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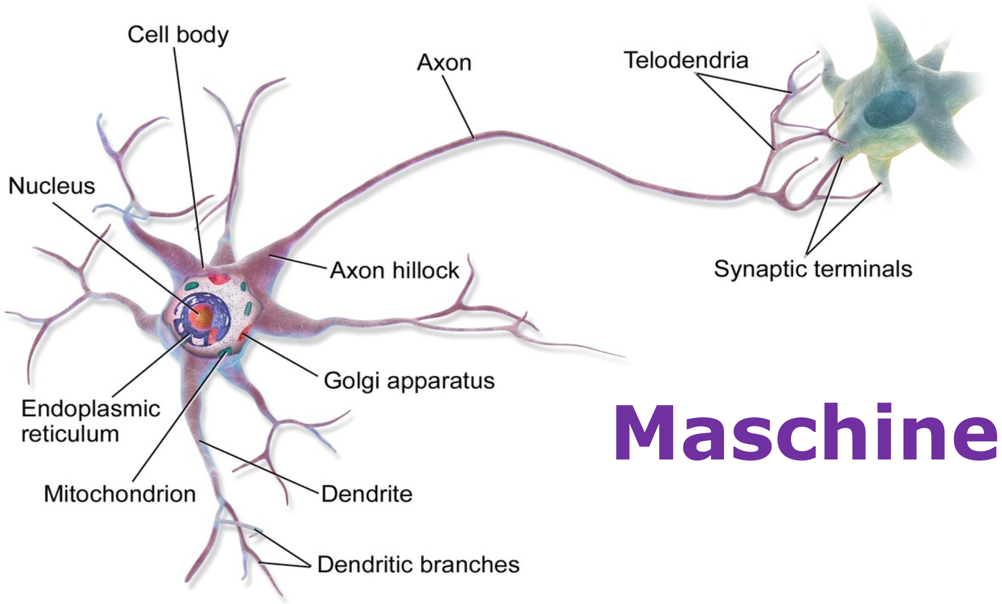

Maschinelles Lernen in der automatischen Auswertung von Punktwolken: Beispiele der Erfahrungen an der Universität Luxemburg

Abdul Awal Md NURUNNABI und Felix Norman Teferle

Geodesy and Geospatial Engineering
Department of Engineering
University of Luxembourg

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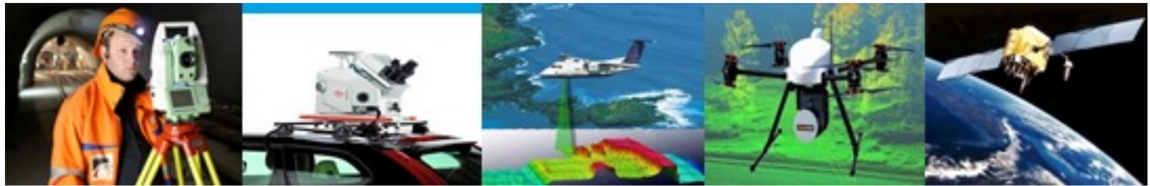

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High-Precision Monitoring, 3D Data Capture and Building Information Modelling in Geodesy and Engineering

GNSS & Positionning

Earth Observation

Reality Capture

Artificial Intelligence

Technologies/Methods

- GNSS Positioning and Developments
- Terrestrial Surveying
- 3D Laser Scanning
- Digital Photogrammetry
- SAR Remote Sensing
- Building Information Modelling
- Geographical Information Systems
- High Performance Computing
- Machine Learning and Statistical Analyses

Applications

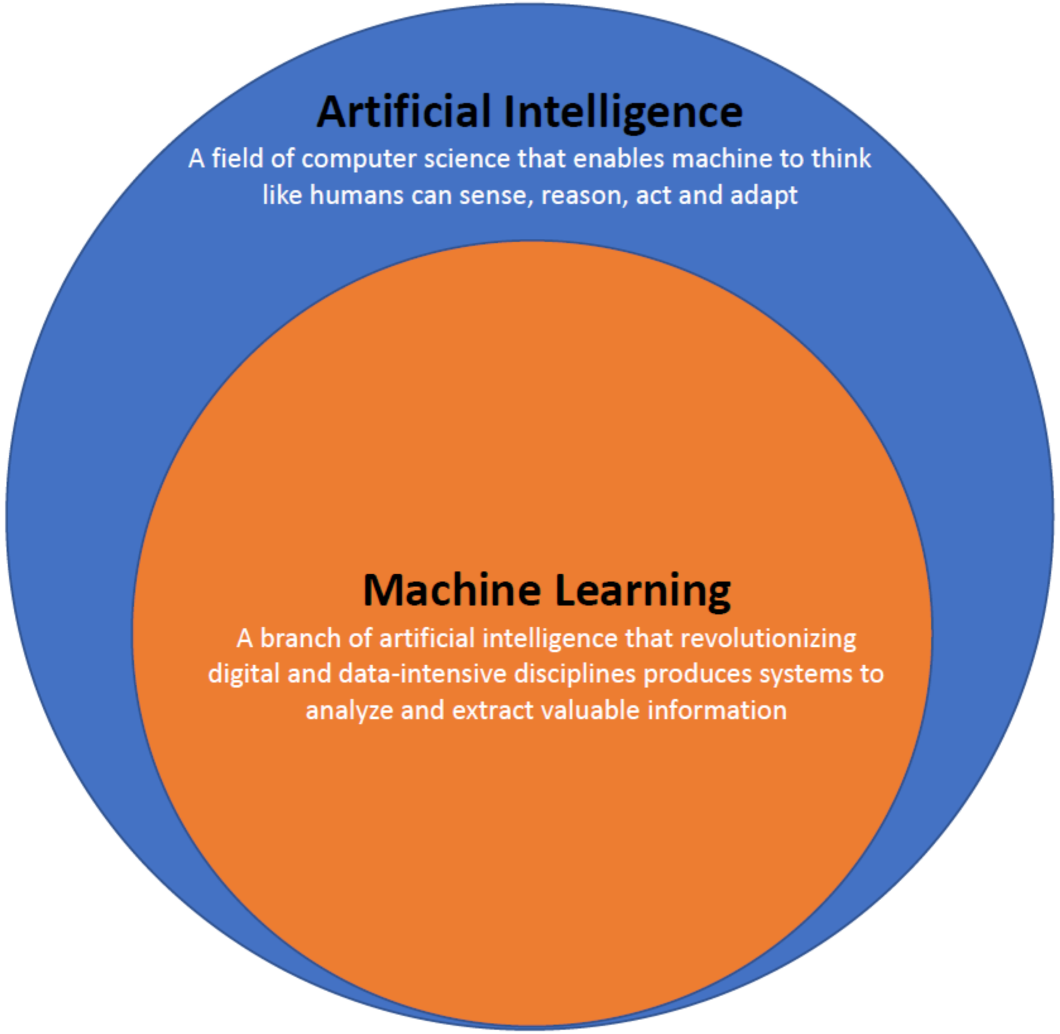
- Deformation and deflection monitoring
- BIM in civil engineering, architecture and cultural heritage
- Digital 3D models for hazard modelling and resources management
- GNSS geodesy and GNSS meteorology
- Machine learning for geospatial data analyses

Inhalt

- Einfuhrung in das maschinelle Lernen (ML) und Deep Learning (DL)
- Erfahrungen/wissenschaftliche Beiträge
  - Untersuchungen zum PointNet Algorithmus
  - Erkennung von Boden und nicht-Boden Flächen
  - 2-Stufen Merkmalsentnahme: DL zur Punktwolken-Klassifizierung
  - Re-sampling Methoden für einen robusten Validierungsdatensatz
  - Bootstrap für Cross-Validierung von DL Modelentwicklung
  - Automatische Erkennung von Straßenflächen und Straßeninstallationen

Was ist maschinelles Lernen und wozu wird es verwendet?

- **Machine learning** (ML) is the science that makes computer able to learn from data.
- A branch of artificial intelligence combined with statistical learning and computing technologies revolutionizes digital and data-intensive disciplines by producing tools and techniques to analyze and extract valuable information and knowledge from big data.



Typen von maschinellen Lernen und deren Anwendung

Supervised learning:

A model is trained based on the given input and output (the label of the input).

Unsupervised learning:

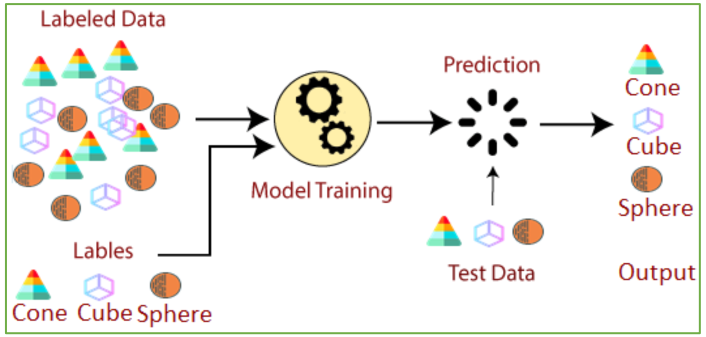
A model is trained only on the inputs, without their labels.

Semi-supervised learning:

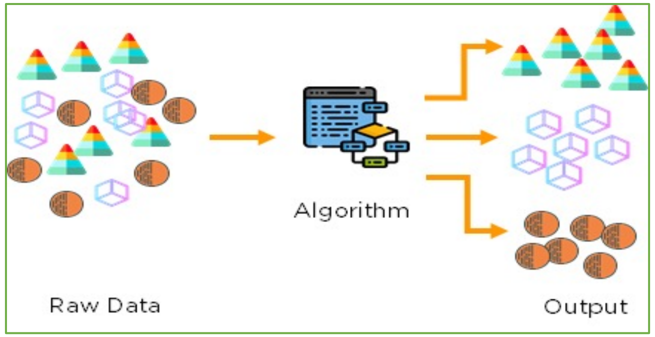
A model is trained based on a small portion of labeled data and a large number of unlabeled data and make predictions on new data.

Reinforcement learning:

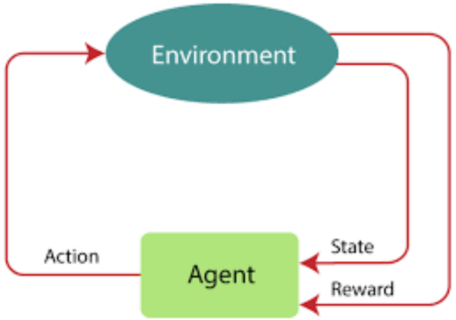
It is concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward.



