	Number of units	Similar to the net internal area, buildings with more storeys generally contain more building units (e.g. apartment blocks).

Figure 3.6: Cadastral features (Roy et al., 2022).

	Feature	Details and relevance
5	Area	Dividing the net internal area by the footprint area can provide an indication of the number of floors (see Section 2.2.2).
6	Perimeter	In combination with area, perimeter can provide information about the footprint shape, such as its compactness and complexity [Lánský, 2020].
7	No. vertices	A higher number of footprint vertices could indicate a more complex shape [Lánský, 2020]. Computed after simplification by Douglas-Peucker.
8	No. neighbours	The number of neighbouring building centroids within a 100m radius of the footprint centroid. Buildings with many storeys are generally surrounded by more open space [Biljecki et al., 2017]. Buildings in rural areas also generally have fewer neighbours [Lánský, 2020].
9	No. adjacent buildings	The number of buildings within a 0.1m buffer of each footprint. Lower storey buildings in urban areas generally have more immediate neighbours.

Figure 3.7: 2D Geometric features (Roy et al., 2022).

	Feature	Details and relevance
10	Building height	Computed for the minimum, maximum, 50th and 70th roof height percentiles (available as attributes of the 3D BAG). Building height is strongly related to number of floors, especially for residential buildings [Biljecki et al., 2017].
11	Roof shape	An attribute provided for each building in the 3D BAG. In combination with building height, roof shape could provide information about the likelihood that storeys are present beneath slanted roofs.
12	Ridge vs. eave height	The difference between the height of the ridge and eaves of the roof. Similar to roof shape, this could provide some indication of whether storeys might be present beneath slanted roofs (Figure 3.3a).
13	Roof surface area	Computed for both LOD1.2 and LOD2.2 to describe building geometry.
14	Wall surface area	Computed for both LOD1.2 and LOD2.2 to describe building geometry.
15	Building volume	Computed for both LOD1.2 and LOD2.2. A larger volume is somewhat linked to a larger number of floors.

Figure 3.8: 3D Geometric features (Roy et al., 2022).

	Feature	Details and relevance
16	Population per km^2	Areas with a higher population density generally have more high storey buildings to accommodate all residents.
17	Percent multi-household	Multi-household buildings, such as apartment blocks, generally have more storeys than single family homes.
18	Average no. of cafes in 1km	The average number of cafes shows a strong link to area morphology (Figure 3.4) and could be used to distinguish central business districts from rural and suburban areas. Other amenities were also considered but the average number of cafes showed the clearest relationship to area morphology (see Section B.2).

Figure 3.9: Census features (Roy et al., 2022).

4 | Method

The method used to address the research question of to what extent machine learning can correctly classify the building stock of the Netherlands consists of four main stages:

1. Data collection and preparation
2. Feature extraction
3. Modeling and prediction
4. Accuracy assessment

First, the data required for the classification needs to be collected and integrated. The building stock of the Netherlands is obtained from the 3D BAG. The data on each building's use, its address, and the number of dwellings in each building is obtained from the BAG. The scope will be the entirety of the Netherlands, but a subset will be used to test the method and different models, however, the method described here can be replicated for the whole country or different parts of the country (different subsets). Rijssen-Holten and Energy label dataset will be used to create a basic training dataset consisting of unique building identifiers and building types or energy labels.

Second, the data needs to be prepared for the training process. Which entails the extraction of features that describes the properties of each building. The methodology and tools of the GBMI and the 3DBM will be used and expanded with our own features which are needed for the classification of the residential buildings. A number of these features can be derived from the classification process of the Kadaster, namely the number of dwellings, the number of neighboring buildings with dwellings, and the number of neighboring buildings of the neighboring building. The features extracted with the GBMI and the 3DBM, which describe the shape of a building, will be used to further classify the apartment residential building type into its subdivisions. The extracted features will then need to be analyzed and assessed to eliminate any redundant or irrelevant features, a process known as feature selection or feature elimination. Feature selection helps with selecting a subset of features that can provide a concise description of the training dataset, while still generating accurate predictions (Chandrashekar & Sahin, 2014).

Third, further research on machine learning will be done to find several suitable algorithms to perform the classification of residential buildings in the Netherlands. Before the algorithms can be trained preprocessing the data is required. A subset of 80% of the data needs to be created for the training of the algorithms. While the other 20% subset will be used to evaluate the model. Evaluating the model on unseen data gives us an unbiased measure of the model's performance. Next, the features extracted from the data need to be converted into formats appropriate for the machine learning algorithms, for example, converting categorical features into one-hot encoding by creating additional columns for each possible feature value. Lastly, research will have to be done to find the most suitable error metrics and each algorithm will be assessed and evaluated by using a combination of error metrics in the evaluation of the resulting models. These error metrics will allow the best model per algorithm to be selected. To further improve the performance of the resulting models, hyperparameter tuning can be performed or even other features can be considered.

