

MSC GEOMATICS – GRADUATION PROJECT

P5 PRESENTATION

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SUPERVISOR #2: WEIXIAO GAO

# Semantic segmentation of the AHN dataset with the Random Forest Classifier

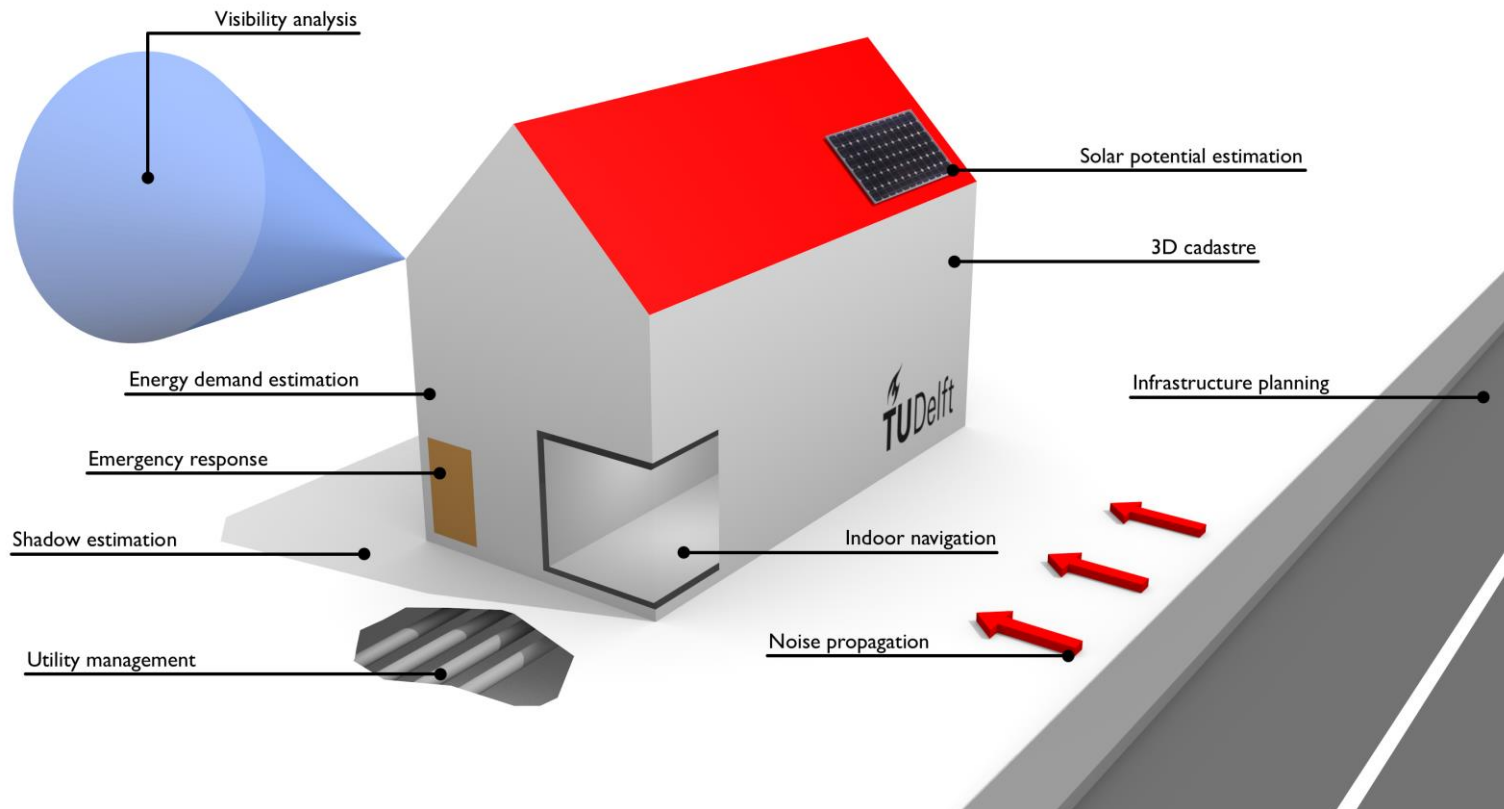
Manos Papageorgiou

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1. Introduction
2. Related work
3. Methodology
4. Datasets
5. Results and discussion
6. Conclusions

# 1. Introduction

# 1.1 Motivation



**limitations faced when reconstructing buildings**

## 1.2 Research Sope & Challenges

### **Purpose:**

assist in the reconstruction of 3D city models

### **Problem:**

classified point clouds are not always available



reliable, accurate and efficient classifiers are needed



Random Forest Classifier



# 1.3 Research questions & objectives

## **Main question:**

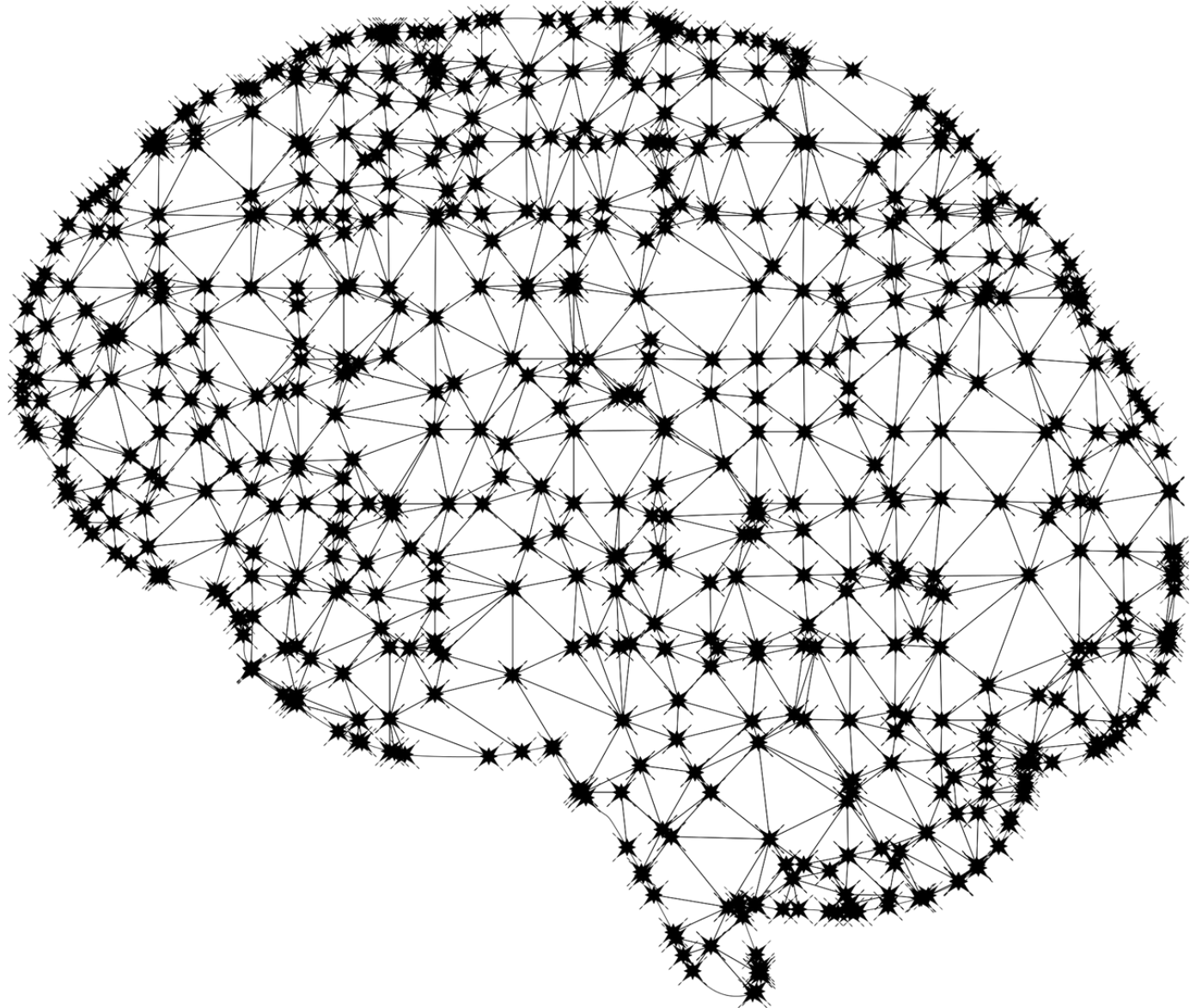
*How well will existing machine learning algorithms perform when classifying a point cloud into three classes, namely ground, buildings and other, if we train and test them with the AHN3 dataset?*

## **Sub-questions:**

1. Hyperparameters?
2. Point density?
3. Size?
4. Features?
5. Other datasets?
6. Machine Learning VS Deep Learning

## 2. Related work

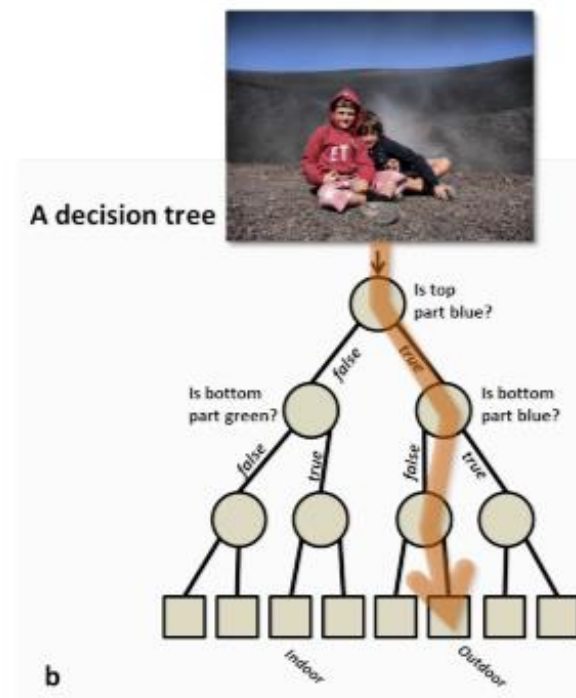
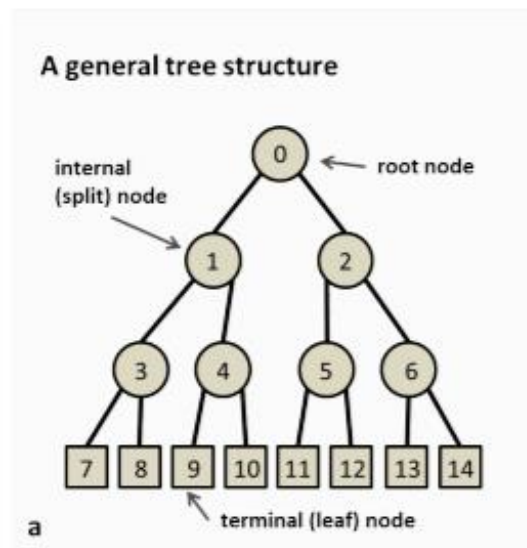
# Classification with Machine Learning and Deep Learning algorithms





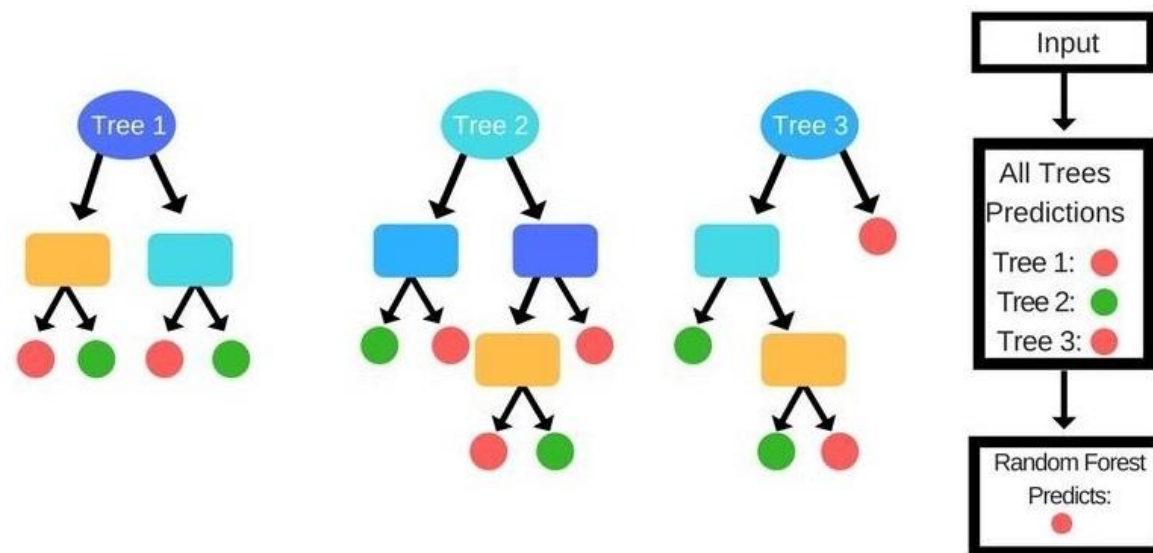
# 2.1 Decision Trees

- Internal node: contains a function, tests the input data and decides
- Branch: corresponds to the outcome of the tests
- Terminal node: contains a class label (prediction)
- splits complex problems into a hierarchy of simpler ones