Supervised learning

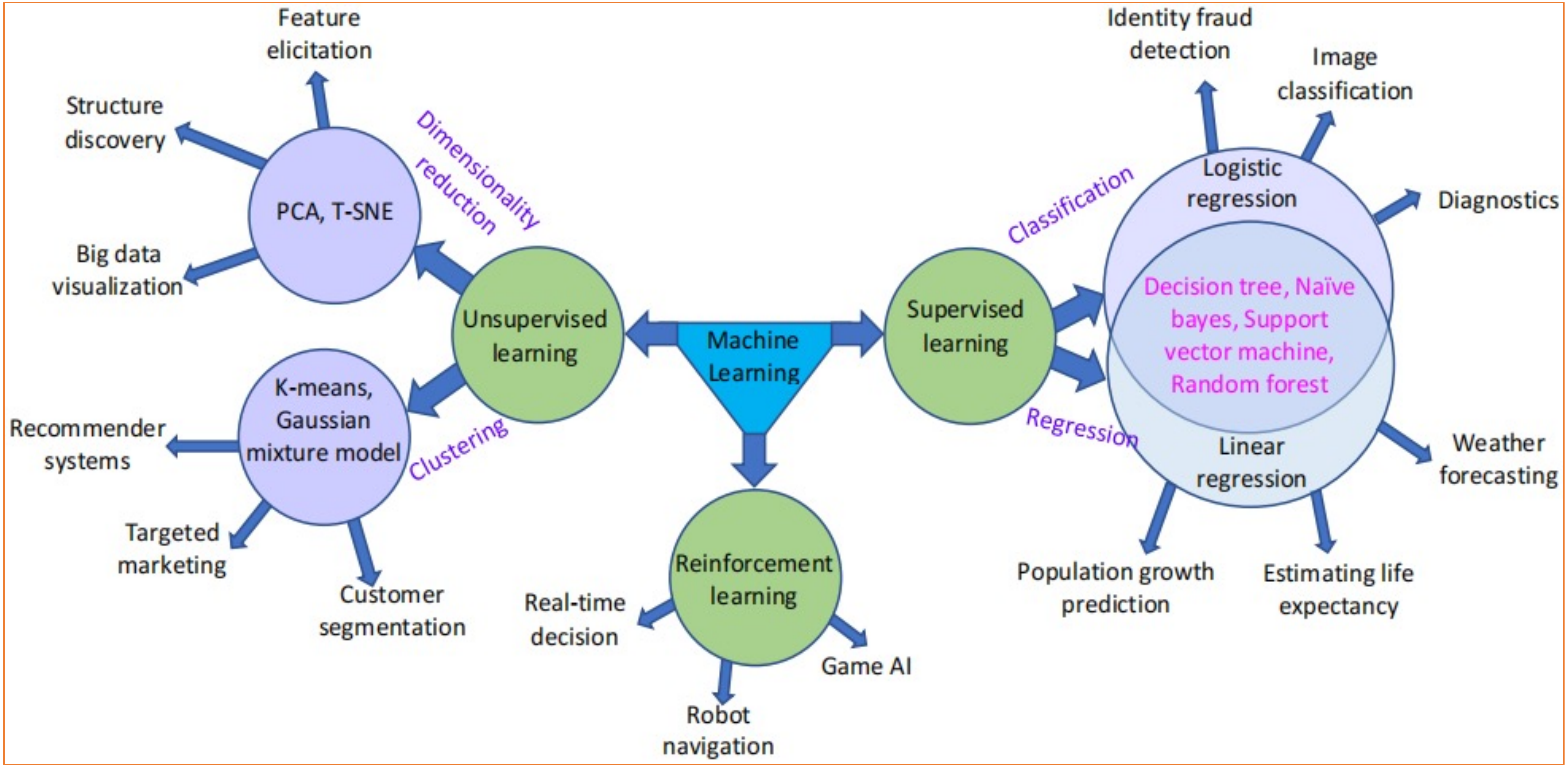


Unsupervised learning



Reinforcement learning

Typen von maschinellen Lernen und deren Anwendung (2)



Was sind die grundlegenden Stufen des maschinellen Lernens?

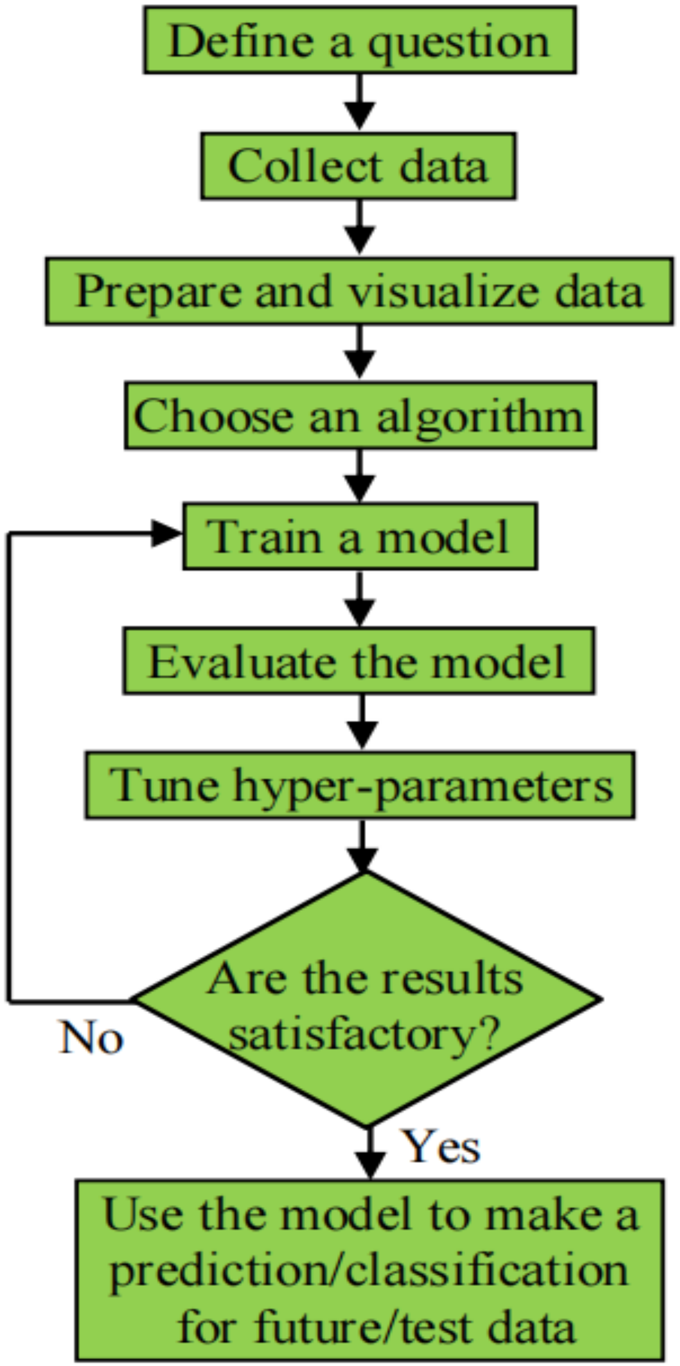
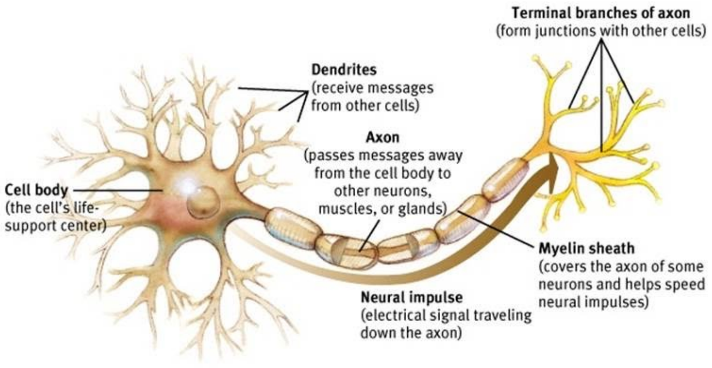


Figure. Machine learning workflow

Deep Learning

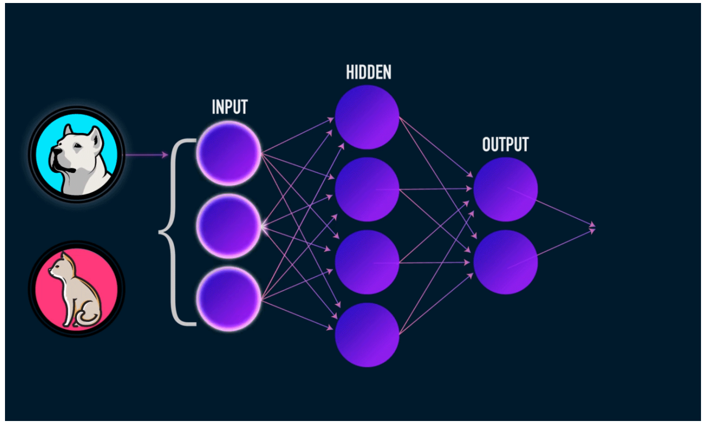
Deep learning (**DL**) is a form of machine learning techniques that *imitates the way human brain (neuron) acquire certain types of knowledge*. The term 'deep learning' refers to the artificial neural networks having many layers that enable learning from data (like human learns from experience).



~ 86 billion neurons are in the human brain, each neuron connected to thousands of other neurons. A neuron receives a sufficient number of signals through synapses from other neurons within a few milliseconds, it fires its own signal. 1

Why DL ?

- DL methods are data-driven, sufficiently automatic, efficient, and intelligent for reliable processing of big (massive) data.
- They can detect and process non-linear complex phenomena.
- They are able to process multi-disciplinary and multi-modal data.

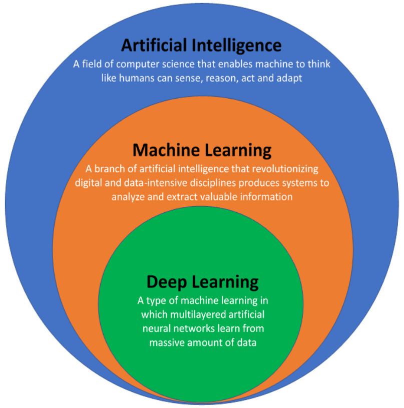


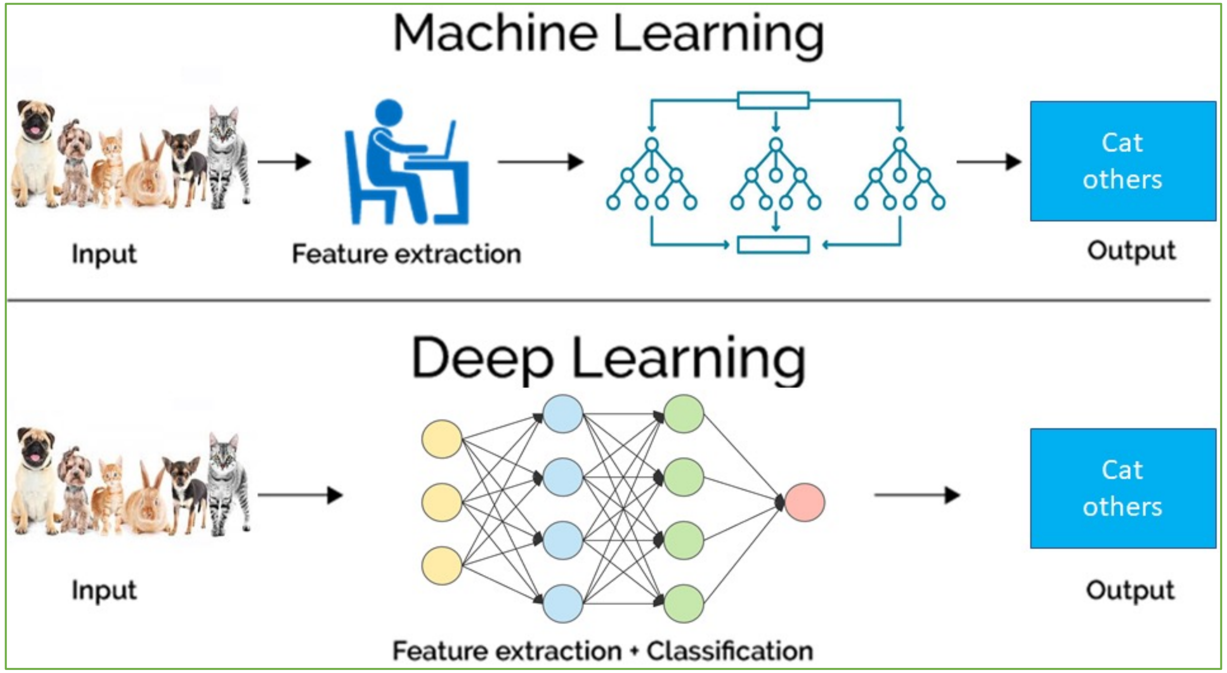
Artificial neural network [2]