Lastly, a more in-depth analysis of model performance will be performed based on the different error metrics used. To determine which machine learning is the most suitable to be used in the classification of the residential buildings of the Netherlands the results of the machine learning algorithms need to be compared to the ground truth. A confusion matrix can be used, it consists of a True Positive, True Negative, False Positive, and False Negative and is usually presented in a tabular format (Nan, 2022), see figure 4.1.

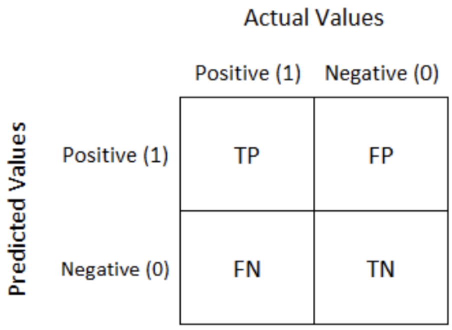

Figure 4.1: Confusion matrix (Nan, 2022).

Each prediction from a model can be one of these four types with regard to performance:

- True Positive (TP), is when a sample is predicted to be positive (e.g. a building is predicted to belong to a certain residential type) and its label is actually positive (e.g. the building actually belongs to that residential type).
- True Negative (TN), is when a sample is predicted to be negative and its label is actually negative.
- False Positive (FP), is when a sample is predicted to be positive, but its label is actually negative.
- False Negative (FN), is when a sample is predicted to be negative, but its label is actually positive.

With these values, several performance metrics can be computed: Accuracy, Precision, Recall (Sensitivity, True Positive Rate, Hit rate), and Specificity (True Negative Rate, Selectivity). Which can be used to evaluate the performances of the models. Accuracy is the fraction of predictions the model predicted correctly out of all the predictions. And is computed as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{4.1}$$

However, Accuracy is not a great metric, especially when the data is imbalanced. Therefore, Precision, Recall, and Specificity are usually used to overcome the limitations of Accuracy. Precision is the fraction of actual positive predictions the model predicted correctly out of all the positive predictions:

$$Precision = \frac{TP}{(TP + FP)} \tag{4.2}$$

While recall is the fraction of actual positives out of all positive predictions:

$$Recall = \frac{TP}{(TP + FN)} \tag{4.3}$$

And lastly, specificity is the fraction of actual negative predictions the model predicted correctly out of all the negative predictions:

$$Specificity = \frac{TN}{(FP + TN)} \tag{4.4}$$

5 | Preliminary results

5.1 Possible features

Based on the related works, possible candidates to be used as features to infer the residential building type has been gathered, see table 5.1 for the possible candidates for features.

#	Feature	Details and relevance	Source
1	Construction year	Construction year might not be relevant to inferring the residential building type, but it is relevant to determining the construction year class of a residential building type.	BAG
2	Building function	In order to filter out the non-residential buildings	BAG
3	Area of dwelling	Might be related to residential building types, exemplary buildings and reference dwellings are often given with a reference area	BAG
4	No. dwellings	See classification process of the Kadaster	BAG
5	No. adjacent buildings	See classification process of the Kadaster	Extracted from BAG
6	No. adjacent buildings with dwellings	See classification process of the Kadaster	Extracted from BAG
7	No. adjacent buildings of adjacent building	See classification process of the Kadaster	Extracted from BAG
8	Area	Footprint area, describes the form of the building.	Extracted from BAG
9	Perimeter	Footprint area, describes the form of the building and provides additional information about the footprint shape, like the compactness and complexity.	Extracted from BAG
10	No. vertices	The number of the vertices gives another indication of the complexity of the footprint shape.	Extracted from BAG
11	No. neighbours	The number of neighbouring building centroids within a certain radius of the footprint centroid. For example, taller buildings, like apartment blocks generally have more open space in the surroundings	Extracted from BAG
12	Building height	Describes the form of the building.	Extracted from 3D BAG
13	Building length	Describes the form of the building.	Extracted from 3D BAG
14	Building width	Describes the form of the building.	Extracted from 3D BAG
15	Roof shape	Might be related to specific residential building types, if there are no special cases.	Extracted from 3D BAG
16	Roof surface area	Describes building geometry, exemplary buildings and reference dwellings are often given with a reference roof surface area	Extracted from 3D BAG
17	Wall surface area	Describes building geometry, exemplary buildings and reference dwellings are often given with a reference wall surface area	Extracted from 3D BAG
18	Building volume	Describes building geometry.	Extracted from 3D BAG

Table 5.1: Possible candidates for features.