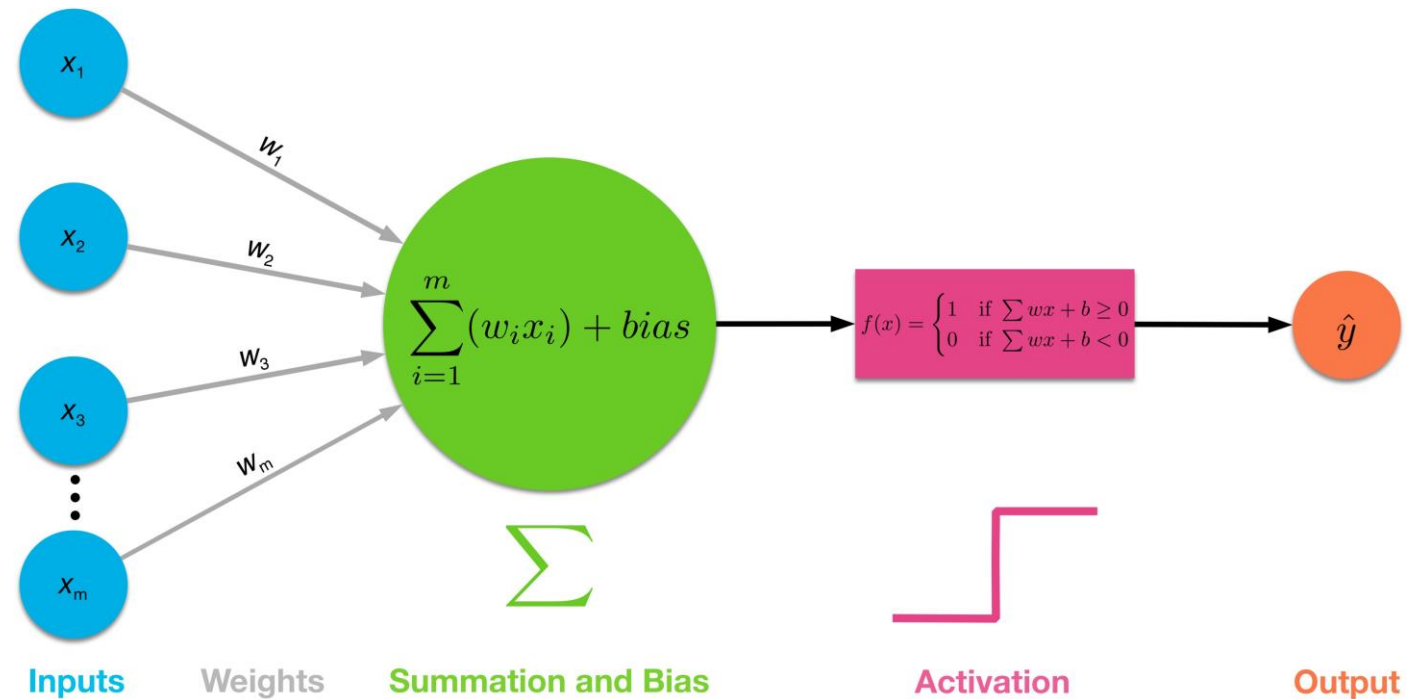
## 2.2 Random Forest Classifier

- Consists of multiple decision trees trained on a random subset
- Their predictions are aggregated to produce a more accurate prediction
- can handle well large datasets with high dimensionality and heterogeneous feature types



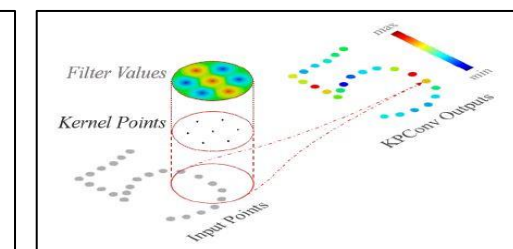
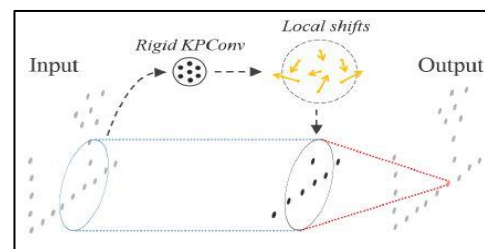
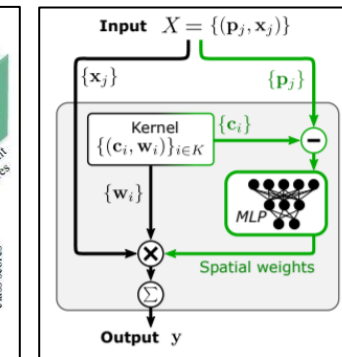
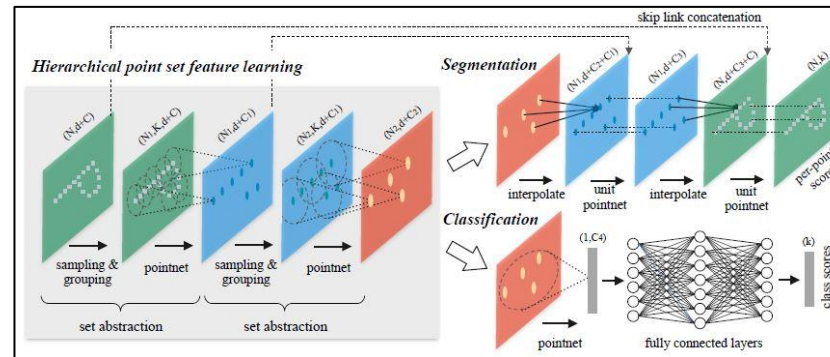
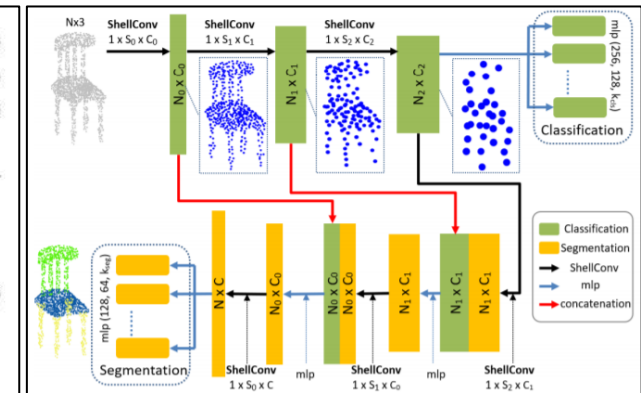
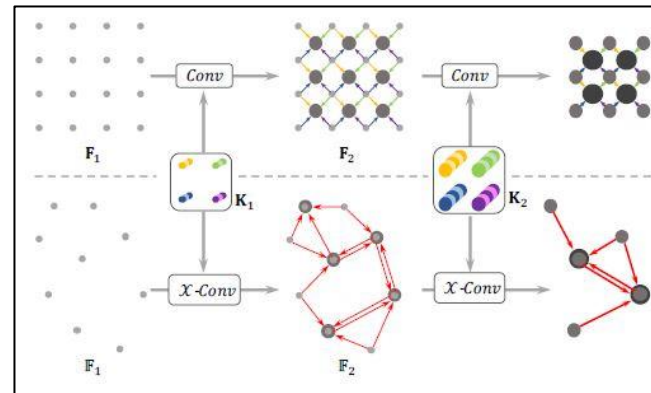
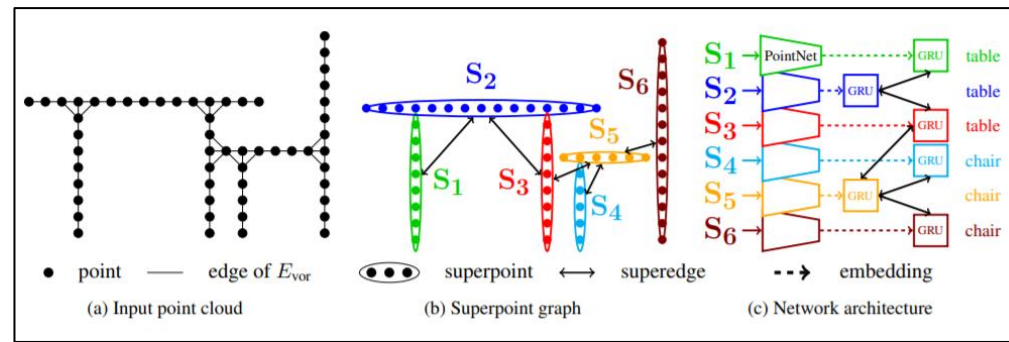
## 2.3 Multilayer perceptron

- Perceptron = algorithm for binary classification
- Feedforward artificial neural networks, cascade of single-layer perceptrons.
- At least three layers of perceptrons:
  1. input layer
  2. hidden layer
  3. output layer
- hidden and output layers can use nonlinear activation functions