Credit: 1, Stevenson; 2, James Liang, 2018.

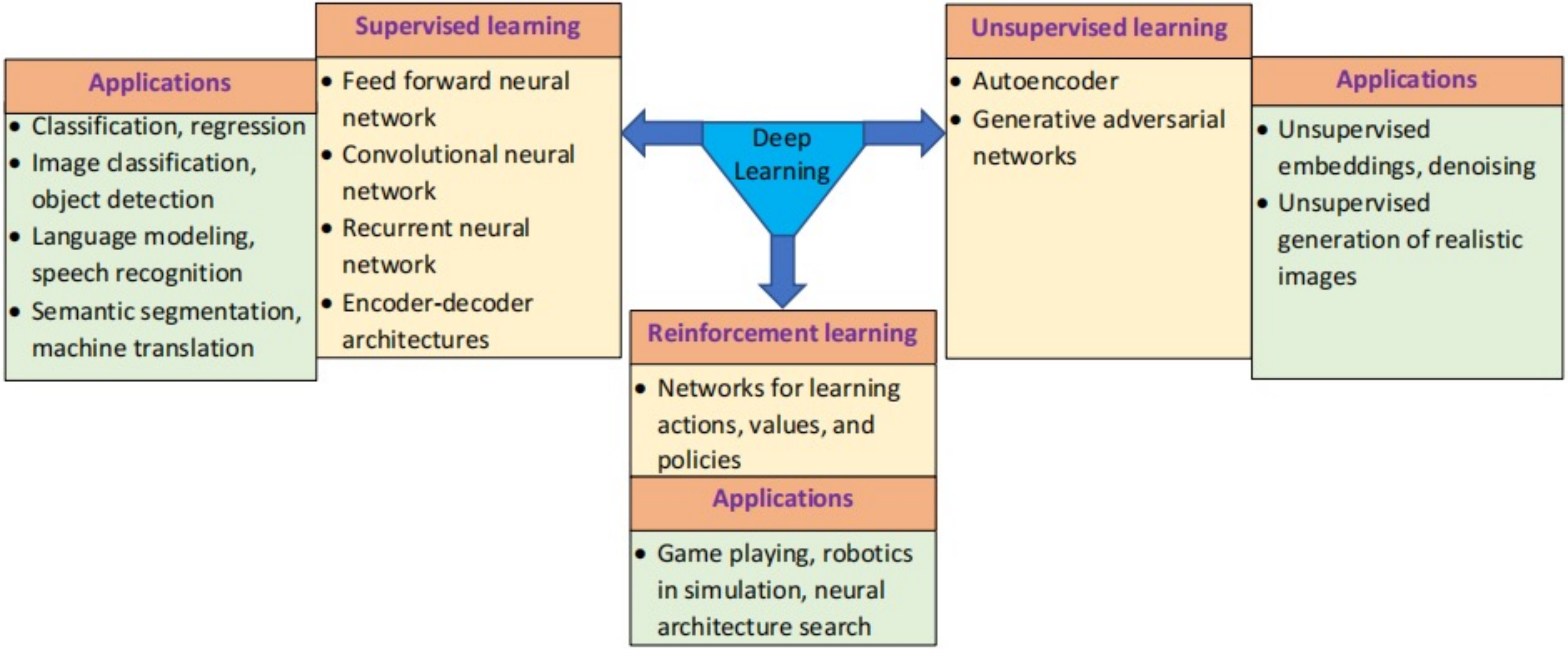
Machine Learning Vs Deep Learning

- For normal/classical methods, we tell the computer very specific instructions what to do. Whereas for machine learning, we tell the computer how to figure out the answer itself, using the data we have.
- DL is a machine learning subfield that performs in an intelligent and automatic fashion, where features are trained by itself.
- DL algorithms attempt to learn (multiple levels of) representation by using a hierarchy of multiple layers.
- If we provide DL system with a lot of information/data, it begins to understand it and responds efficiently.





Was sind die Typen des Deep Learning und dessen Anwendungen?



Wie beeinflussen ML and DL raumbezogene Big Data?

Geo/GIS science research can be characterized by massive (**big**) and multimodal-multidisciplinary sources of geolocated (**geospatial**) **data**, from which it is often crucial to extract high level information in the form of spatial semantics, spatial object relationships, trajectories, or more generally, numeric codes related to objects embedded in geographical coordinates.

Applications: city modelling, object detection, semantic segmentation, geometry generation, change detection, autonomous navigation, disaster monitoring, mapping, environment analysis, urban planning, weather forecasting, earth observation, ….

Wie hilft Deep Learning bei der semantischen Segmentierung?

Semantic segmentation:

Point-wise (pixel for image) classification/labelling.

Uses:

Visualisation

Classification

Modeling

Reconstruction

Scene understanding, …..

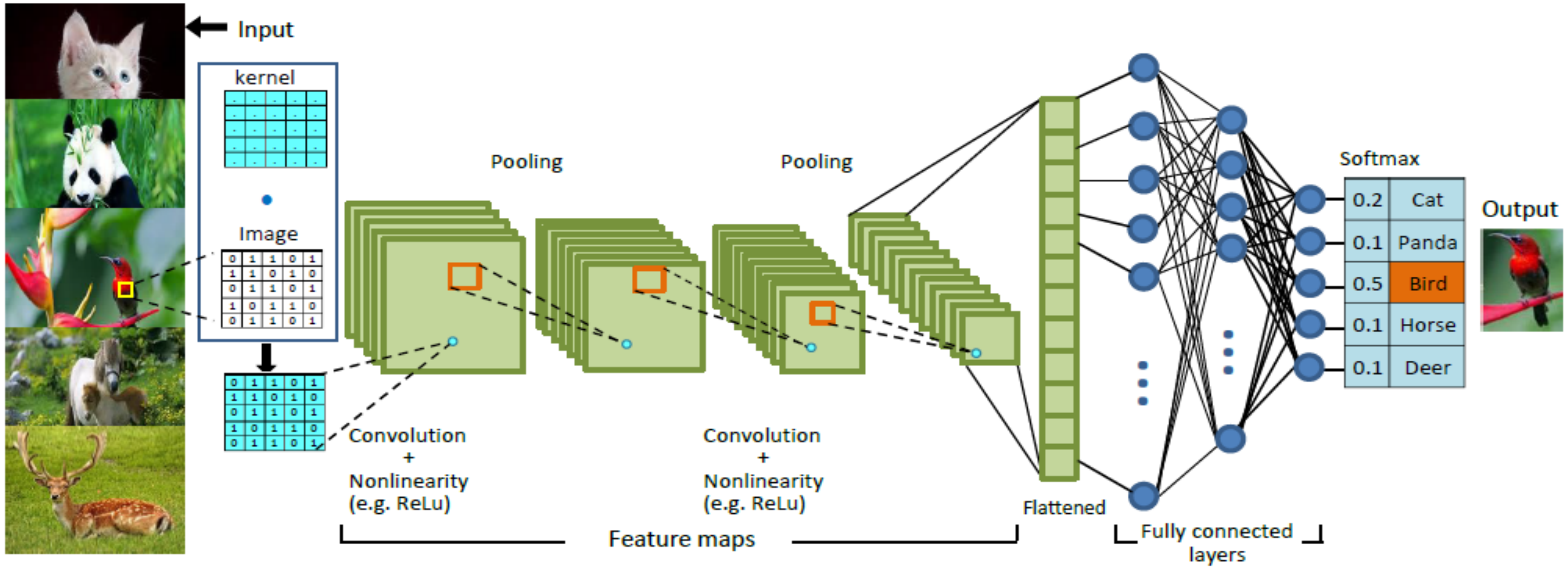
Problems of standard methods: usually not automatic or even not sufficiently semi-automatic

We need sufficiently automatic, robust, reliable and efficient methods

Solution: Data-driven approaches like deep neural networks (Deep Learning)

Convolutionales Neurales Netzwerk (CNN)

CNN (LeCun, 1989) is the most well-known supervised DL architecture that has gained unprecedent success in image segmentation and classification.



CNN Architecture

a.Nurunnabi@gge.uni.lu

A CNN architecture comprises a set of convolutional layers that are followed by a ReLU layer, then a pooling layer, then another set of convolutional layers followed by a ReLU layer, then another pooling layer, this process continues several times. At the top of the stack, a regular feedforward neural network is added, composed of a few fully connected layers with ReLUs, and the final layer produces the classification outputs having class probabilities obtained by a Softmax layer.

A standard CNN needs regular and structured data.

Punktwolken: Vorteile und Herausforderungen

Point cloud, collection of a large number of single spatial measurements of points that represent objects or space. These points usually defined by 3D vectors, the geometric coordinates (*x*, *y*, and *z*). Additional characteristics (e.g., color, intensity, return number, etc.) may be available.

Source: LiDAR, SAR, product of photogrammetry, structure from motion, etc.