5.2 Tools and datasets used

Furthermore, a table (5.1) has been made with a list of datasets relevant to this master thesis. The 3D BAG contains the 3D geometry of the building stock of the Netherlands. The BAG is the Dutch National cadastral dataset and contains the 2D geometries of the buildings (panden) in the Netherlands and their dwellings (verblijfsobjecten), some relevant attributes from the BAG are the functions of the dwellings and their areas. Rijssen-Holten is a dataset similar to the 3D BAG, but it covers only the municipality of Rijssen-Holten. However, different from the 3D BAG the Rijssen-Holten dataset has given semantics to the surfaces of the 3D geometry of the buildings and different attributes some of which are relevant, namely, the number of adjacent buildings and the building type. With the inclusion of the building type, the Rijssen-Holten dataset can be considered labeled data for this thesis and can be used as ground truth in the evaluation of the prediction models. Likewise, the EP-online contains the energy labels and performance of the buildings of the Netherlands and also the building type.

Dataset name	Description	Version	Source
3D BAG	3D building models of the building stock of the Netherlands	21.09.8	(Peters et al., 2022)
BAG	National cadastral dataset	01-08-2023	(Kadaster, 2023)
Rijssen-Holten	Open testbed for energy applications, study area is located in the municipality of Rijssen-Holten	11-07-2022	(León-Sánchez et al., 2022)
EP-online	Official national database containing energy labels and energy performance indicators of buildings	01-01-2023	(Rijksoverheid, 2023)

Table 5.2: Relevant datasets.

6 | Time planning

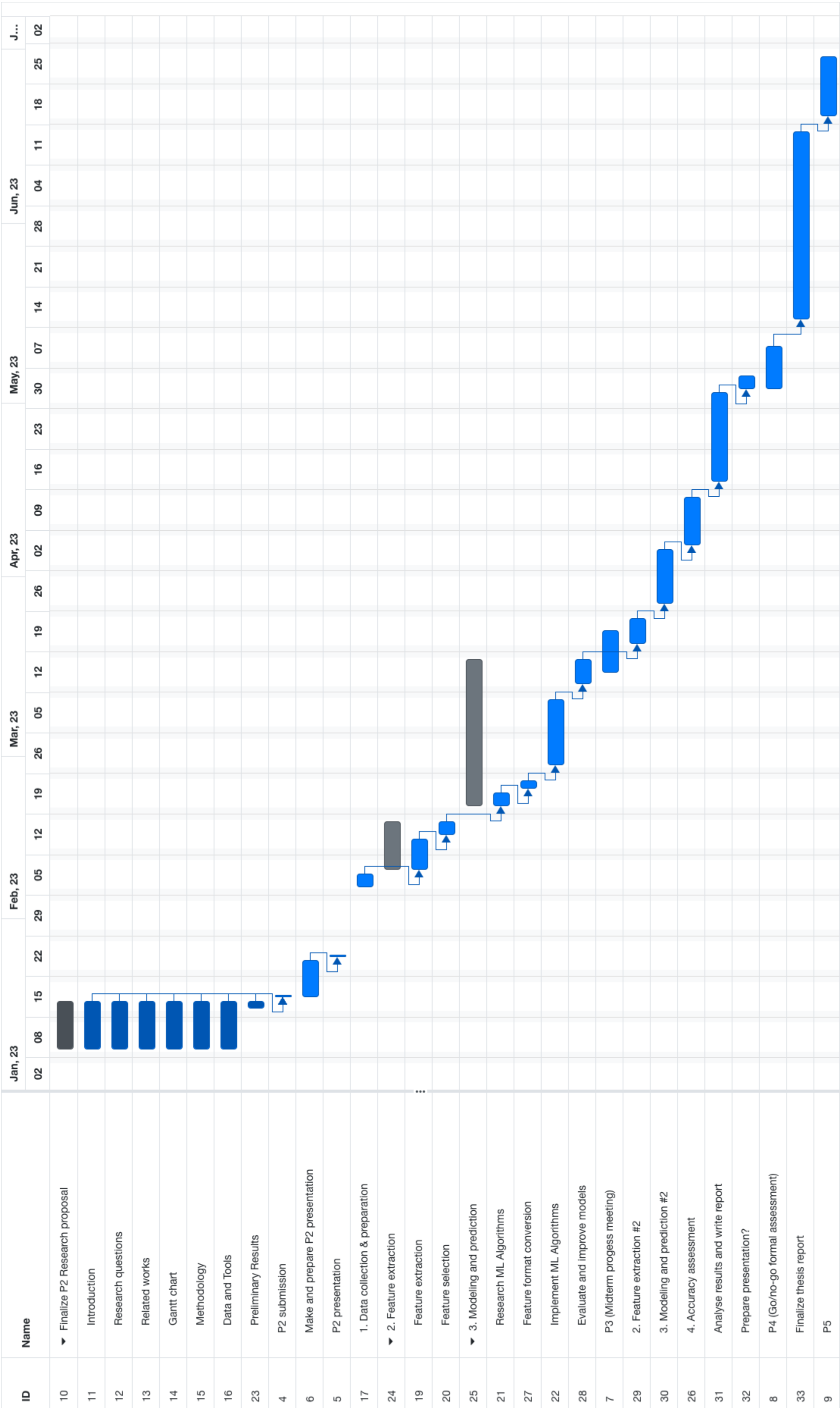

Figure 6.1: Gantt chart.

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