# 2.4 Convolutional Neural Networks

- KPConv
- PointNET++
- PointCNN
- ConvPoint
- ShellNet
- SuperPoint

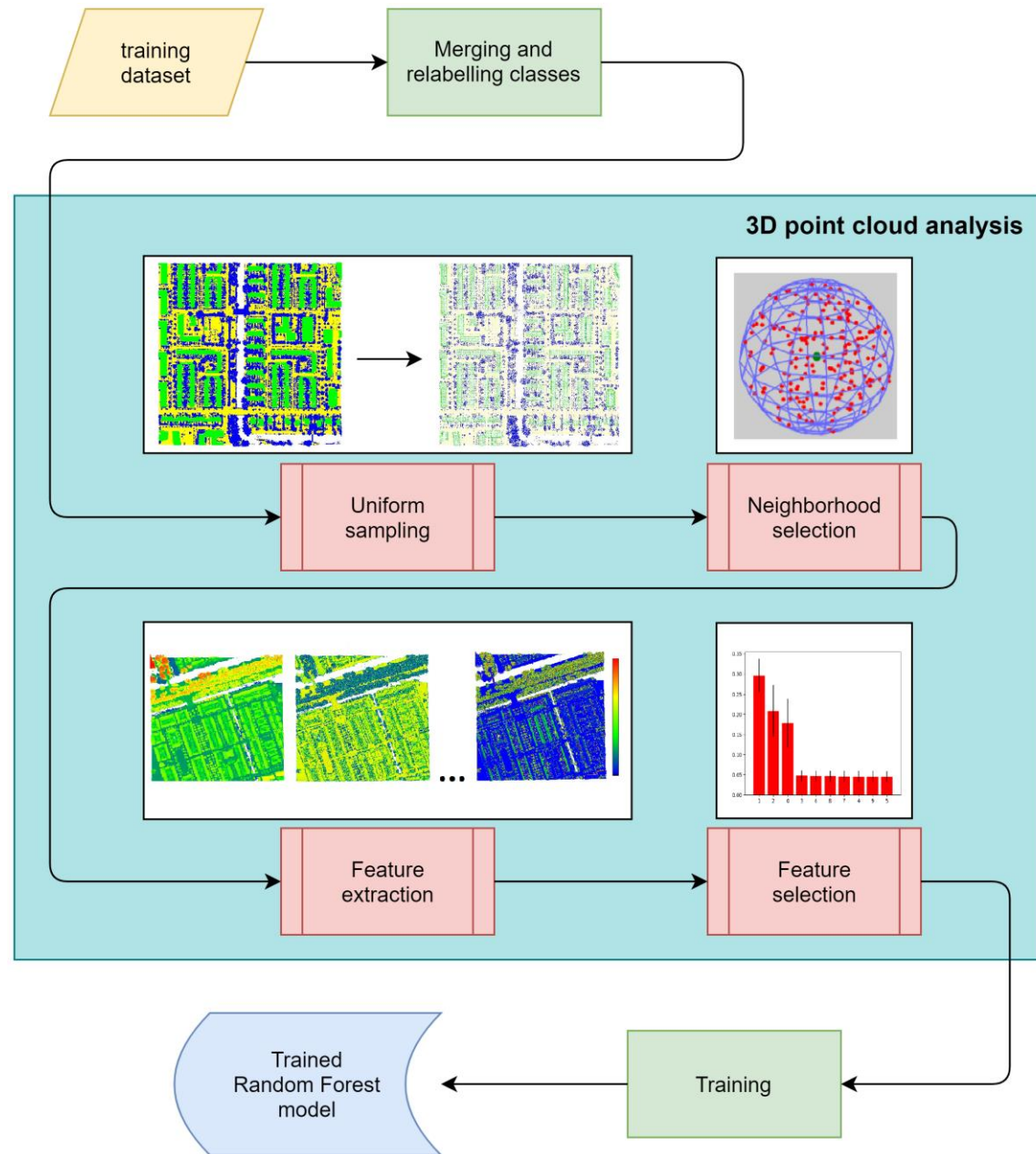


# Machine Learning VS Deep Learning

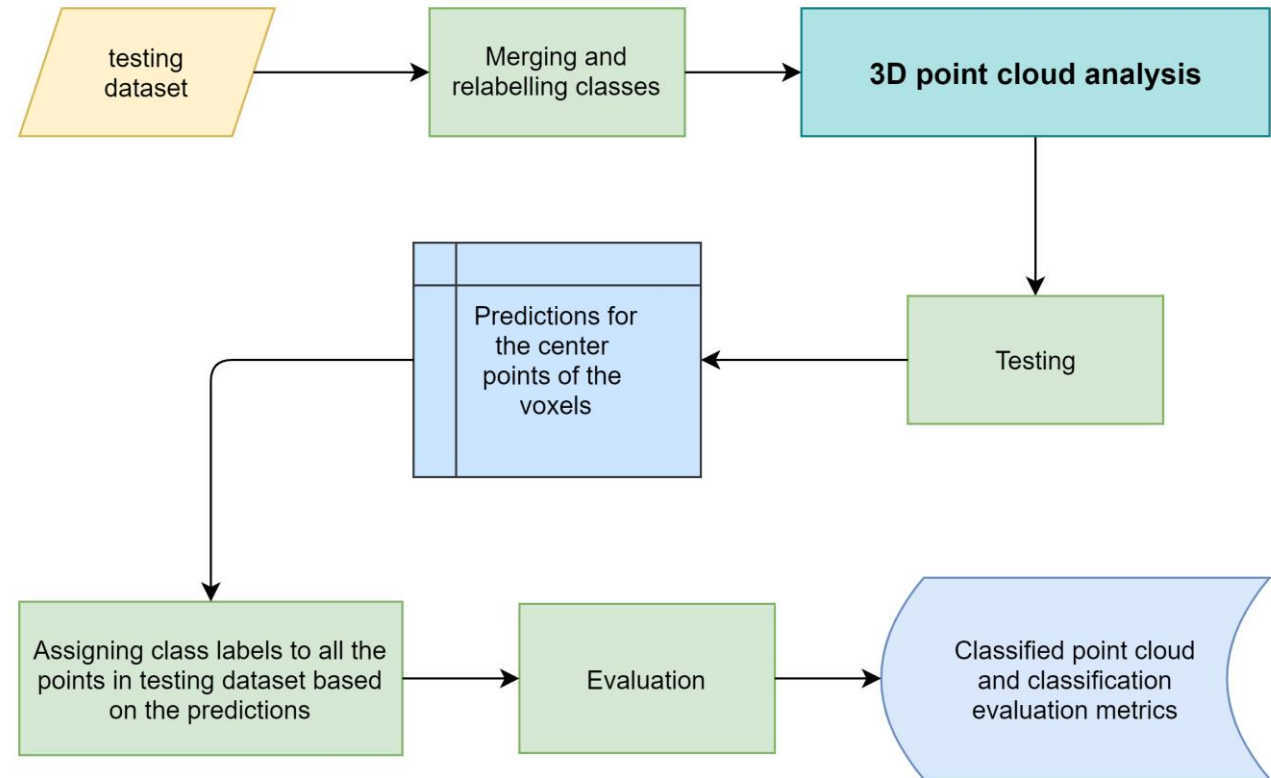
Characteristic	Machine Learning algorithm (Random Forests)	Deep Learning algorithm (CNNs)
Data dependency	+	
Computer specifications	+	
Computational cost & time	+	
Features		+
Accuracy		+
Interpretability	+	

# 3. Methodology

# 3.1 Training flowchart diagram



## 3.2 Testing flowchart diagram





## 3.3 Equations

- Data diversification:

$$F_m = \frac{\sum_{i=1}^{N_f} \sigma_i^2}{N_f} \quad \text{value}_{normalized} = \frac{\text{value} - \text{min}}{\text{max} - \text{min}}$$

- Height features:

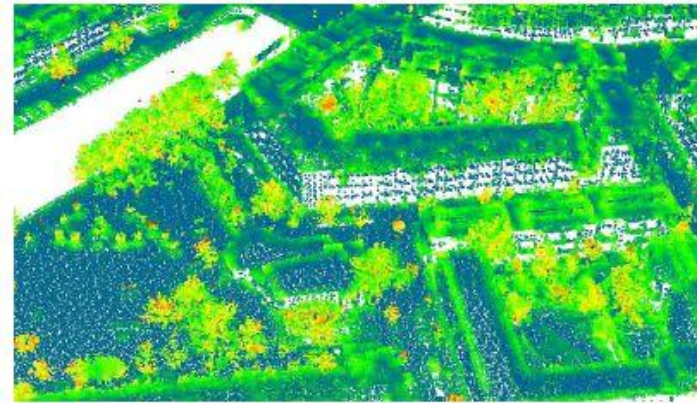
$$Z_{normalized} = \sqrt{\frac{(Z_i - Z_{min})}{(Z_{max} - Z_{min})}} \quad Z_{below} = Z_i - Z_{min}$$

- Eigen features:

$$\text{cov}(N) = \frac{1}{N} \sum_{p \in N} (p - \bar{p})(p - \bar{p})^T \quad \lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$$

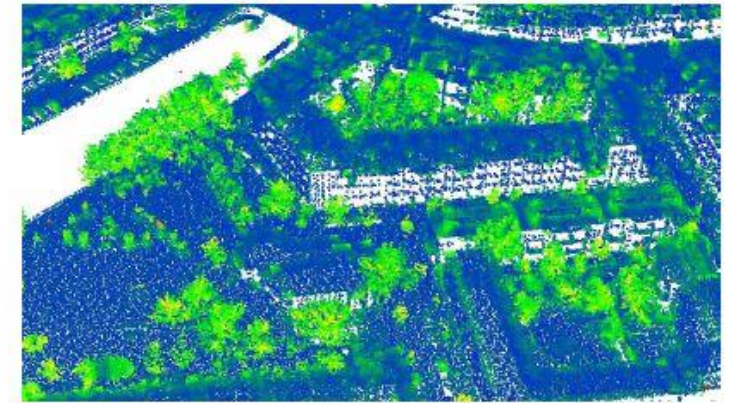
## 3.3.1 Eigen features & Density

Feature	Equation
Omnivariance	$(\lambda_1 \cdot \lambda_2 \cdot \lambda_3)^{\frac{1}{3}}$
Anisotropy	$(\lambda_1 - \lambda_3)/\lambda_1$
Planarity	$(\lambda_2 - \lambda_3)/\lambda_1$
Linearity	$(\lambda_1 - \lambda_2)/\lambda_1$
Surface Variation	$\lambda_3/(\lambda_1 + \lambda_2 + \lambda_3)$
Sphericity	$\lambda_3/\lambda_1$
Verticality	$1 -  n_z $



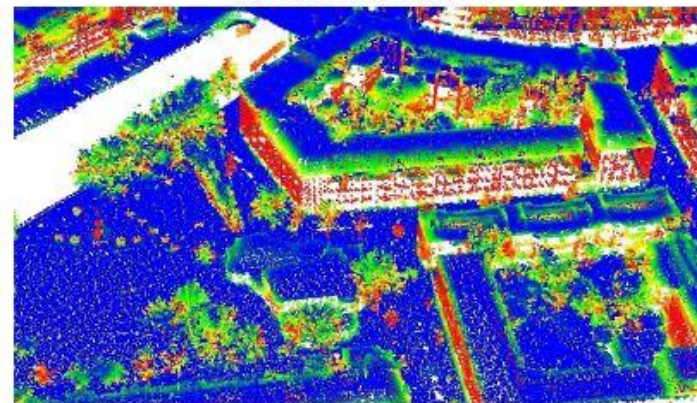
Low High

(e) Surface variation



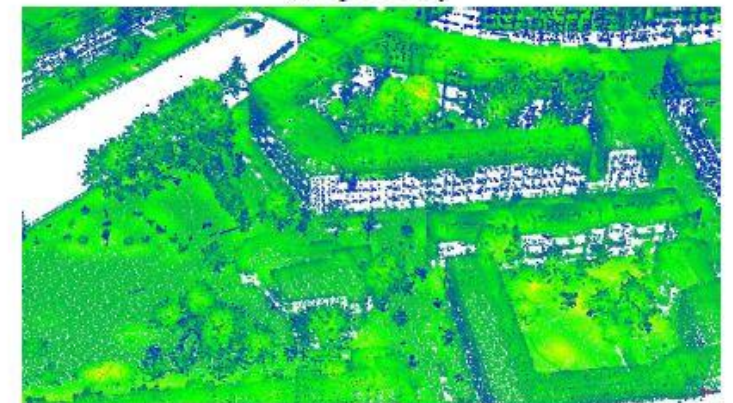
Low High

(f) Sphericity



Low High

(g) Verticality



Low High

(h) Density

## 3.4 Evaluation metrics

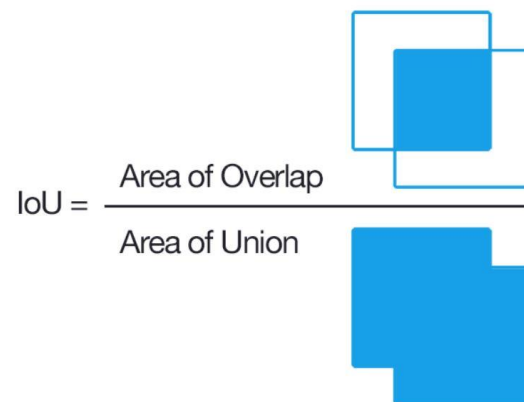
- Confusion matrix:

		Predicted Class	
		No	Yes
Observed Class	No	TN	FP
	Yes	FN	TP

- Overall accuracy:

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{FN} + \text{TP}}$$

- Intersection over Union:



- Class Consistency Index:

$$\text{CCI} = 1 - \frac{\sigma^2}{|\text{IoU}|}$$

- F1 score:

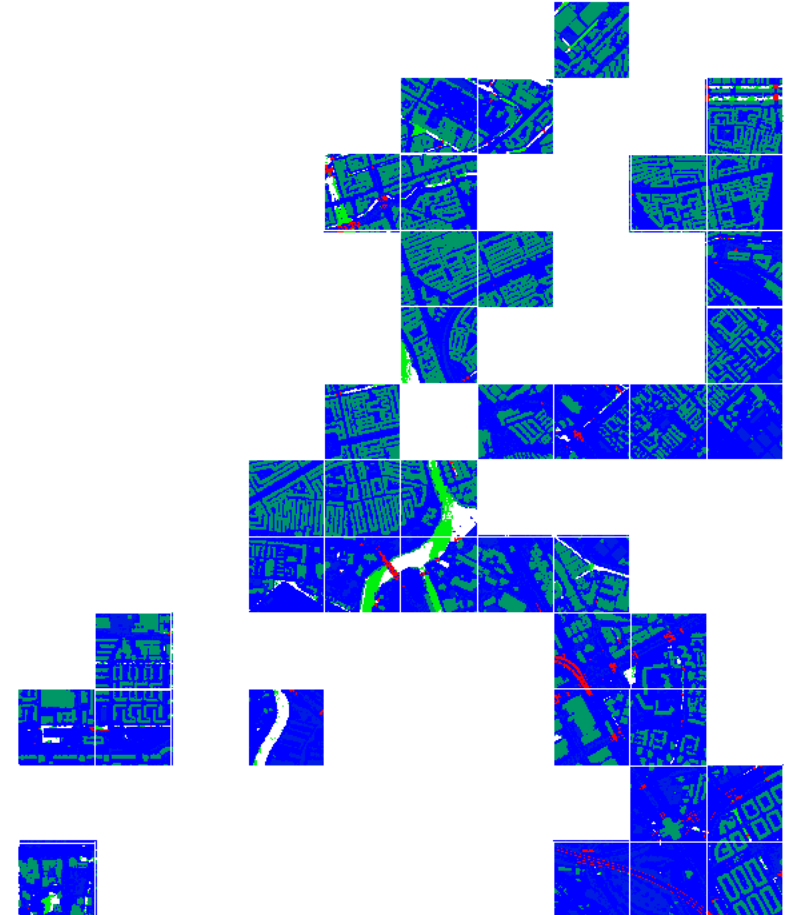
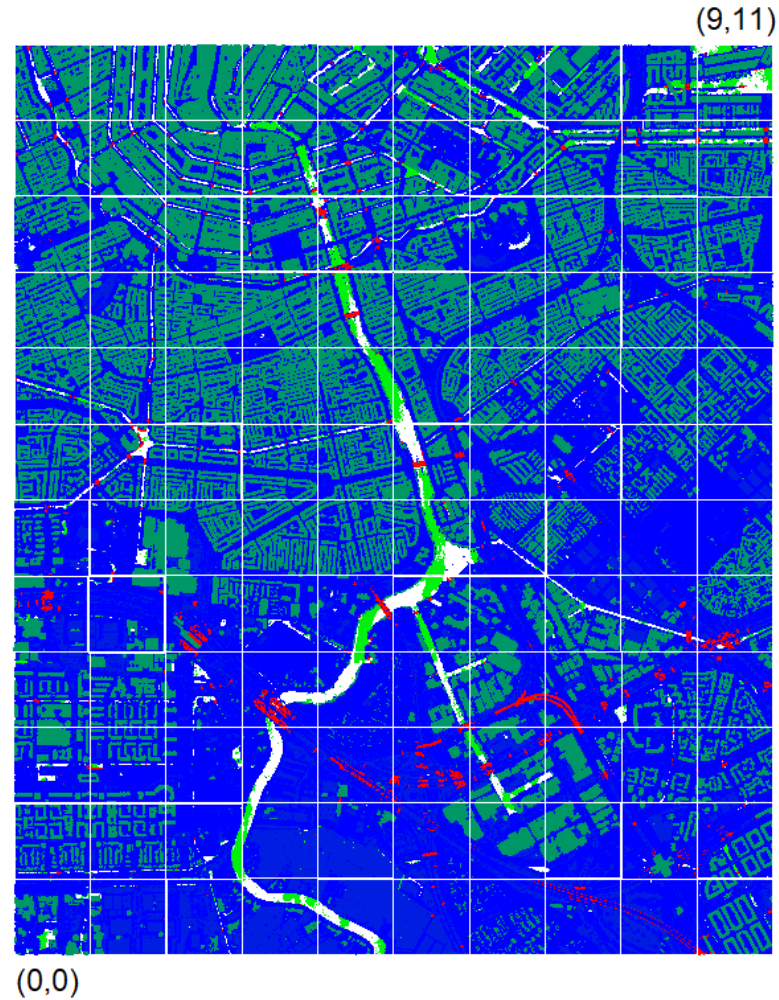
$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