Advantage:

- Point clouds can capture geometry of objects: shape, size, orientation, etc.
- Point clouds can avoid combinatorial irregularities and so easier to learn

Challanges:

- Unstructured
- Irregular/unordered data format
- Permutation-invariance
- Sparse
- Inhomogeneous data density
- Presence of data acquisition artefacts
- Presence of noise, occlusions, and outliers
- Huge data volume

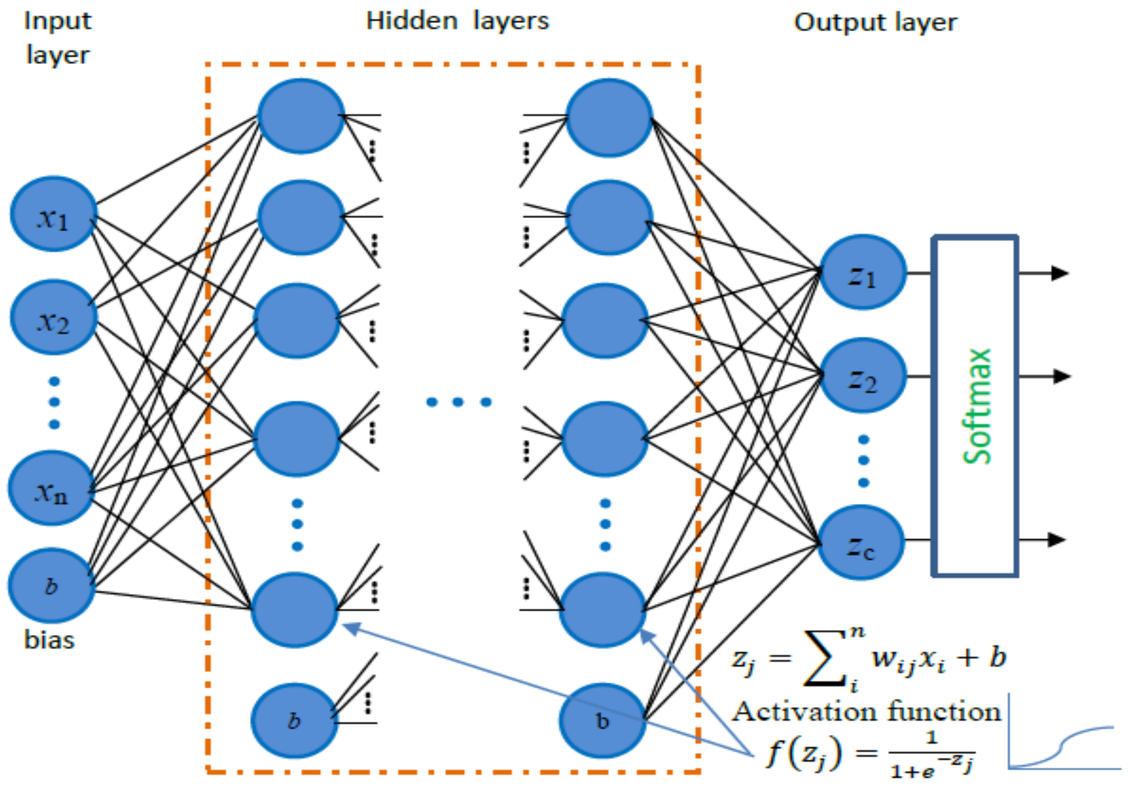
Punktbasierdendes Deep Learning und das Multi-Layer Perceptron (MLP)

- ➢ A multi-layer perceptron (MLP) is composed of one input layer, one or more hidden layers and one output layer.
- ➢ Every layer excluding the output layer includes a bias neuron and is fully connected to the next layer.

Point clouds are orderless and unstructured that makes standard CNN infeasible for semantic segmentation.

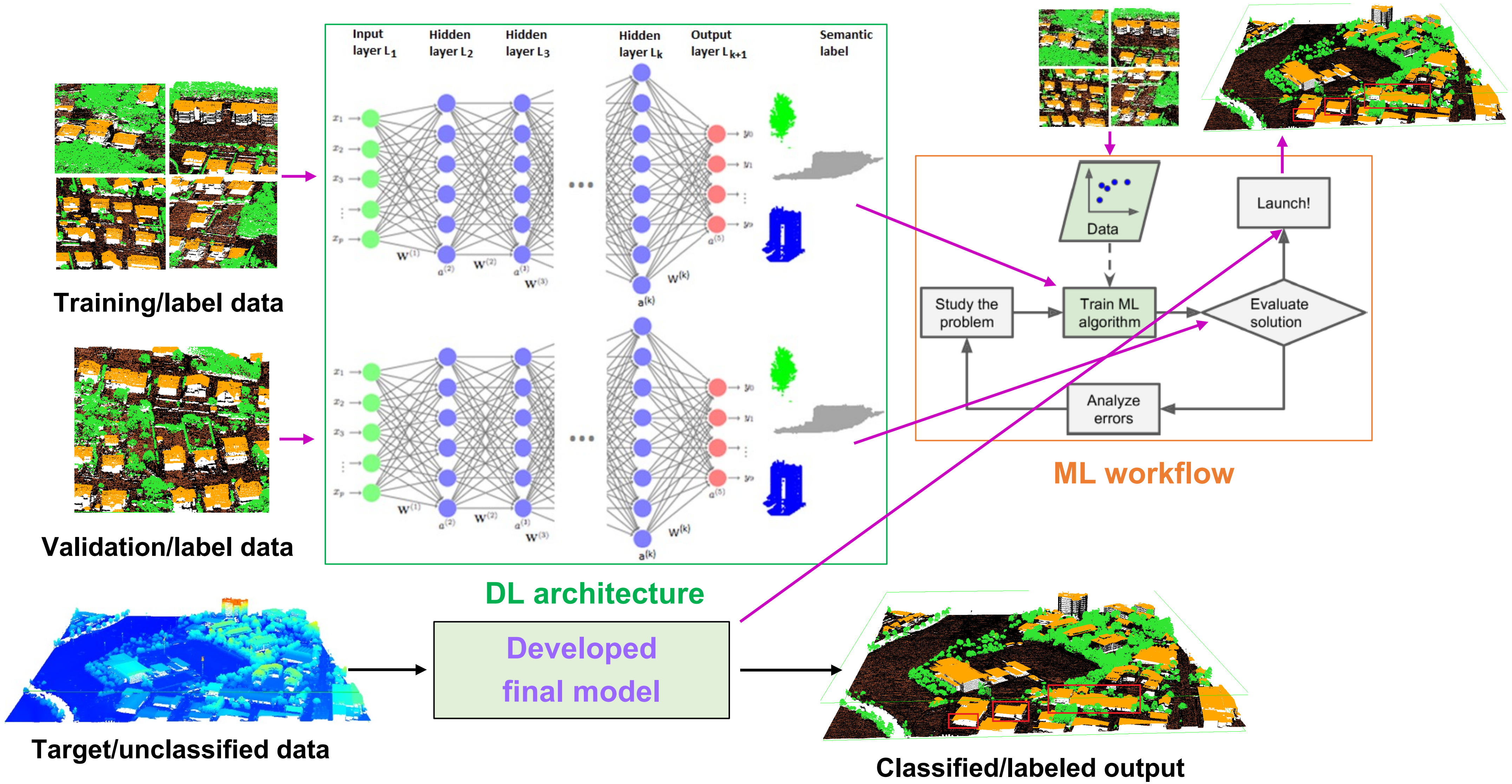
Point-based networks directly work on irregular point clouds.

Point-based networks usually use shared MLP as the basic unit for its high efficiency.



A multilayer perceptron (including sigmoid and softmax)

Semantische Segmentierung von Punktwolken



Untersuchungen zum PointNet Algorithmus

- PointNet (Qi et al., 2017)
- Processes each point identically and independently
- Learns per-point features using a set of shared multi-layer perceptrons (MLPs)
- Three Basic Modules:
- A symmetry function (max pooling)
- Local and global information aggregation
- Two joint alignment (transformation) networks

Sensitive to the standard hyper-parameters
- block size
- number of points in a block
- batch size
- input vectors
- number of points in an object class
- point density

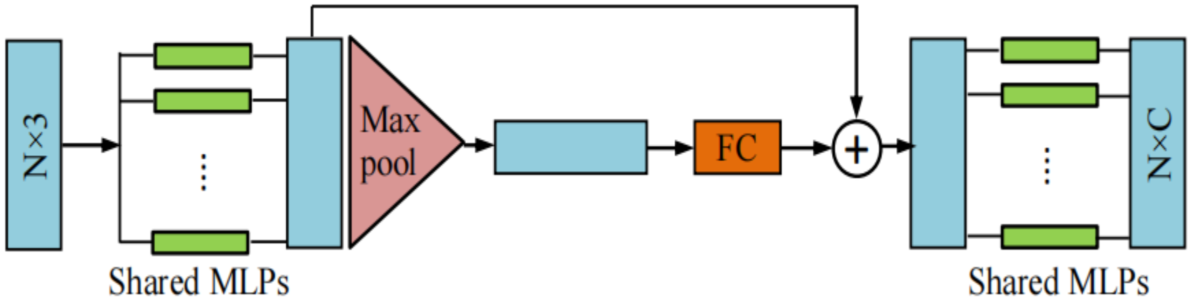


Figure. PointNet architecture

Sensibilität bzgl. Blockgröße, Auswahlsgröße, und der Anzahl der Punkte in einem Block

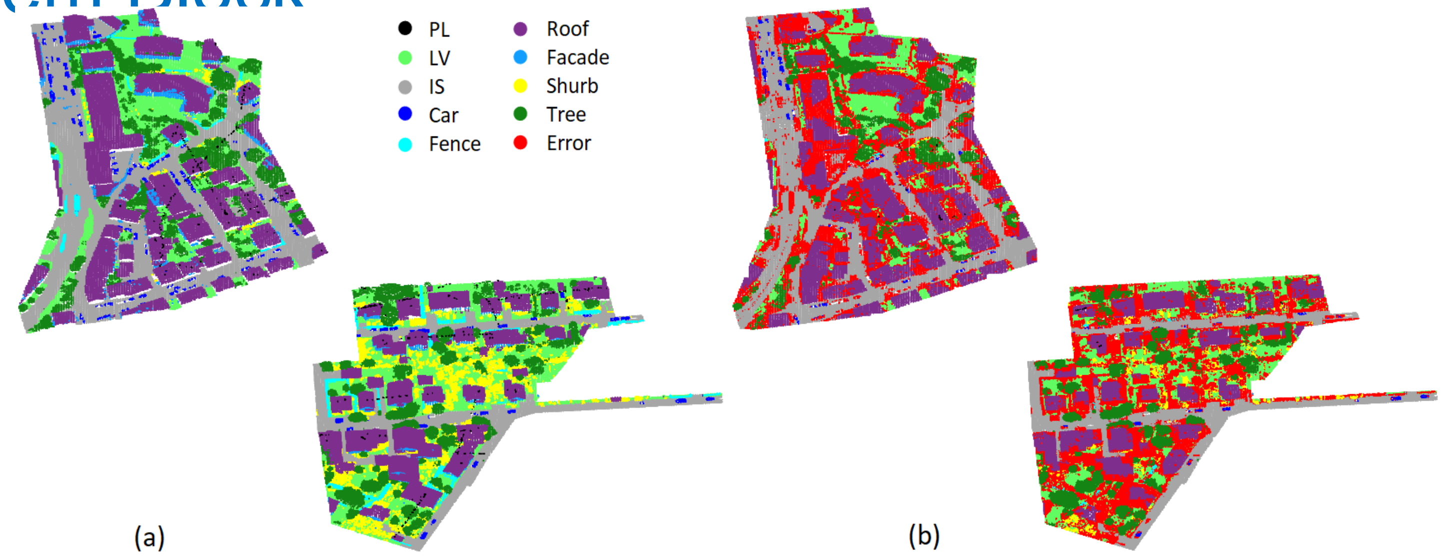


Figure. (a) Vaihingen test dataset with ground-truth labels, and (b) semantic segmentation results with error (false negative, red) for the test dataset.