# 4. Datasets

# 4.1 AHN3 & AHN4

- Type: LiDAR datasets
- Number of classes: las classification codes + custom code 26
- Point density:  $18 \pm 12$  and  $42 \pm 25$  points per squared meter
- Number of tiles: 1100
- Size of tiles: 6.25 x 5 Km<sup>2</sup>

→ Tile area = 0.25 Km<sup>2</sup>



## 4.1.2 Feature diversity of tiles

no.	tile	$F_m$	no. of classes	other (%)	building (%)	ground (%)	no. of points
1	(7,3)	0.0433	3	53.2	12.8	34.1	4,563,251
2	(5,5)	0.043	3	39.5	33.7	26.8	3,017,251
3	(9,0)	0.0428	3	48.1	17.8	34.1	4,114,615
4	(7,2)	0.0428	3	46.5	19.4	34.2	4,519,839
5	(5,4)	0.0427	3	62	10.3	27.7	3,596,646
6	(3,2)	0.0425	3	70.9	0.5	28.6	4,681,849
7	(9,1)	0.0421	3	55.7	11.9	32.4	4,513,323
8	(8,0)	0.042	3	58.7	0.5	40.8	4,452,822
9	(9,9)	0.0419	3	59.3	20.7	20	4,856,019
10	(8,3)	0.0418	3	59	11.9	29.1	3,828,687
11	(1,2)	0.0418	3	60.3	12.7	27.1	5,332,243
12	(7,11)	0.0416	3	31.7	39.6	28.7	3,447,268
13	(4,4)	0.0414	3	70.6	3.7	25.7	4,375,794
14	(0,0)	0.0413	3	54.5	15.5	29.9	4,418,212
15	(6,6)	0.0413	3	51.4	18.1	30.4	4,204,809
16	(9,10)	0.0411	3	39.7	35.3	25	3,990,567
17	(7,4)	0.0411	3	43	25.2	31.8	3,734,563
18	(0,2)	0.0411	3	55.7	17.4	26.9	4,566,563
19	(6,10)	0.041	3	57.1	22.3	20.6	4,415,975
20	(9,8)	0.0409	3	46.1	16	37.9	3,860,100

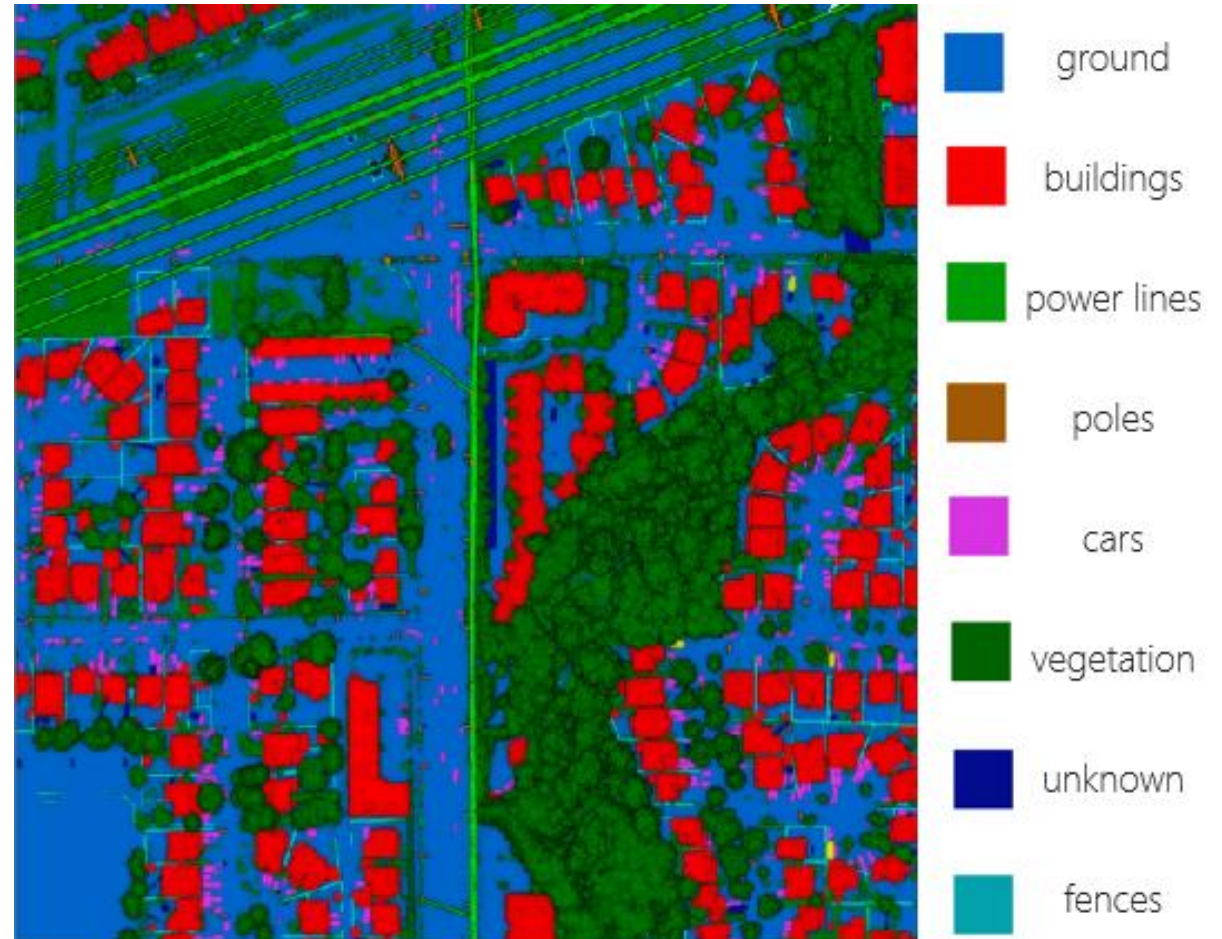
AHN3

no.	tile	$F_m$	no. of classes	other (%)	building (%)	ground (%)	no. of points
1	(7,3)	0.0404	3	50.1	12.7	37.2	9,111,285
2	(5,5)	0.0413	3	35.7	30.8	33.5	7,805,095
3	(9,0)	0.0416	3	46.6	20	33.3	10,592,425
4	(7,2)	0.0385	3	44.5	18.5	37	9,981,479
5	(5,4)	0.0433	3	57.4	8.1	34.4	8,981,406
6	(3,2)	0.0405	3	68.2	0.4	31.4	10,298,226
7	(9,1)	0.0396	3	56.1	9.9	34	10,638,417
8	(8,0)	0.0393	3	56.8	0.5	42.7	8,990,897
9	(9,9)	0.0401	3	61.2	17.4	21.4	10,541,974
10	(8,3)	0.0406	3	54.5	15.7	29.8	9,755,432
11	(1,2)	0.0411	3	70.4	9.6	20	12,783,974
12	(7,11)	0.0376	3	34.2	36.8	29	7,731,449
13	(4,4)	0.0407	3	72.6	3.9	23.4	10,990,093
14	(0,0)	0.0406	3	61.8	10.9	27.2	9,351,733
15	(6,6)	0.0407	3	43.7	22.9	33.4	10,560,537
16	(9,10)	0.0401	3	37.3	40.6	22.1	10,489,806
17	(7,4)	0.0403	3	42.5	22.1	35.4	9,655,165
18	(0,2)	0.0414	3	68.3	13.5	18.3	12,015,153
19	(6,10)	0.0400	3	53.6	25.6	20.8	10,891,964
20	(9,8)	0.0386	3	44.5	20.8	34.7	10,971,698

AHN4

## 4.2 DALES

- Type: LiDAR dataset
- Number of classes: 8
- Point density: 50 ppm
- Number of tiles: 40
- Size of tiles: 0.5 Km<sup>2</sup>
- Accuracy: 8.5 cm mean error for the hard surface vertical accuracy



# 5. Results and discussion



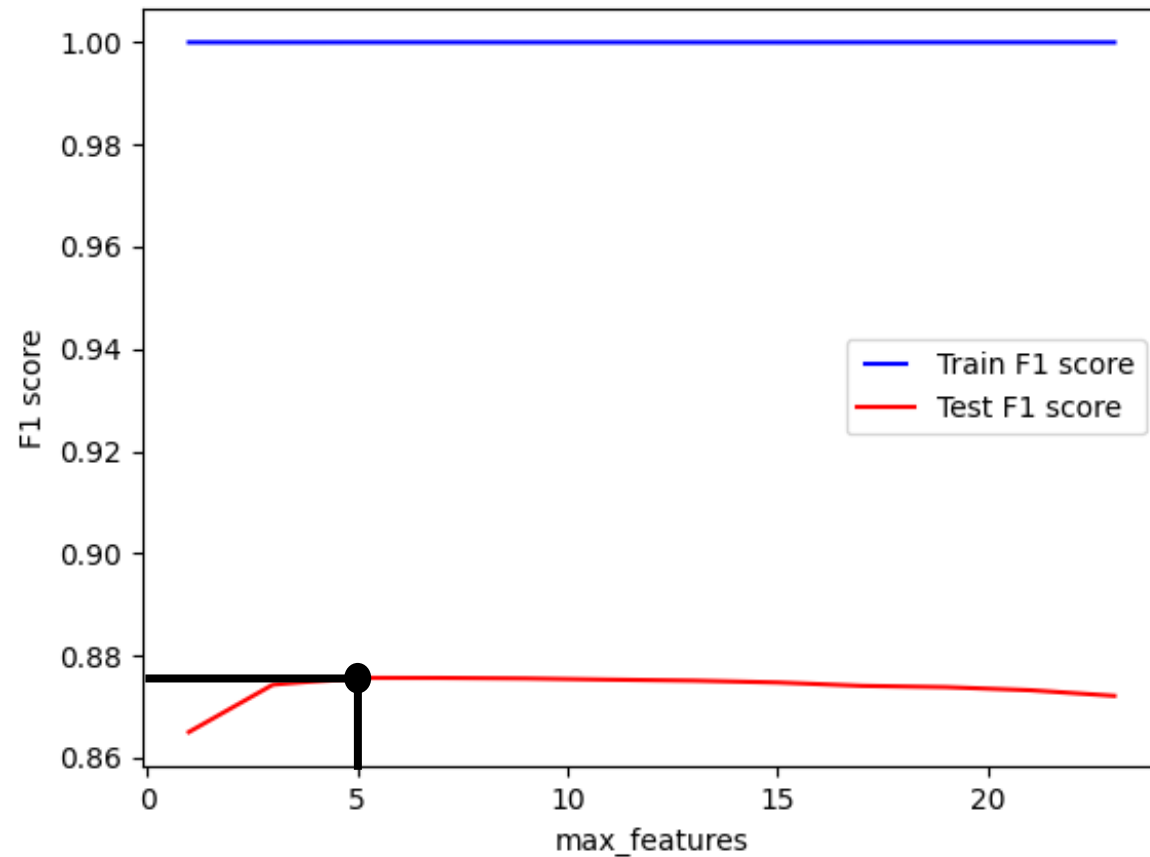
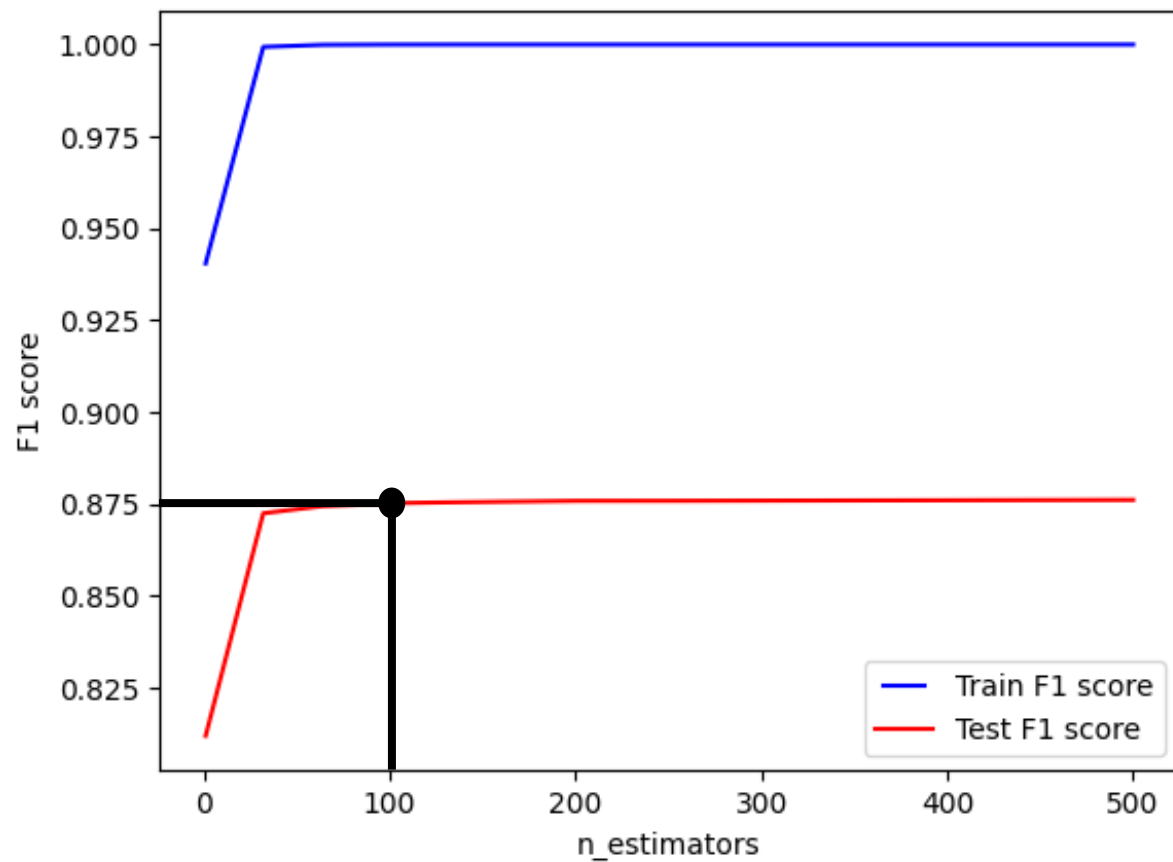
# 5. Experiments

1. Hyperparameters
2. Point density (voxel size of uniform sampling algorithm)
3. No. of training tiles
4. Features
5. Other datasets
6. Comparison with deep learning methods
7. Comparison with MLP
8. Comparison of LOD1 3D city models

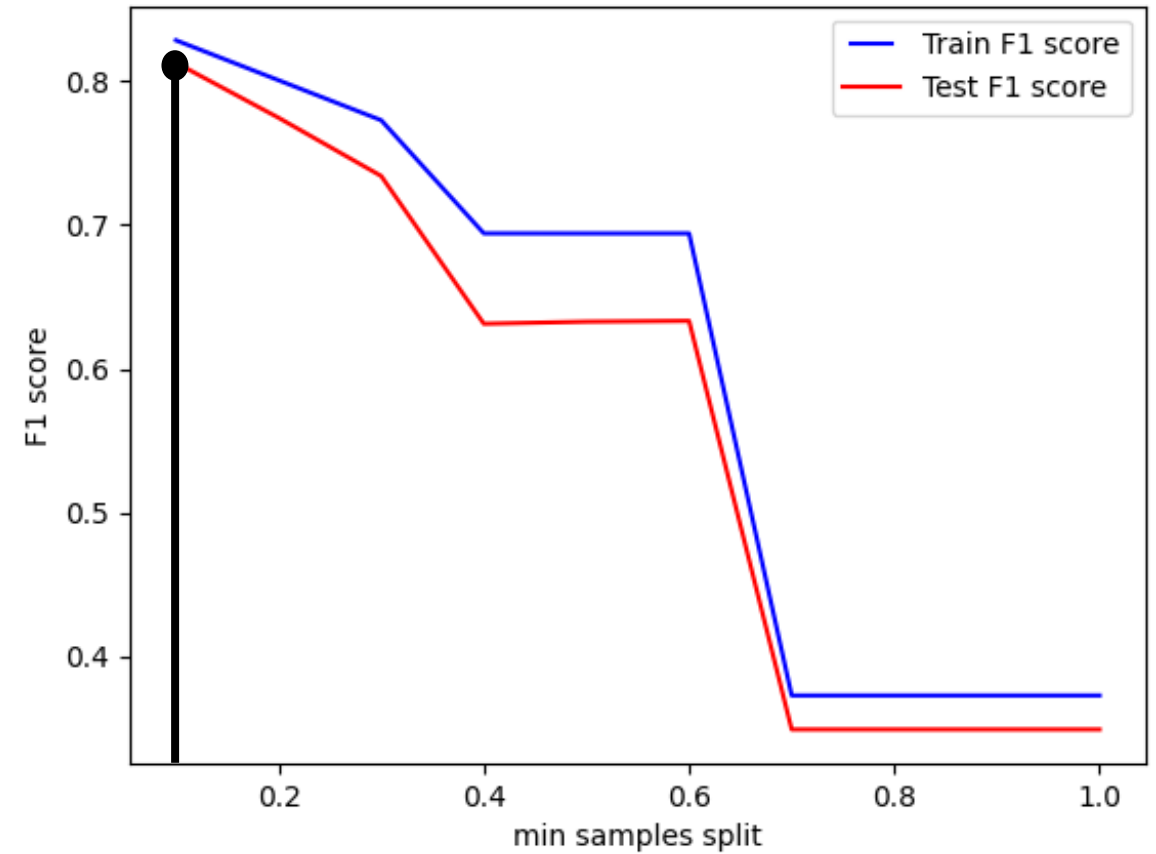
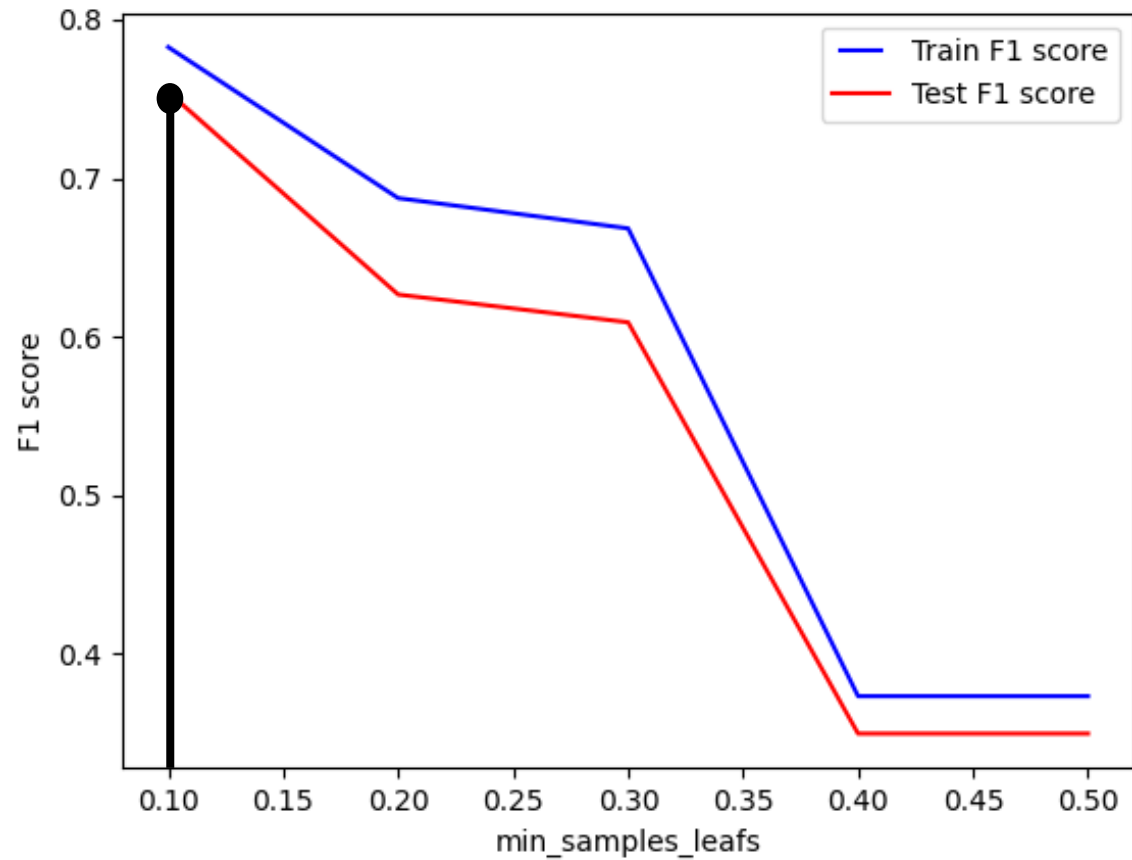
## 5.1.1 Hyperparameters

Parameter	Value (default)
n_estimators	100
criterion	Gini
max_depth	None
min_samples_split	2
min_samples_leaf	1
max_features	Sqrt
bootstrap	True
oob_score	False