- It provides a promising opportunity for semantic segmentation without any data transformation. This algorithm performs better for the data with sufficient density.
- PointNet is vulnerable to hyper-parameters: (i) point density, (ii) block size, (iii) number of sample points within a block, (iv) batch size, and (v) input point vectors.

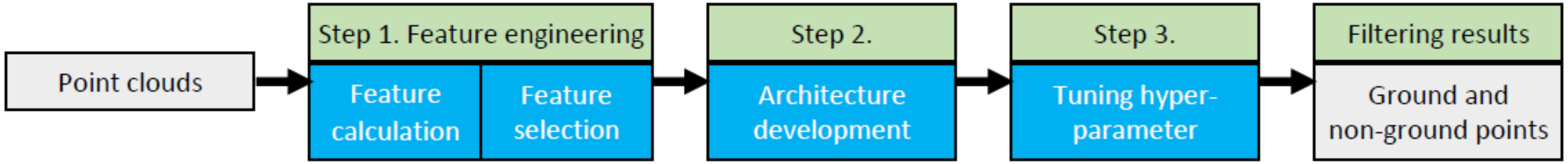
Block size (No. of points)	5m×5m (2,048)						10m×10m (2,048)						15m×15m (2,048)						10m×10m (4,096)	
Batch size	24		32		36		24		32		36		24		32		36		32	
Class\Metrics	F_1	IoU	F_1	IoU	F_1	IoU	F_1	IoU	F_1	IoU	F_1	IoU	F_1	IoU	F_1	IoU	F_1	IoU	F_1	IoU
PL	12.4	6.6	4.6	2.4	21.2	11.9	3.0	1.5	15.1	8.2	5.7	2.9	4.4	2.4	0.8	0.4	1.1	0.5	1.6	0.8
LV	70.3	54.3	74.2	58.9	76.7	62.1	75.5	60.7	74.8	59.7	71.9	56.2	73.4	57.9	73.3	57.9	73.2	57.7	73.9	58.6
IS	83.9	72.3	82.9	70.7	86.7	76.5	88.5	79.3	87.5	77.7	87.7	78.1	87.9	78.4	86.7	76.5	85.9	75.3	86.3	75.9
Car	24.8	14.2	**52.8**	35.9	51.1	34.3	38.1	23.5	39.7	24.8	32.5	19.4	30.0	17.7	29.6	17.3	30.3	17.8	39.3	24.6
Fence	16.6	9.1	14.4	7.8	19.9	11.1	11.5	6.1	17.4	9.4	11.1	5.9	12.0	6.4	10.3	5.4	15.8	8.6	23.1	13.1
Roof	69.8	53.6	71.0	55.1	75.0	59.9	73.0	57.4	79.9	66.5	59.6	42.4	65.6	48.8	71.1	55.2	65.3	48.4	72.2	56.5
Facade	15.1	8.2	14.8	8.0	12.4	6.6	14.0	7.5	14.7	7.9	10.4	5.1	7.5	3.9	5.7	2.9	10.8	5.9	13.3	7.1
Shurb	26.5	15.3	29.6	17.3	33.6	20.2	22.5	12.7	24.3	13.8	28.2	16.4	28.3	16.7	28.7	16.7	20.7	11.6	17.6	9.7
Tree	61.3	44.2	63.2	46.2	66.5	49.8	59.2	42.1	61.0	43.9	52.2	35.3	50.9	34.2	53.9	36.9	49.9	33.2	58.9	41.7
mF_1, mIoU	42.3	30.9	45.3	**33.6**	49.2	36.9	43.3	32.3	46.0	34.7	39.9	29.1	40.0	29.6	39.6	**29.9**	39.2	28.8	**42.9**	**32.0**
OA	64.4		**67.7**		70.4		70.0		**72.8**		64.4		66.6		**68.2**		65.2		68.1	

Table. PointNet performance metrics for the Vaihingen test dataset (values are in %).

DL zur Erkennung von Boden und nicht-Boden Flächen

- Precise ground surface topography is crucial for 3D city analysis, digital terrain modelling, natural disaster monitoring, high-density map generation and autonomous navigation, …
- Pointwise classification of ground and non-ground points in Aerial Laser Scanning (ALS) point clouds.

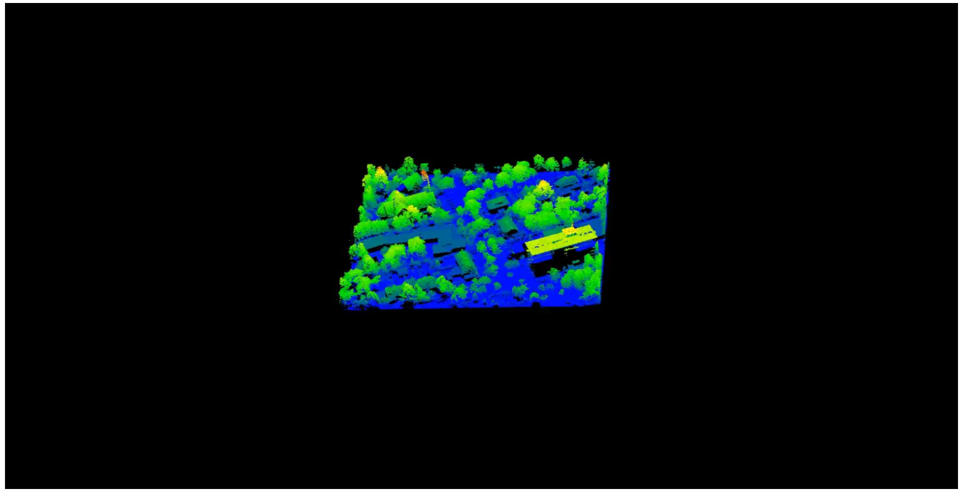
Figure: Workflow of the proposed algorithm.



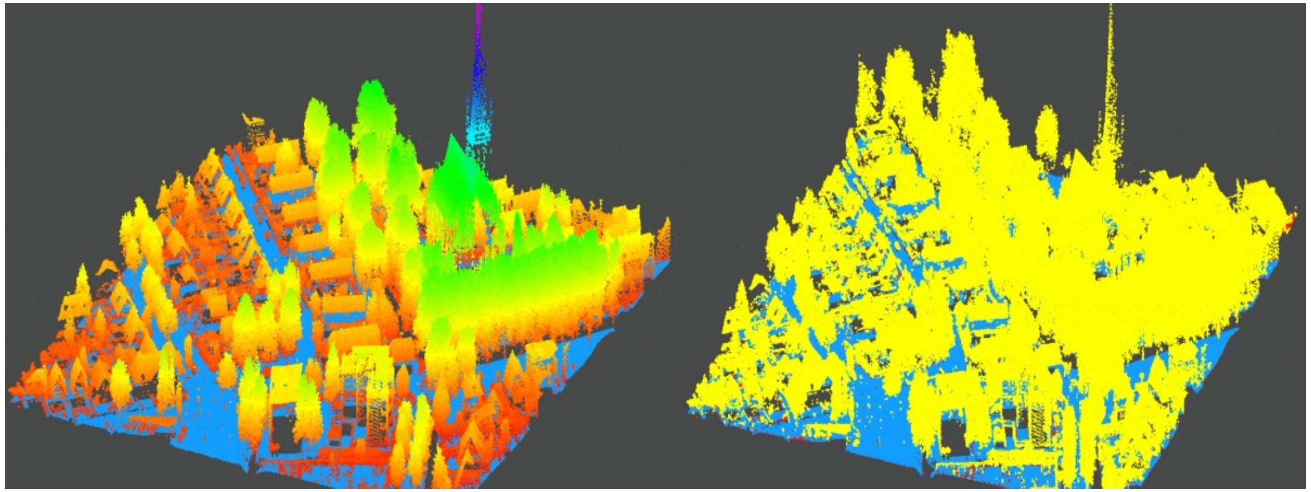
Features				Models	Required features
Covariance Features (*CovF*)	**z Features (*zF*)**	**LiDAR Features (*LiF*)**	**Others**		
Eigenvalues (λ_2, λ_1, λ_0), PC1 (ν_2), Normal (ν_0), Curvature (σ_p), Linearity (L_λ), Planarity (L_p), Scattering (S_λ), Omnivariance (O_λ), Eigentropy (E_λ), Plane Offset (PO), Verticality (θ)	Minimum z (M_z), Range (R_z), Mean z ($\bar{z}$), Variance z (σ_z^2), Point height z (P_z), Relative position (RP_z)	Intensity (I), Return Number (RN)	Point Density (PD), Positive Openness (PO), Echo Ratio (ER)	Model 1	All features; $(CovF \cup zF \cup LiF) \cup (PD, PO, ER)$
				Model 2	$(CovF \cup zF \cup LiF) \cup (PD, PO, ER) - (\theta, \sigma_p, L_\lambda, L_p, S_\lambda, O_\lambda, E_\lambda, \bar{z}, RN)$
				Model 3	$(CovF \cup zF \cup LiF) \cup (PD, PO, ER) - (\lambda_2, \lambda_1, \lambda_0, \nu_2, M_z, RP_z, RN)$

Table: Features and developed models.

DL zur Erkennung von Boden und nicht-Boden Flächen (2)



Training scene; Actueel Hoogtebestand Nederland data



Test scene; Digital terrain modelling; ground (blue) and non-ground (yellow) surface extraction

- The feature-based ground point filtering algorithm follows a not end-to-end DL architecture.
- It needs less training data than end-to-end DL approach.
- It does not require multi-scale features.
- It performs well in the presence of steep slopes and height discontinuties in the terrain.
- New method achieves accuracy of 97% for per-point ground surface points classification.
- It requires clear understanding about underlying data structure, and the feature vectors.

2-Stufen Merkmalsentnahme: Anwendung von DL zur Punktwolken Klassifizierung

- Not end-to-end deep learning (DL) methods use multi-type and multi-scale (MTMS) hand-crafted features (HcF) that make the network heavy, challenging, computationally intensive and vulnerable to overfitting.

- Efficient feature management can reduce storage and computational complexities, builds better classifiers, and improves overall performance.

- This study presents a two-step PCA (Principal Component Analysis) based feature extraction algorithm that extends the PointNet (a DL) framework for use on large-scale aerial LiDAR data, and contributes by
  (i) developing a new feature extraction algorithm, (ii) exploring the impact of dimensionality reduction in feature extraction, and (iii) introducing a non-end-to-end PointNet variant for per point classification in point clouds.