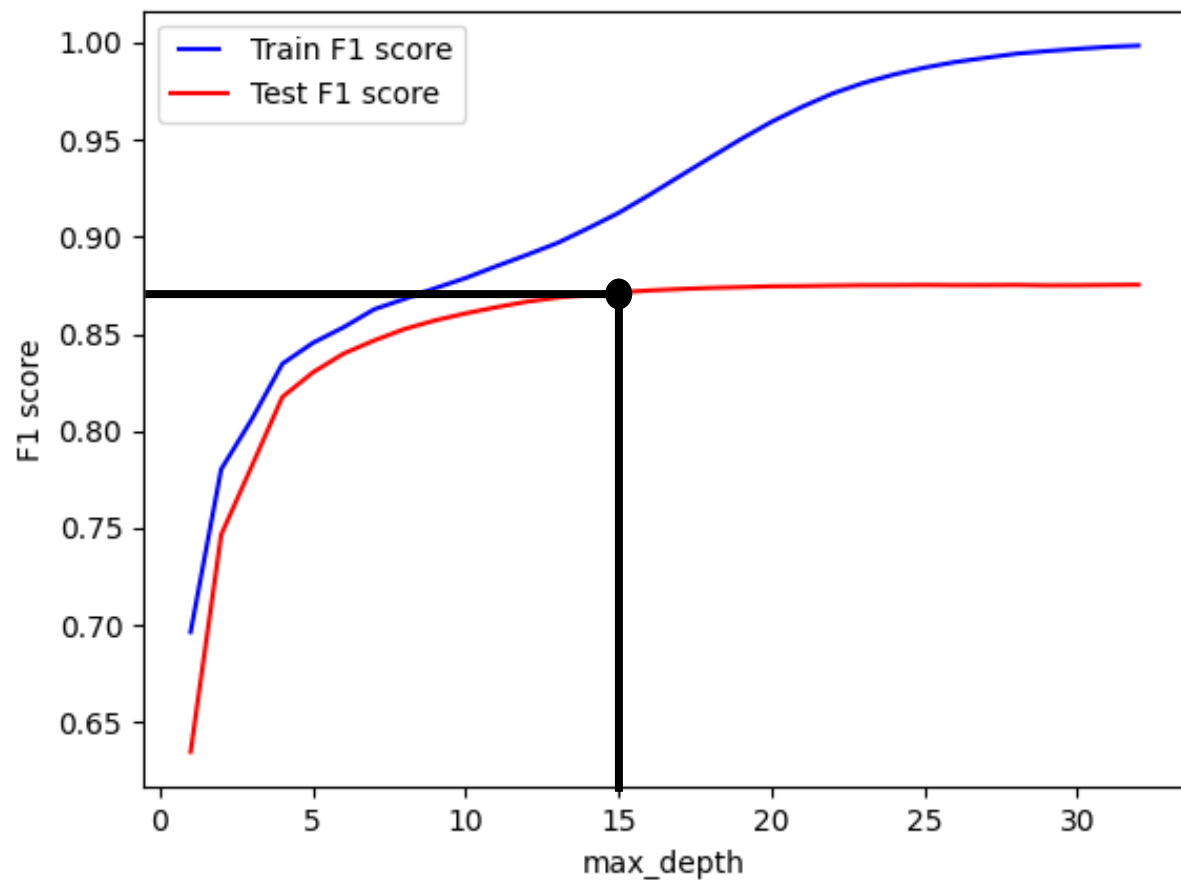
## 5.1.2 Hyperparameters



## 5.1.3 Hyperparameters



## 5.1.4 Hyperparameters



Parameter	Value
Bootstrap	True
criterion	Gini
out-of-bag samples	True

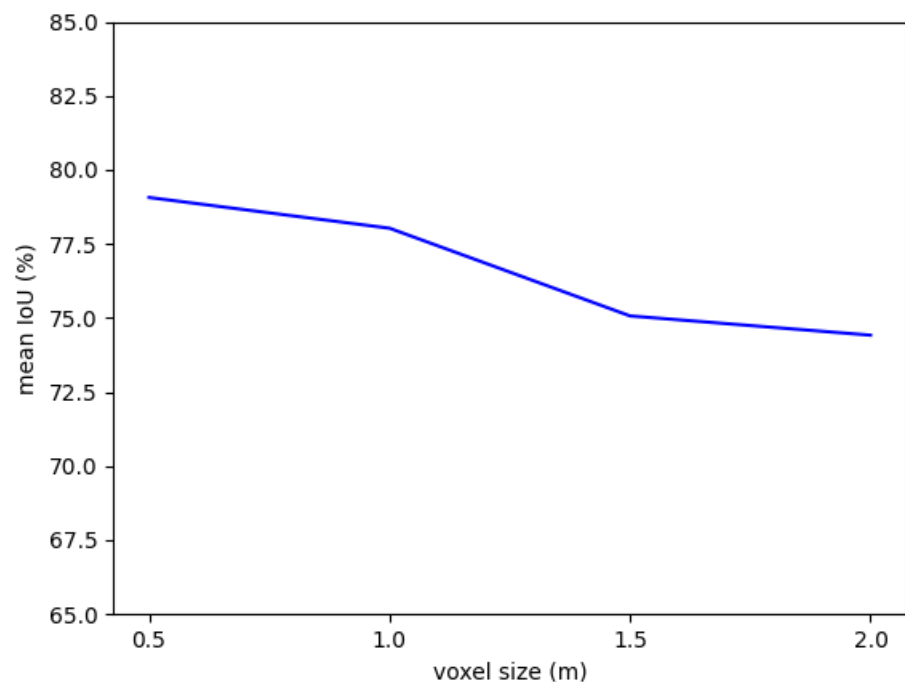
## 5.1.5 Hyperparameters

Parameter	Value (default)
n_estimators	100
criterion	Gini
max_depth	None
min_samples_split	2
min_samples_leaf	1
max_features	Sqrt
bootstrap	True
oob_score	False

Parameter	Value (optimal)
n_estimators	100
criterion	Gini
max_depth	15
min_samples_split	2
min_samples_leaf	1
max_features	Sqrt
bootstrap	True
oob_score	True

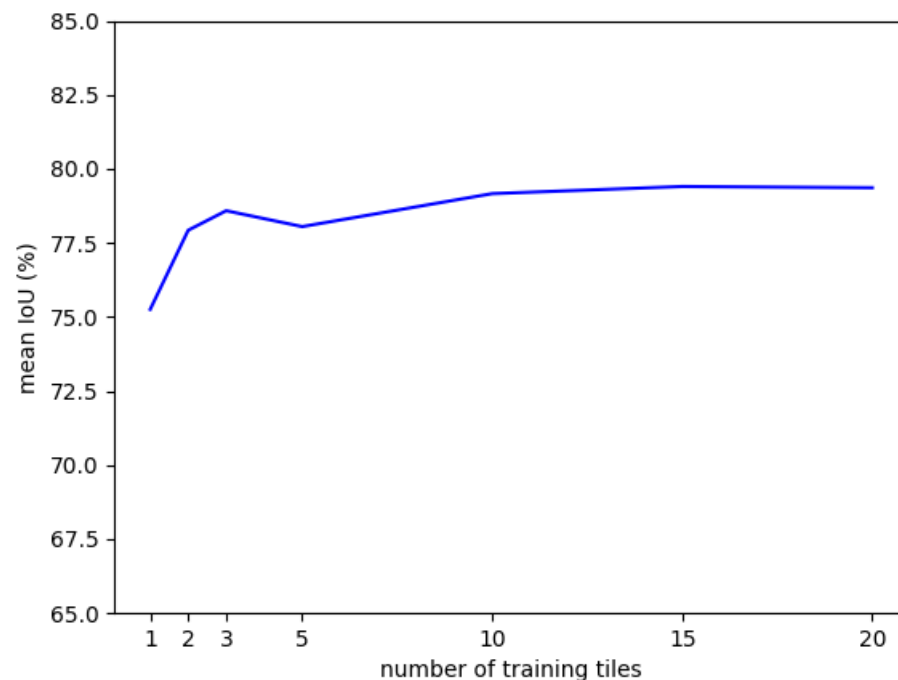
## 5.2 Point density

voxel size (m)	OA (%)	IoU (%)				CCI (%)	$F_1$ score	no. of points in the training data	training time (minutes)	RAM (GB)	model size (KB)
		mean	other	building	ground						
0.5	89.70	79.07	78.63	72.07	86.51	99.56	0.90	19,654,135	187.79	33.7	14,581,904
1	89.04	78.03	77.32	71.46	85.31	99.59	0.89	6,644,360	73.41	8.3	5,638,778
1.5	87.45	75.07	82.09	63.39	79.73	99.08	0.87	3,034,839	33.85	4.6	3,299,808
2	87.41	74.42	73.29	65.21	84.75	99.14	0.87	1,648,188	14.94	2.7	1,946,693
-	86.41	73.64	76.66	62.46	81.81	99.09	0.86	42,144,302	460.34	59.9	24,501,065



## 5.3 Training data size

no. of training tiles	OA (%)	IoU (%)				CCI (%)	$F_1$ score	no. of points in the training data	training time (minutes)	RAM (GB)	model size (KB)
		mean	other	building	ground						
1	87.21	75.26	76.63	66.93	82.21	99.47	0.87	662,595	6.74	1.1	569,095
2	88.42	77.93	78.39	72.47	82.93	99.77	0.88	1,178,285	15.48	1.9	1,154,913
3	88.82	78.59	78.67	73.53	83.57	99.79	0.89	1,777,401	25.82	2.9	1,618,543
5	88.54	78.05	78.71	72.28	83.17	99.74	0.89	2,976,008	30.15	4.4	2,668,248
10	89.27	79.17	78.99	73.92	84.58	99.76	0.89	6,644,360	80.04	9	5,496,317
15	89.34	79.41	79.02	74.56	84.64	99.79	0.89	10,159,167	96.38	13.8	8,378,902
20	89.27	79.36	79.24	74.54	84.32	99.80	0.89	13,290,986	129	24.4	11,704,444





## 5.4.1 Features

1. different number of features
2. different neighborhoods
3. different combinations

no. of features	radii of spherical neighborhoods	OA (%)	IoU (%)				CCI (%)	$F_1$ score	training time (minutes)
			mean	other	building	ground			
10	2	86.34	72.74	72.49	61.95	83.77	98.91	0.86	7.17
10	3	86.91	74.39	73.19	66.92	83.06	99.41	0.87	5.62
10	4	87.16	75.29	72.85	70.28	82.72	99.62	0.87	5.41
17	2, 3	88.91	77.701	76.69	70.64	85.78	99.50	0.89	7.54
17	2, 4	89.68	79.29	78.13	73.50	86.23	99.65	0.90	7.46
17	3, 4	89.13	78.45	76.47	73.40	85.49	99.66	0.89	7.31
24	2, 3, 4	90.16	80.12	78.69	74.71	86.96	99.68	0.90	7.75

no. of features	features used for training	OA (%)	IoU (%)				CCI (%)	F1 score
			mean	other	building	ground		
3	$Z_{normalized}$ , $Z_{below}$ , Density	75.58	56.97	54.17	43.04	73.67	97.18	0.76
4	$Z_{normalized}$ , $Z_{below}$ , Density, Omnivariance	80.68	64.23	63.49	51.72	77.49	98.27	0.81
5	$Z_{normalized}$ , $Z_{below}$ , Density, Omnivariance, Anisotropy	82.78	67.45	66.93	55.90	79.51	98.62	0.83
6	$Z_{normalized}$ , $Z_{below}$ , Density, Omnivariance, Anisotropy, Planarity	84.96	70.84	70.49	60.11	81.93	98.88	0.85
7	$Z_{normalized}$ , $Z_{below}$ , Density, Omnivariance, Anisotropy, Planarity, Linearity	85.26	71.33	70.73	60.92	82.35	98.92	0.85
8	$Z_{normalized}$ , $Z_{below}$ , Density, Omnivariance, Anisotropy, Planarity, Linearity, Surface Variation	85.49	71.72	70.87	61.61	82.67	98.96	0.85
9	$Z_{normalized}$ , $Z_{below}$ , Density, Omnivariance, Anisotropy, Planarity, Linearity, Surface Variation, Sphericity	85.06	71.00	70.58	60.36	82.08	98.89	0.85
10	$Z_{normalized}$ , $Z_{below}$ , Density, Omnivariance, Anisotropy, Planarity, Linearity, Surface Variation, Sphericity, Verticality	86.29	72.64	72.48	61.75	83.69	98.90	0.86
9	$Z_{below}$ , Density, Omnivariance, Anisotropy, Planarity, Linearity, Surface Variation, Sphericity, Verticality	86.04	72.04	71.62	60.79	83.72	98.78	0.86
9	$Z_{normalized}$ , Density, Omnivariance, Anisotropy, Planarity, Linearity, Surface Variation, Sphericity, Verticality	86.32	72.74	72.25	62.24	83.73	98.94	0.86

## 5.4.2 Features

- **Permutation importances:**

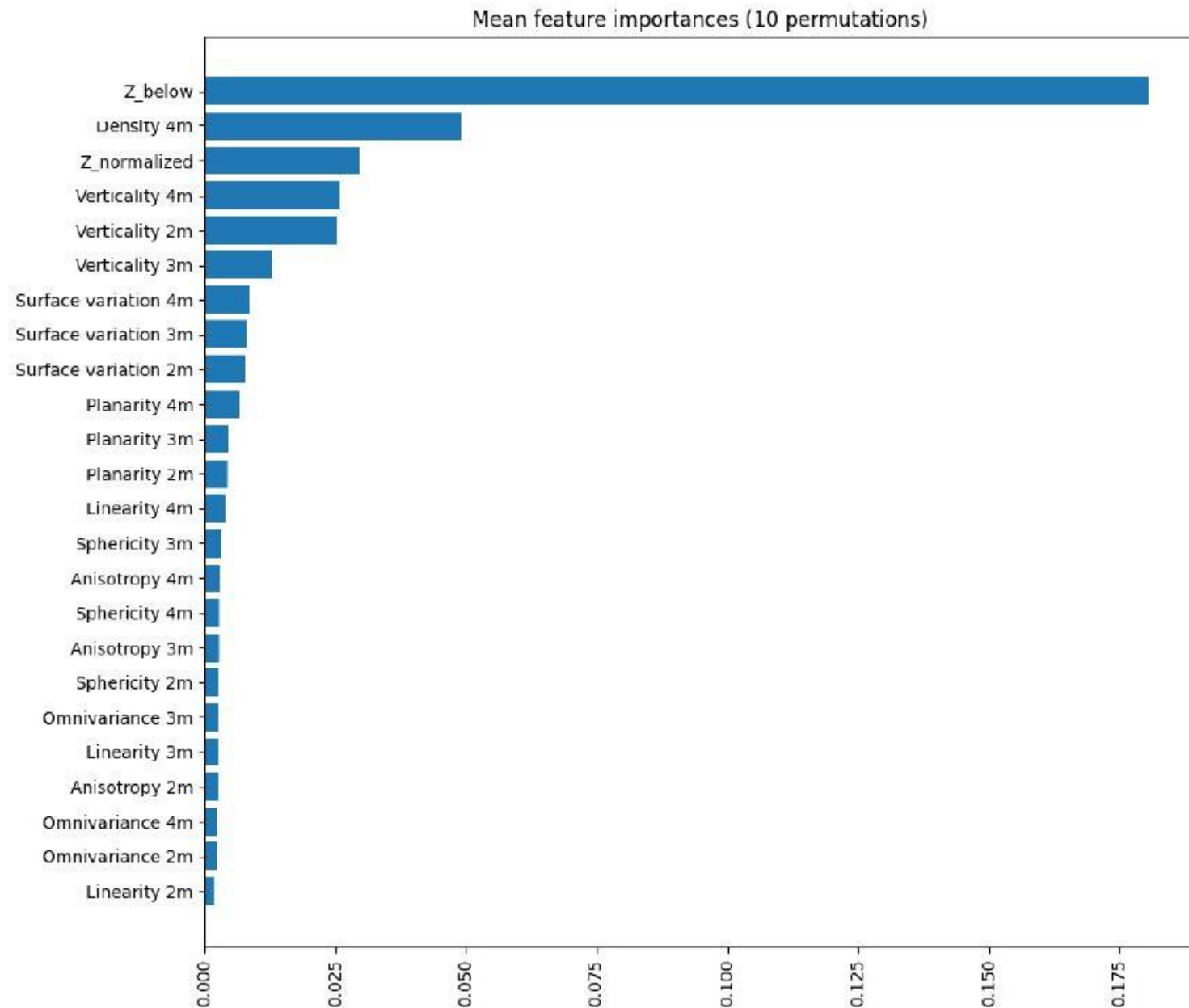
observe how random re-shuffling (permutations) of the values of a feature influences the performance of the model.

- **Impurity based importances:**

mean and standard deviation of accumulation of the impurity decrease within each tree

- **Impurity:**

how homogeneous are the labels of a node which can be calculated using measures like the Gini impurity and entropy



## 5.5.1 Final model

### 1. Hyperparameters

Parameter	Value (optimal)
n_estimators	100
criterion	Gini
max_depth	15
min_samples_split	2
min_samples_leaf	1
max_features	Sqrt
bootstrap	True
oob_score	True

2. Point density → 1 meter voxel size
3. No. of training tiles → 3 tiles
4. Features → 3 different spherical neighborhoods → more tests needed

## 5.5.2 Final model

no. of features	feature removed	OA (%)	IoU (%)				CCI (%)	F1 score
			mean	other	building	ground		
24	-	89.72	79.50	79.88	72.98	85.65	99.66	0.90
23	Linearity (2m)	89.73	79.52	79.91	73.01	85.64	99.67	0.90
22	Omnivariance (2m)	89.75	79.57	79.94	73.09	85.67	99.67	0.90
21	Omnivariance (4m)	89.76	79.60	79.94	73.18	85.67	99.67	0.90
20	Anisotropy (2m)	89.79	79.65	80.01	73.26	85.69	99.68	0.90
19	Linearity (3m)	89.78	79.65	80.01	73.27	85.68	99.68	0.90
18	Omnivariance (3m)	89.80	79.69	80.03	73.36	85.69	99.68	0.90
17	Sphericity (2m)	89.81	79.72	80.08	73.40	85.69	99.68	0.90
16	Anisotropy (3m)	89.82	79.73	80.11	73.41	85.69	99.68	0.90
15	Sphericity (4m)	89.84	79.74	80.08	73.40	85.75	99.68	0.90
14	Anisotropy (4m)	89.81	79.72	80.02	73.40	85.75	99.68	0.90
13	Sphericity (3m)	89.83	79.75	80.08	73.44	85.72	99.68	0.90
12	Linearity (4m)	89.78	79.68	80.08	73.34	85.69	99.68	0.90
11	Planarity (2m)	89.74	79.61	79.99	73.26	85.58	99.68	0.90
10	Planarity (3m)	89.64	79.43	79.87	73.00	85.42	99.68	0.90
9	Planarity (4m)	89.26	78.69	79.22	71.79	85.07	99.62	0.89
8	Surface Variation (2m)	89.16	78.49	78.58	71.68	85.20	99.61	0.89
7	Surface Variation (3m)	88.80	77.78	77.79	70.61	84.93	99.56	0.89
6	Surface Variation (4m)	86.71	73.51	73.27	62.90	84.37	98.96	0.86
5	Verticality (3m)	85.93	72.11	72.18	60.62	83.54	98.79	0.86
4	Verticality (2m)	82.87	67.21	67.08	54.30	80.25	98.33	0.86

### 13 features of the final model

Z\_below

Density (4m)

Z\_normalized

Verticality (2m,3m & 4m )

Surface variation (2m,3m & 4m)

Planarity (2m,3m & 4m)

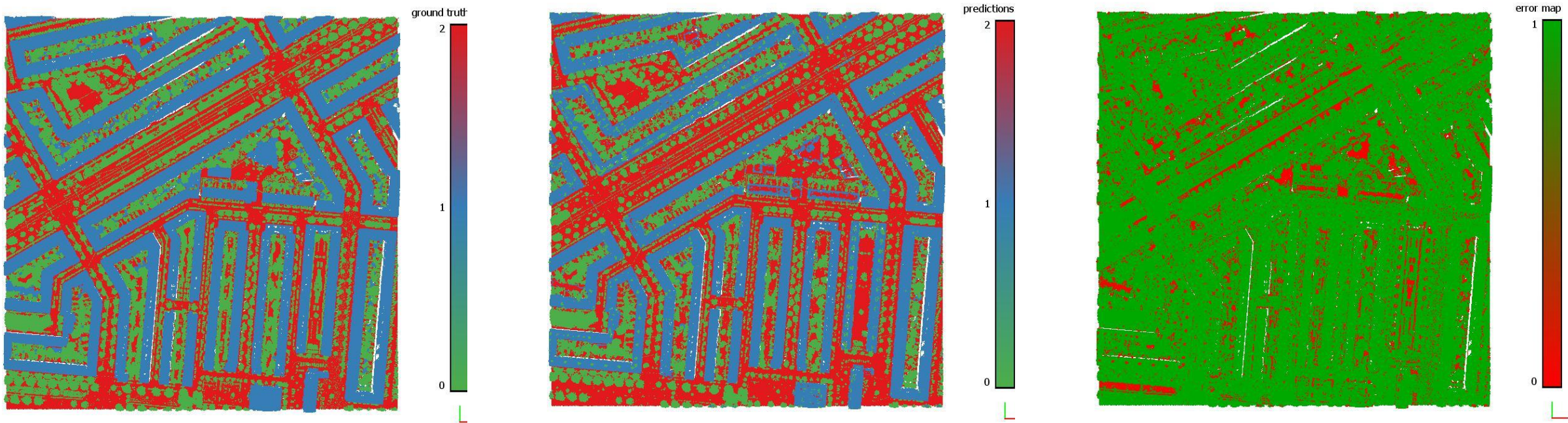
Linearity (4m)

## 5.5.3 Final model classification results

no.	tile	OA (%)	IoU (%)				CCI (%)	F1 score
			mean	other	building	ground		
1	(7,3)	-	-	-	-	-	-	-
2	(5,5)	-	-	-	-	-	-	-
3	(9,0)	-	-	-	-	-	-	-
4	(7,2)	87.67	75.96	76.19	69.56	82.14	99.65	0.88
5	(5,4)	92.18	81.34	85.52	68.56	89.95	98.96	0.92
6	(3,2)	92.15	61.55	87.35	9.60	87.70	78.07	0.93
7	(9,1)	90.93	81.04	81.78	75.08	86.27	99.74	0.91
8	(8,0)	87.80	56.43	81.16	5.13	82.99	76.67	0.90
9	(9,9)	92.32	85.44	83.87	84.07	88.38	99.95	0.92
10	(8,3)	89.85	76.78	84.82	59.86	85.66	98.14	0.90
11	(1,2)	94.40	87.31	83.91	84.83	93.18	99.80	0.94
12	(7,11)	89.92	78.90	66.31	81.13	89.26	98.86	0.90
13	(4,4)	92.92	74.37	88.92	44.43	89.75	93.97	0.93
14	(0,0)	90.43	78.88	76.89	71.87	87.88	99.43	0.90
15	(6,6)	90.78	80.79	80.46	74.22	87.68	99.63	0.91
16	(9,10)	88.96	79.19	72.12	81.87	83.59	99.68	0.89
17	(7,4)	86.74	74.65	75.94	65.98	82.03	99.41	0.86
18	(0,2)	88.06	75.13	81.17	60.11	84.12	98.48	0.88
19	(6,10)	89.00	79.62	78.76	77.01	83.11	99.92	0.89

20	(9,8)	86.62	71.96	71.34	60.45	84.08	98.70	0.87
21	(8,2)	91.49	78.96	88.04	62.98	85.86	98.37	0.91
22	(4,6)	90.03	81.19	75.79	81.35	86.42	99.77	0.90
23	(7,0)	85.52	55.49	77.27	8.24	80.97	79.84	0.87
24	(6,8)	90.68	82.80	78.94	83.03	86.43	99.89	0.91
25	(9,6)	93.73	84.39	89.47	73.77	89.93	99.33	0.94
26	(9,7)	90.89	82.65	81.35	80.32	86.27	99.92	0.91
27	(3,5)	90.16	81.13	72.31	84.67	86.40	99.52	0.90
28	(6,4)	84.33	67.92	67.72	54.20	81.85	98.12	0.84
29	(5,8)	89.30	79.41	70.02	82.66	85.55	99.43	0.89
30	(8,1)	81.56	61.39	72.92	38.34	72.92	95.67	0.82
31	(5,9)	90.97	83.15	78.67	83.33	87.44	99.85	0.91
32	(5,7)	89.30	79.50	74.22	77.20	87.10	99.62	0.89
33	(7,6)	90.18	68.58	87.25	33.76	84.73	91.14	0.90
34	(1,3)	91.03	80.41	69.43	83.49	88.32	99.20	0.91
35	(8,9)	91.96	83.75	74.10	87.89	89.25	99.44	0.92
36	(3,4)	91.95	81.61	86.28	71.13	87.43	99.32	0.92
37	(8,6)	88.40	76.06	83.13	62.50	82.54	98.79	0.88
38	(4,9)	85.56	73.40	66.07	72.73	81.42	99.46	0.86
39	(4,5)	89.66	80.72	76.24	80.17	85.76	99.81	0.90
40	(5,10)	89.92	81.06	81.10	76.52	85.54	99.83	0.90
		89.82	79.75	80.09	73.47	85.69	99.69	0.90

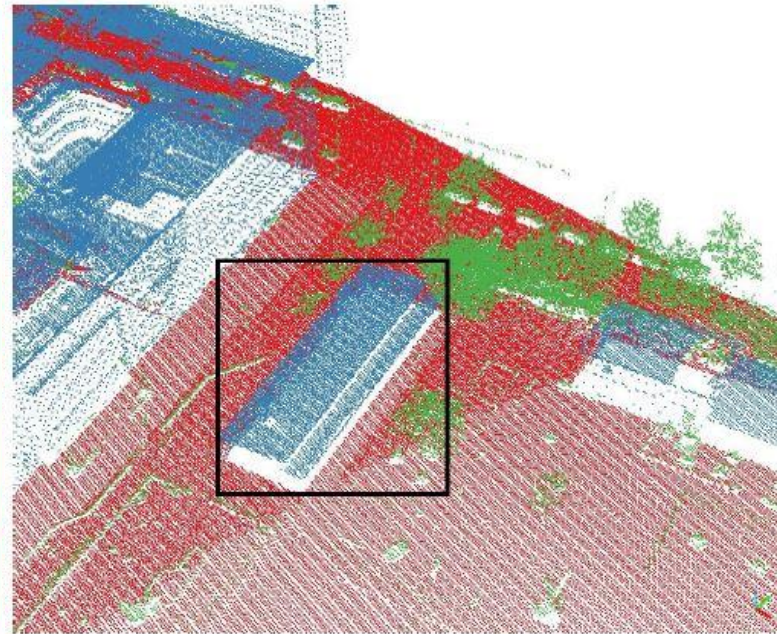
## 5.5.4 Examples of results



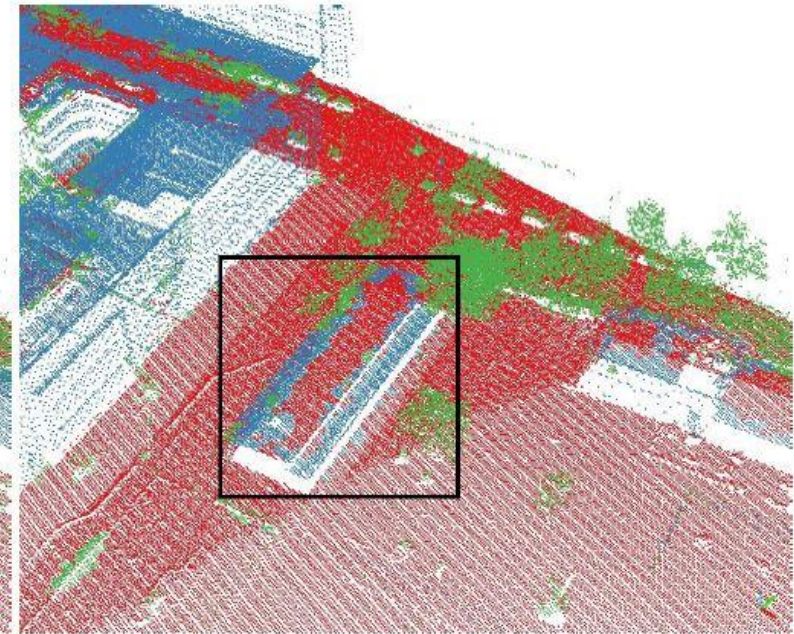
## 5.5.5 Problems related to buildings

1. Short building parts
2. Small separated building parts under trees
3. Flat buildings roof surface

ground truth



predictions



## 5.6 Testing with other datasets

- Model - AHN3

Testing dataset	OA (%)	IoU (%)				CCI (%)	$F_1$ score
		mean	other	building	ground		
AHN3	88.419	77.929	78.387	72.471	82.929	99.765	0.88
AHN4	88.161	77.267	72.423	75.439	83.938	99.692	0.88
DALES	80.31	64.512	70.579	51.426	71.532	98.67	0.81