Vorgeschlagene Methode zur 2-Stufen Merkmalsentnahme

Multi-type-multi-scale (MTMS) features: HcF generated by different type of neighborhood with different sizes.

Prospects of MTMS features: MTMS can provide more detail about point local neighborhood information, and help to understand correspondence with neighboring objects.

Problems with MTMS features: It makes the network heavy, can create unnecessary and redundant features to the learning process, and may leads to over fitting.

Why feature dimension reduction?

It can manage the available features in a optimal way that can reduce the related complexities for the deep networks.

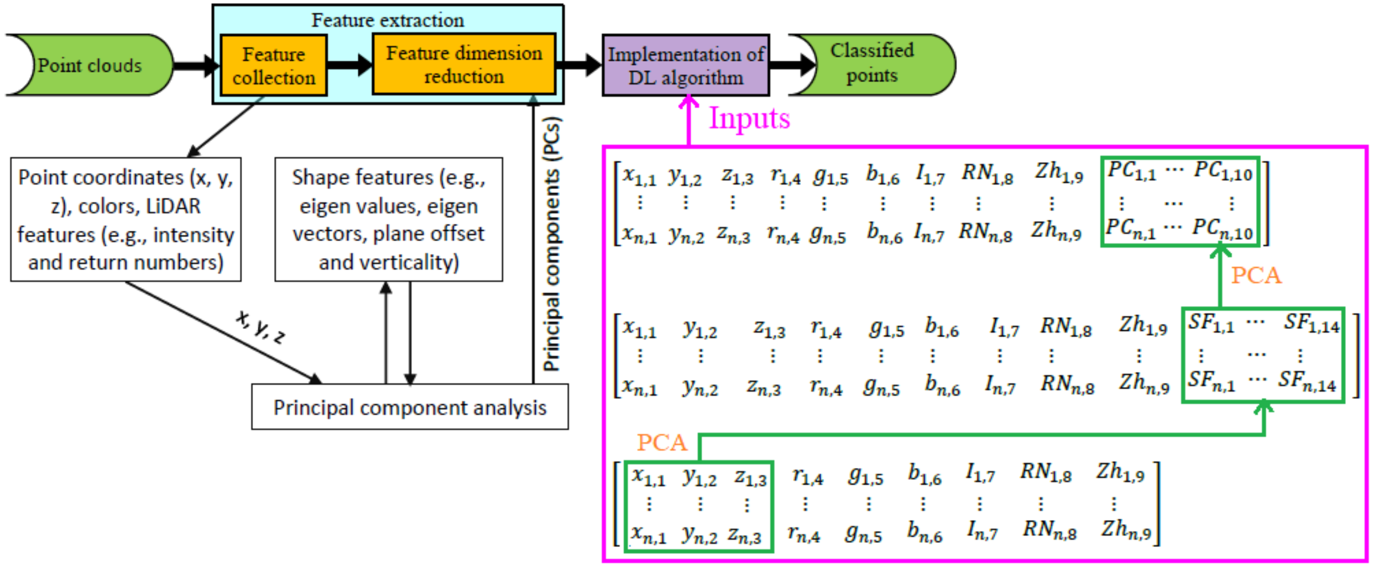


Figure. Workflow of the proposed feature extraction approach

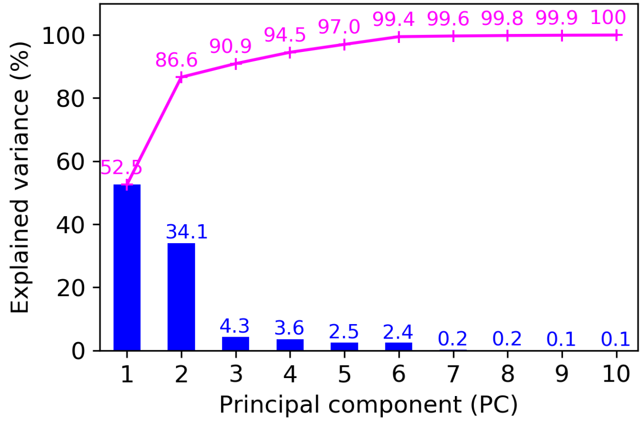


Figure. Variants explained by PCs

Versuchsergebnisse

Input features	Group 1	Group 2 (LiFs)	Group 3 (LiFs+SFs)	Group 4	Group 5	Group 6	Group 7
	x, y, z	$x, y, z, x_n, y_n, z_n, RN, I, z_h$	Group 2 + all SFs	Group 2+10PCs	Group 2+ 7PCs	Group 2+ 5PCs	Group 2+ 3PCs

Table. Groups of features that are used in the network as the input vectors. Point coordinates (x, y, z), normalized point coordinates (x_n, y_n, z_n), RN (return number), I (intensity), z_h (height of the interest point), and NPCs (N: number of PCs).

Class	Group 2 (LiFs) ($x, y, z, x_n, y_n, z_n, RN, I, z_h$)		Group 3 LiFs + all SFs		Group 6 LiFs+5PCs	
	F_1	IoU	F_1	IoU	F_1	IoU
PL	27.88	16.19	52.79	35.86	54.65	37.60
LV	69.70	53.49	73.67	58.32	73.55	58.17
IS	87.66	78.04	88.64	79.59	88.92	80.05
Car	37.45	23.03	36.34	22.20	42.37	26.88
Fence	09.45	04.96	09.95	05.23	10.73	05.67
Roof	71.20	55.28	83.98	72.39	85.73	75.02
Facade	15.12	08.18	30.61	18.07	28.91	16.90
Shrub	19.34	10.71	29.35	17.20	25.72	14.76
Tree	54.92	37.8	67.47	50.91	67.01	50.39
mF_1, mIOU	43.64	32.10	52.53	39.97	53.07	40.60
OA	66.78		74.64		75.36	

Point density: 4-6 pt/m^2
No. of points for training set: 753, 876
No. of points for test set: 411, 772

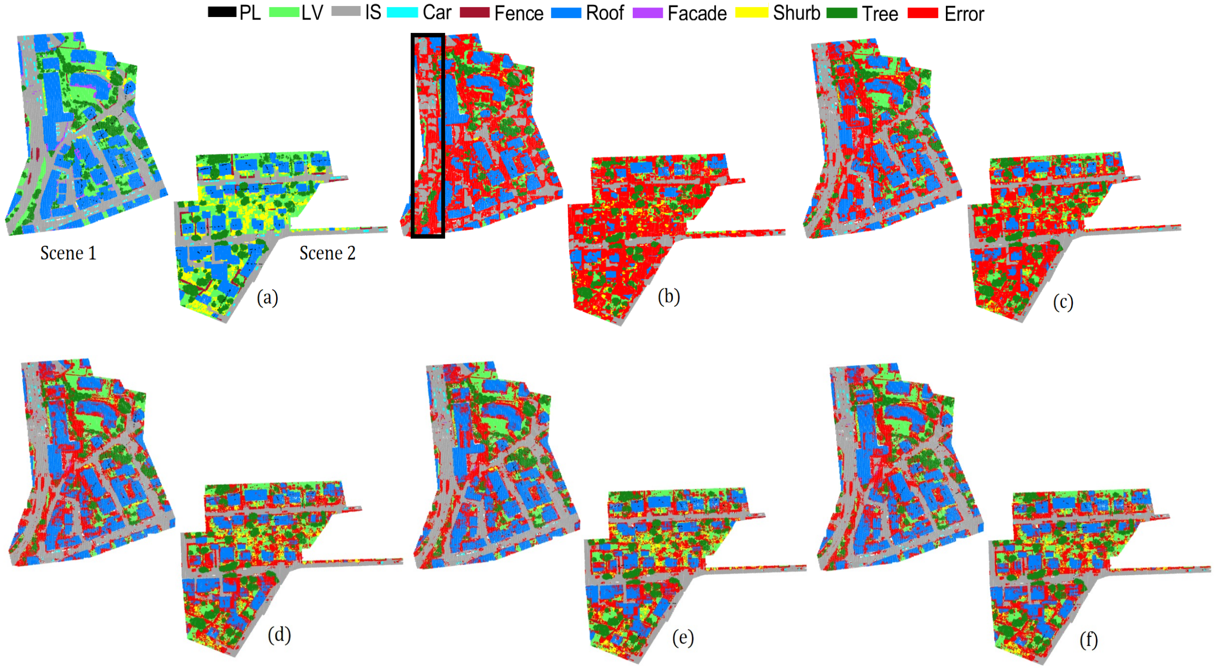


Figure. Vaihingen test data set, (a) ground-truth; classification results for the inputs (b) Group 1; (c) Group 2; (d) Group 3; (e) Group 4; (f) Group 6. Results in the black rectangle in (b) show that many points of the impervious surface, fence and low vegetation are misclassified (red). Misclassifications for the same part are almost similar in the figures (e) and (f), but significantly better than (b).

- It is justified that dimension reduction in feature space has potential for increasing the performance of feature-based DL algorithm. The new non-end-to-end PC-based variant of PointNet outperforms the original PointNet.
- The new algorithm achieves an Overall Accuracy (OA) of 74.64% by using 9 input vectors and 14 shape features, whereas with the same 9 input vectors and only 5PCs (principal components) it achieves a higher OA of 75.36%.

Resampling Methoden für einen robusten Validierungsdatensatz in der DL Punktwolkenklassifizierung

- A validation data set is important for training a supervised ML model.
- Selecting a part of available data to produce a validation set can produce overfitted results.
- Resampling techniques involve repeatedly drawing many samples, hence, DL models based on resampling methods can give better generalization power to a model with a good performance for the unseen (test/future) data.

Contributions:

- ❑ Investigating the generalization capability of the four most popular resampling methods: *k*-fold cross-validation (*k*-CV), repeated *k*-CV (R*k*-CV), Monte Carlo CV (MC-CV) and bootstrap for creating training and validation data sets used for developing, training and validating DL based point cloud classifiers (e.g., PointNet),
- ❑ Justifying Mean Square Error (MSE) as a statistically consistent estimator, and
- ❑ Exploring the use of MSE as a reliable performance metric for supervised DL.

Versuch: Resampling Methoden für einen robusten Validierungsdatensatz in der DL Punktwolkenklassifizierung

- Experiment shows that a specific resampling method does not always produce the best results for all data sets.
- The train/test split method did not achieve better results than a resampling method.
- Since Bootstrap draws samples with replacement, it has more possibility of getting autocorrelation between points, however, results show that Bootstrap has more potential for small data sets.