- Model - AHN4

Testing dataset	OA (%)	IoU (%)				CCI (%)	$F_1$ score
		mean	other	building	ground		
AHN3	88.39	77.879	78.37	72.378	82.889	99.762	0.88
AHN4	88.16	77.266	72.442	75.436	83.921	99.694	0.88
DALES	80.382	64.611	70.595	51.59	71.65	98.685	0.81

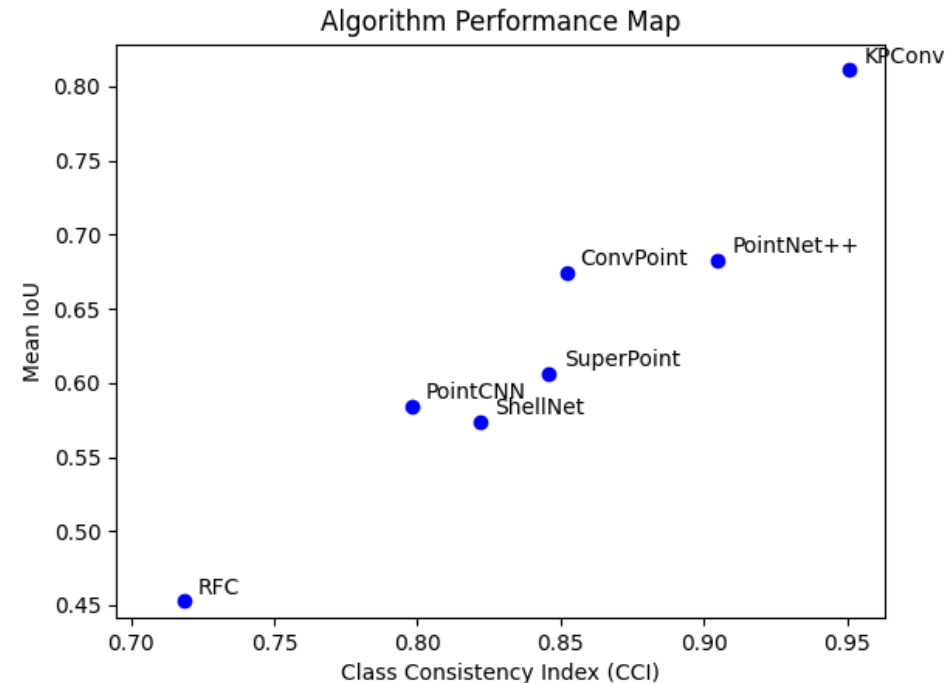
- Model - DALES

Testing dataset	OA (%)	IoU (%)				CCI (%)	$F_1$ score
		mean	other	building	ground		
AHN3	86.581	74.533	75.926	67.118	80.556	99.583	0.86
AHN4	86.109	73.487	69.796	69.372	81.293	99.585	0.86
DALES	89.746	79.411	79.618	73.066	85.549	99.673	0.90



## 5.7 Comparison with CNNs on the DALES dataset

Method	OA	IoU									CCI
		mean	ground	buildings	cars	trucks	poles	power lines	fences	vegetation	
KPConv	0.978	0.811	0.971	0.966	0.853	0.419	0.75	0.955	0.635	0.941	0.951
PointNet++	0.957	0.683	0.941	0.891	0.754	0.303	0.4	0.799	0.462	0.912	0.905
ConvPoint	0.972	0.674	0.969	0.963	0.755	0.217	0.403	0.867	0.296	0.919	0.852
SuperPoint	0.955	0.606	0.947	0.934	0.629	0.187	0.285	0.652	0.336	0.879	0.846
PointCNN	0.972	0.584	0.975	0.957	0.406	0.048	0.576	0.267	0.526	0.917	0.798
ShellNet	0.964	0.574	0.96	0.954	0.322	0.396	0.2	0.274	0.6	0.884	0.822
RFC	0.890	0.451	0.860	0.720	0.059	0.000	0.202	0.817	0.149	0.799	0.721

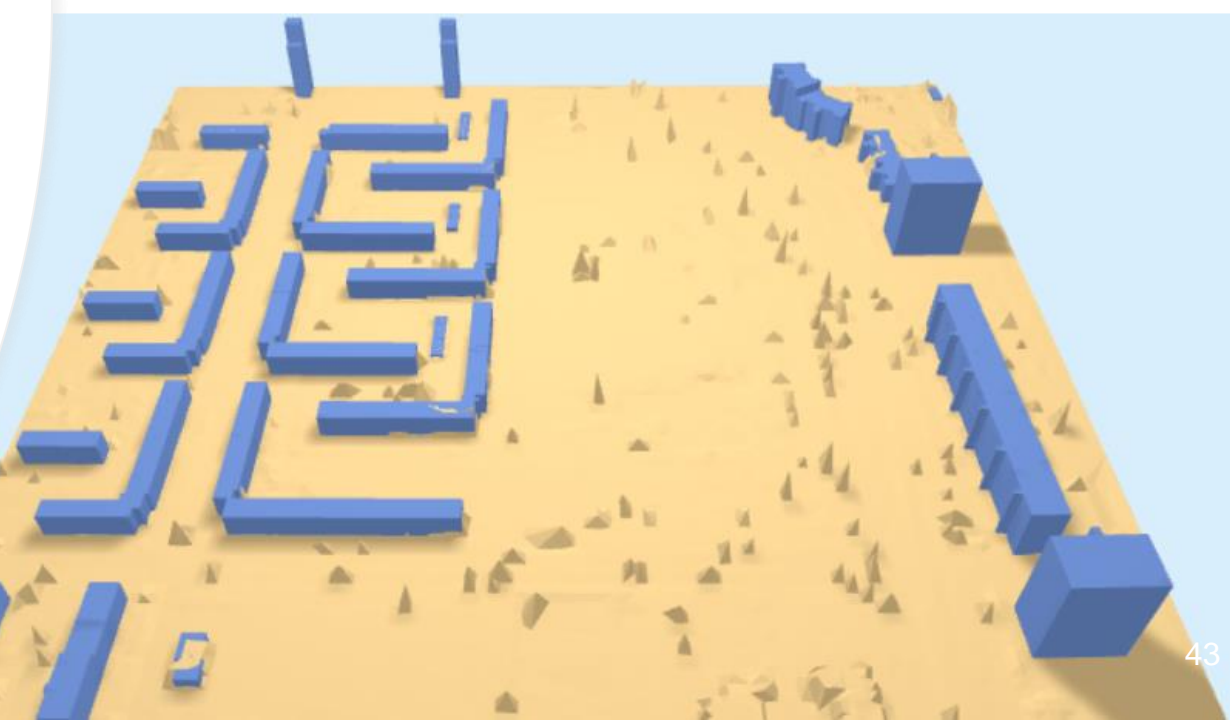
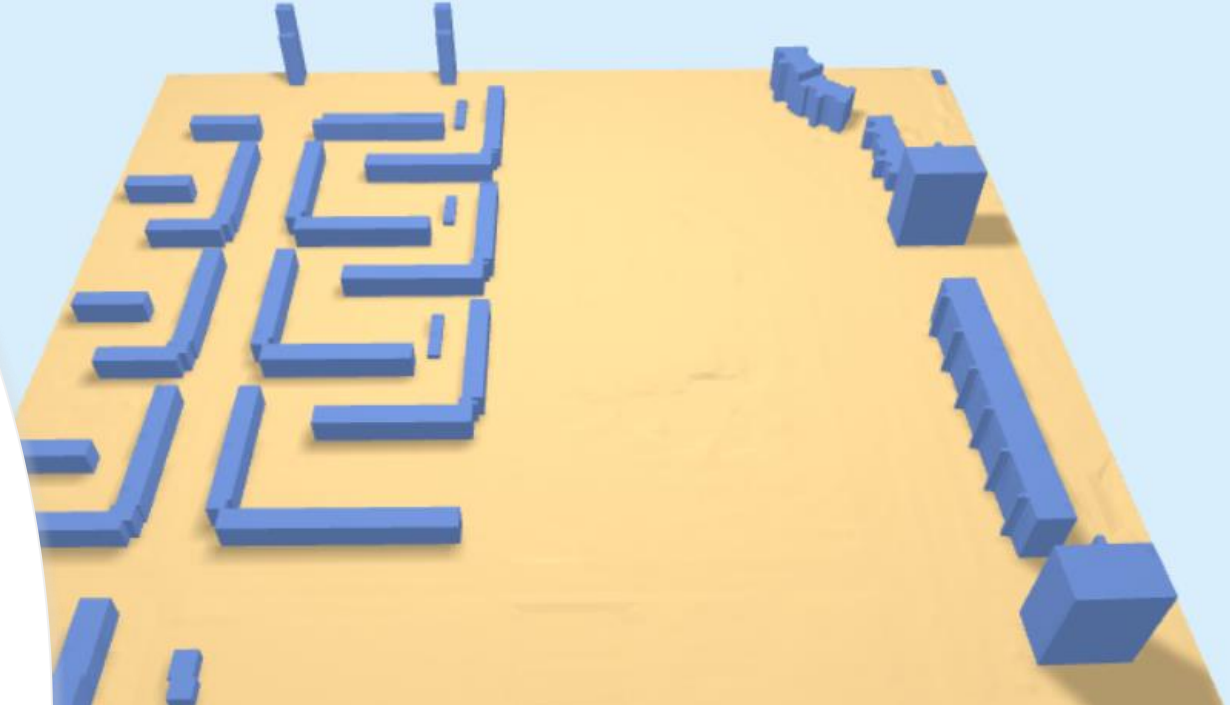


## 5.8 Comparison with MLP on the AHN3 dataset

method	OA (%)	IoU (%)				CCI (%)	F1 score	training time (minutes)	RAM (GB)	model size (KB)
		mean	other	building	ground					
RFC	89.82	79.75	80.09	73.47	85.69	99.69	0.90	12.45	1.1	229,494
MLP	88.25	76.79	79.58	67.70	83.10	99.44	0.88	72.26	0.79	598

- Pros:
  - less RAM
  - smaller model size
- Cons:
  - longer training time
  - less accurate

# 5.9 Application



no.	building roof surface		
	ground truth	predicted	h_dak_50p
1	10.782	10.783	10.784
2	10.744	10.744	10.742
3	10.813	10.813	10.816
4	10.888	10.887	10.888
5	1.854	1.851	1.858
6	24.627	24.636	24.632
7	24.738	24.738	24.745
8	1.744	1.745	1.743
9	10.813	10.813	10.820
10	1.824	1.821	1.801
11	10.869	10.868	10.871
12	42.518	43.919	44.106
13	1.861	1.854	1.862
14	10.895	10.895	10.894
15	1.846	1.840	1.845
16	1.809	1.814	1.798
17	10.866	10.866	10.868
18	10.747	10.747	10.748
19	13.686	13.683	13.691
20	1.845	1.842	1.846

no.	building ground surface		
	ground truth	predicted	h_dak_min
1	-0.654	-0.661	-0.640
2	-0.798	-0.796	-0.822
3	-0.757	-0.762	-0.735
4	-0.729	-0.697	-0.728
5	-0.752	-0.701	-0.817
6	-0.780	-0.739	-0.788
7	-0.670	-0.656	-0.680
8	-0.823	-0.807	1.681
9	-0.771	-0.774	-0.789
10	-0.714	-0.713	-0.700
11	-0.905	-0.899	-0.898
12	-0.915	-0.913	-0.964
13	-0.693	-0.672	1.798
14	-0.729	-0.731	-0.741
15	-0.697	-0.636	-0.675
16	-0.711	-0.711	-0.626
17	-0.621	-0.618	-0.610
18	-0.690	-0.685	-0.655
19	-0.581	-0.578	-0.550
20	-0.684	-0.622	-0.664

# 6. Conclusions

# 6.1 Answers to research questions

1. AHN3 as training data → F1 score 0.9 and mean IoU 0.79
2. Features → 13, 3 neighborhoods + Z coordinate features + density
3. Testing with other datasets → accuracy ↓
4. Size of training data → 0.75 Km<sup>2</sup> → ≤ F1 score 0.9 for 9.25 Km<sup>2</sup>
5. Density → 1 point per cubic meter
6. Machine learning < Deep learning

## 6.2 Limitations & future work

### Limitations:

- Only 3 classes: other, building & ground
- Only 2 machine learning algorithms were tested
- Low building IoU
- Sub-optimal parameters for efficiency

### Future work:

- Test deep learning methods on the AHN3 dataset
- Further improve the proposed methodology
- Additional processing steps for further automatization

Thank you for your attention

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