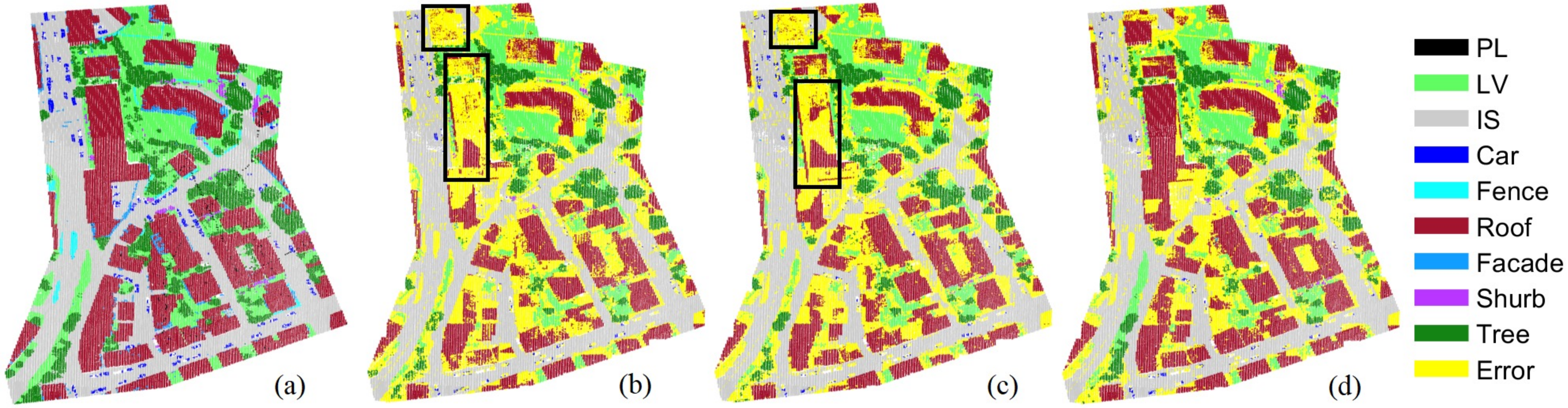


Figure. Classification results for the Vaihingen test data set (Scene 1). (a) ground-truth, results of: (b) simple random sampling-based train/test split, (c) stratified sampling-based train/test split, and (d) stratified sampling based R*k*-CV. Many points are misclassified in the black rectangles for plots b and c.

Methods	Stratified sampling					Simple random sampling				
	MSE results		Classification results			MSE results		Classification results		
	m_{MSE}	sd_{MSE}	mF$_1$	mIoU	OA	m_{MSE}	sd_{MSE}	mF$_1$	mIoU	OA
Train/test split	0.0257	---	41.53	31.53	**70.24**	0.0269	---	39.44	29.81	**68.04**
k-CV	0.0284	0.0019	41.39	31.12	71.22	0.0269	0.0004	41.19	29.81	69.69
R*k*-CV	**0.0248**	0.0016	42.57	32.52	**71.74**	0.0273	0.0018	42.44	32.08	70.33
MC-CV	0.0275	0.0016	41.47	31.73	71.69	0.0267	0.0009	41.35	31.59	70.69
Bootstrap	0.0309	0.0003	42.41	32.15	**71.72**	0.0304	0.0003	40.55	30.84	71.21

Table. Results based on train/test split and resampling methods (*k*-CV, R*k*-CV, MC-CV and bootstrap). Outcomes reveal impact on error metrics, and classification performance metrics (in %) for the ISPRS benchmark Vaihingen test data set (Scene 1 and 2).

*k*CV-B: Bootstrap mit Cross-Validierung für die DL Modelentwicklung, -prüfung und -auswahl

This study investigates the inability of train/test split and *k*-fold cross-validation methods to create training and validation data sets, and to achieve sufficient generality for supervised DL.

In response, the bootstrap is a computer based statistical resampling method that has been used efficiently for estimating the distribution of a sample estimator and to assess a model without having knowledge about the population.

This paper couples cross-validation and bootstrap to have their respective advantages in view of data generation strategy and to achieve better generalization of a DL model.

Contributions:

- Developing an algorithm for better selection of training and validation data sets,
- Exploring the potential of bootstrap for drawing statistical inference on the necessary performance metrics (e.g., mean square error), and
- Introducing a method that can assess and improve the efficiency of a DL model. The proposed method is applied for semantic segmentation and is demonstrated via a DL based classification algorithm, PointNet, through aerial laser scanning point cloud data.

Vorgeschlagene Methode

Training	Validation	Test

Figure. Train/test split method

Training	Training	Training	Training	Validation	Test
Training	Training	Training	Validation	Training	Test
Training	Training	Validation	Training	Training	Test
Training	Validation	Training	Training	Training	Test
Validation	Training	Training	Training	Training	Test

Figure. *k*-fold Cross Validation (*k*CV)

Training	Training	Training	Training	Validation	Test
Training	Training	Training	Validation	Training	Test
Training	Training	Validation	Training	Training	Test
Training	Validation	Training	Training	Training	Test
Validation	Training	Training	Training	Training	Test

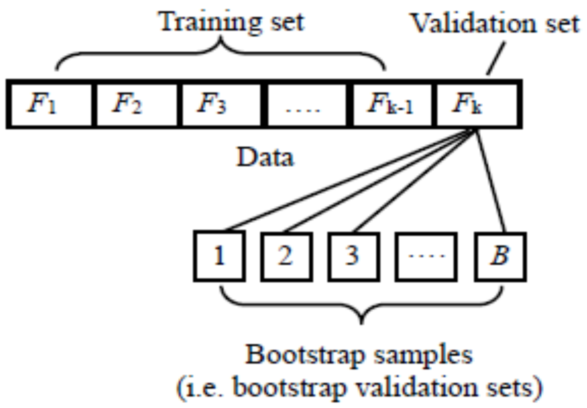


Figure. A schematic diagram; ***k*CV-B**: cross-validation couples with bootstrap to get *B* validations sets for each of *k* training sets. F_i is the *i*th (i =1,2,…,k) fold for a data set having *k* folds, where *k*-1 folds are used as a training set, and *B* bootstrap validations sets are used to validate the model developed by the training set.

Versuch mit dem ALS Datensatz

Class	Training points	Test points	Train/test split	Boot-strap	kCV	kCV-B
			F_1	F_1	F_1	F_1
uC	1,878,838	693,778	85.2	80.3	84.3	89.2
Ground	2,152,235	1,680,188	81.9	85.5	91.1	93.2
Building	1,441,483	902,834	78.9	82.9	89.9	89.2
Mean F_1			81.9	82.9	88.5	90.5
OA			81.6	83.5	89.2	91.1

Table. Classification results of an ALS test data set.

- The proposed bootstrap coupling with *k*CV has demonstrated to improve model quality.
- Using large values of *k* and *B* improve the generality and performance of a model, but there is a trade-off between generalization, accuracy and time to compete the process.
- Reasonably, *k*CV-B takes more time than the existing methods, but with high-powered computing facilities it can produce higher generalization power for the test and future data.

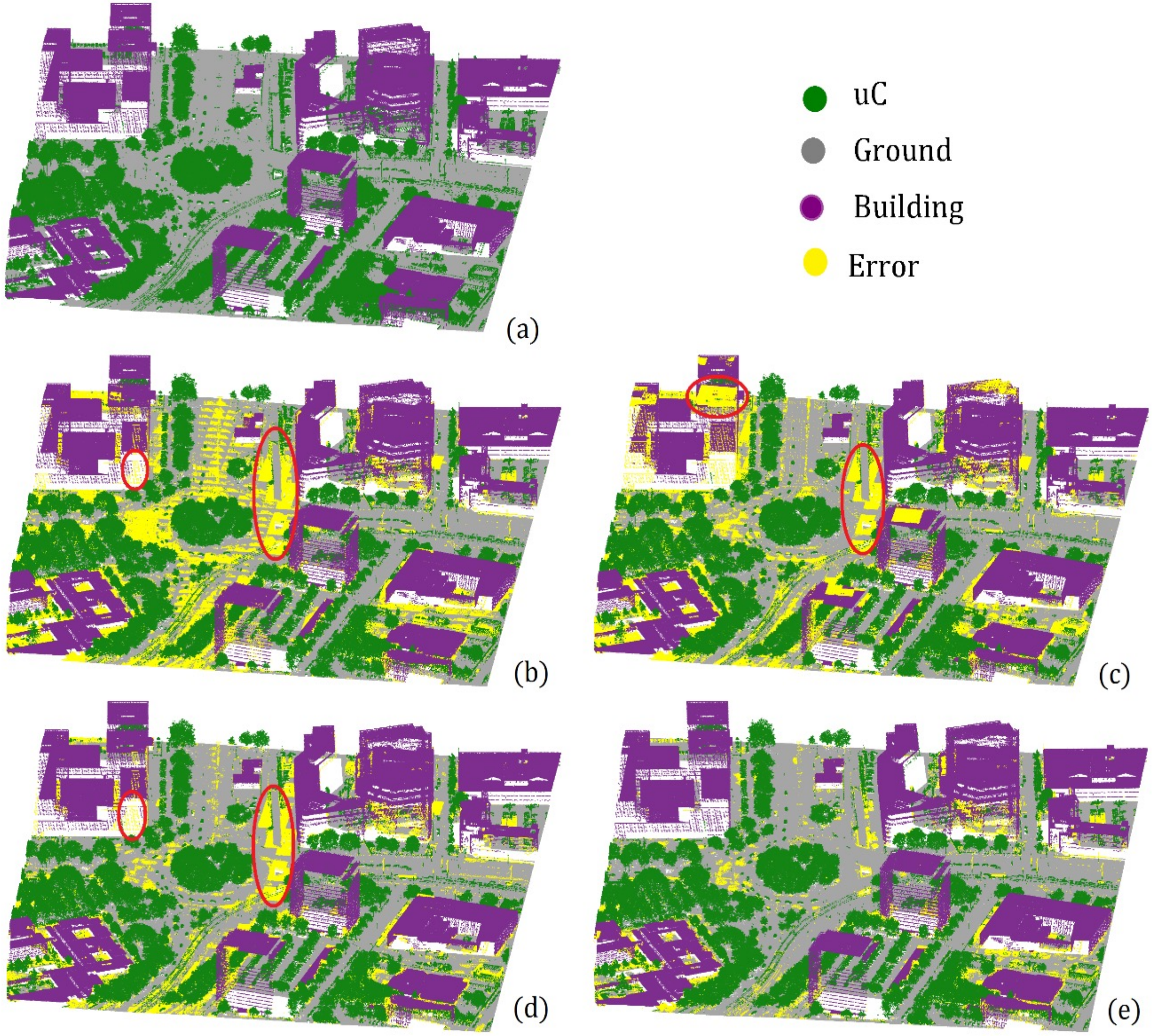
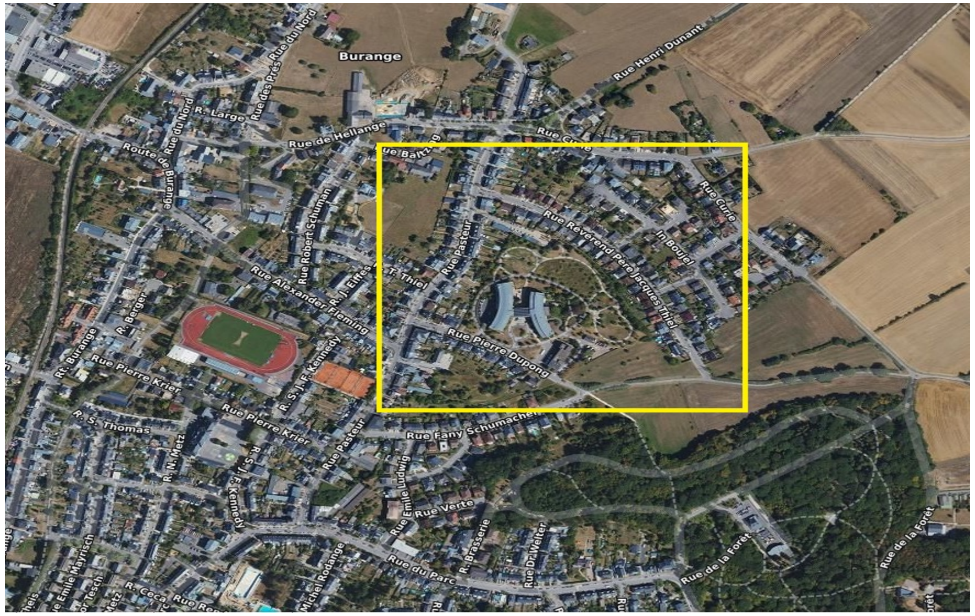


Figure. Classification results (misclassified points in yellow): (a) ground-truth, (b) train/test split, (c) bootstrap, (d) *k*CV, and (e) *k*CV-B. Many building and ground points are misclassified in red ellipses.

DL für die semantische Segmentierung (laufende Arbeiten)



Test data; Dudelange, Luxembourg

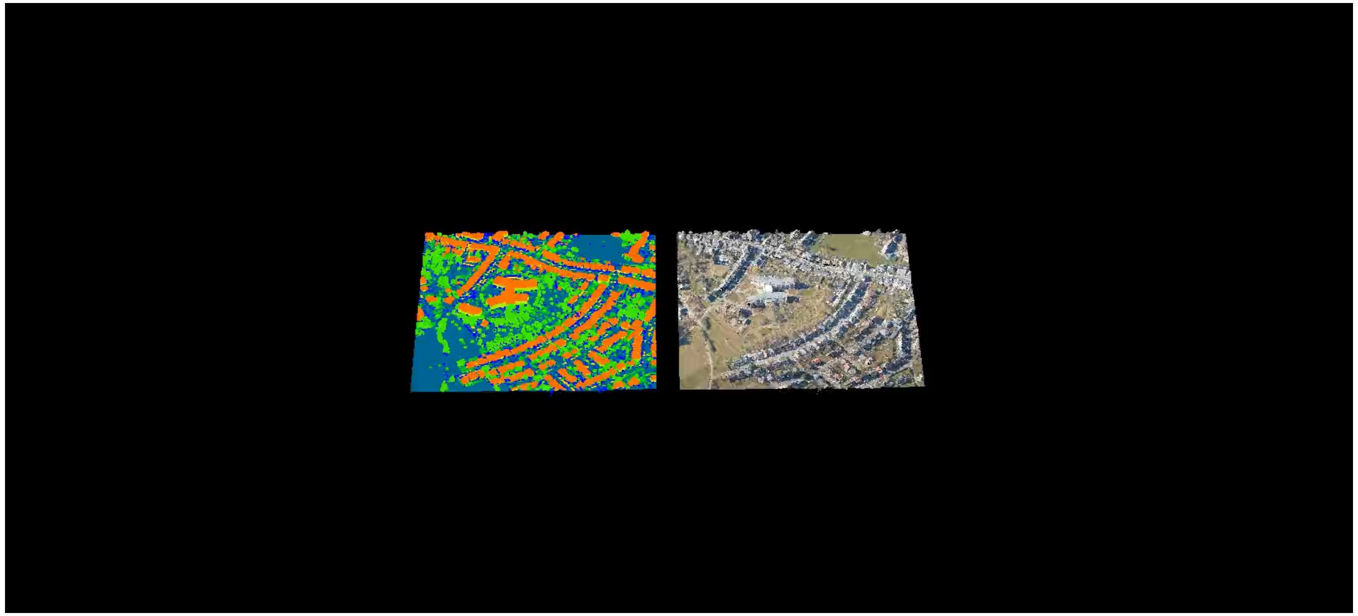


Figure. Semantic segmentation for large scale outdoor scene classification

Robuste Methode zur Erkennung der Gebäudeausmaße

- The building footprint is crucial for a volumetric 3D representation of a building that is applied in urban planning, 3D city modeling, cadastral extraction, topographic map generation, and many more…
- Aerial laser scanning (ALS) has been recognized as the most suitable means of large-scale 3D point cloud data acquisition.
- Besides the presence of noise and outliers, data incompleteness and occlusions are two common phenomena for point clouds.
- Most of the existing methods for building footprint extraction employ classification, segmentation, voting techniques (e.g., Hough-Transform or RANSAC), or Principal Component Analysis (PCA) based methods, but most of them are not free from outlier effects and do not produce good results in the presence of data gaps.

This paper presents a novel algorithm that employs MCMD (maximum consistency within minimum distance), MSAC (a robust variant of RANSAC) and a robust regression to extract reliable building footprints in the presence of outliers, missing points and irregular data distributions. The algorithm is successfully demonstrated through ALS point clouds.

Vorgeschlagene Methode

Step 0: We employ RandLA-Net (a DL) approach to segment/label building points.

Step 1: Vertical surface (e.g., building walls) are separated from non-vertical surfaces (e.g., roofs) using surfaces points slope and height measurements based on MCMD algorithms.

Step 2: Projection of 3D points onto 2D plane, footprint-lines detection from 2D points using robust variant of RANSAC.

Step 3: Footprint-lines refinement using spatial segmentation.

Step 4: Footprint-lines fitting using robust regression.

Step 5: Final footprint extraction.

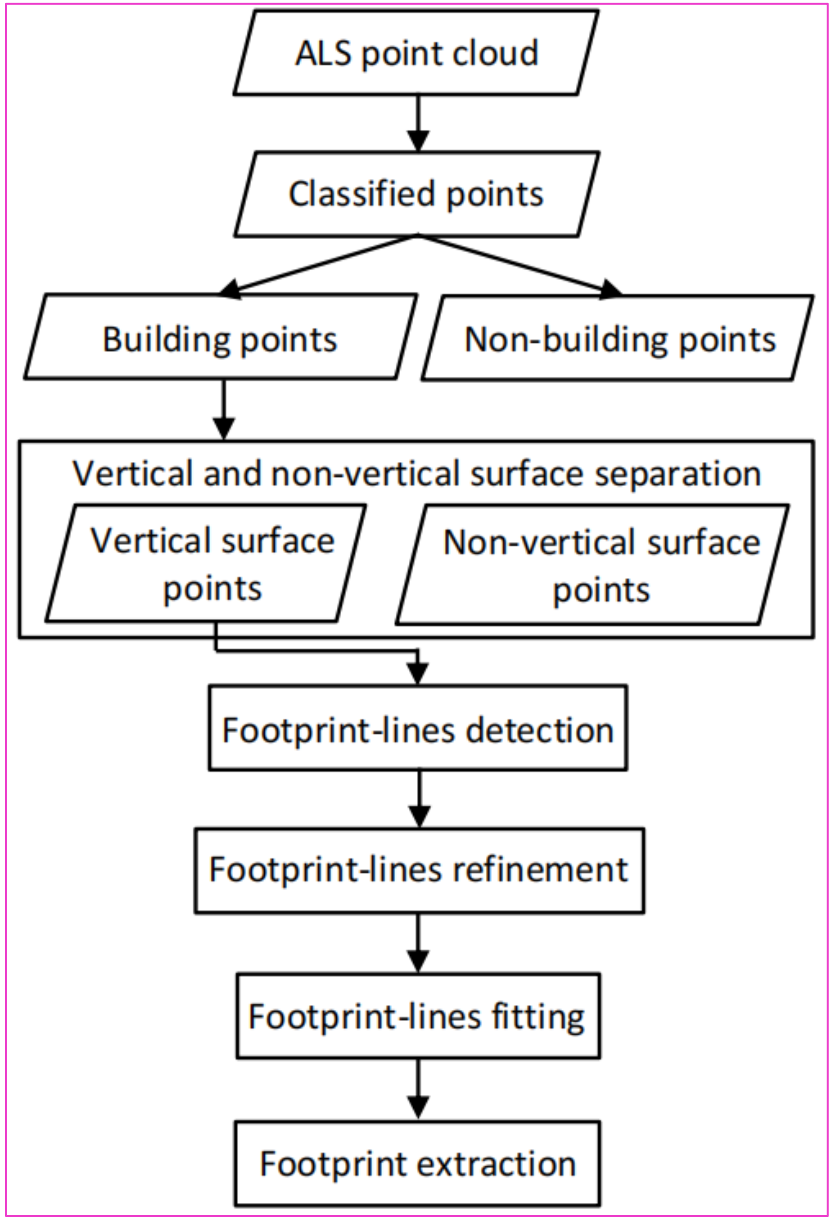


Figure. Flowchart of the proposed algorithm.

Versuch zur Erkennung von Gebäudeausmaßen

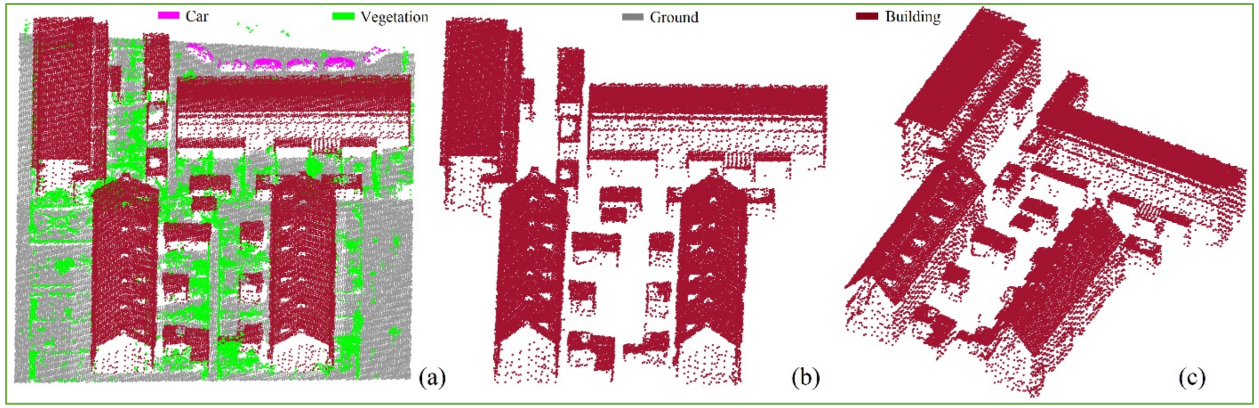
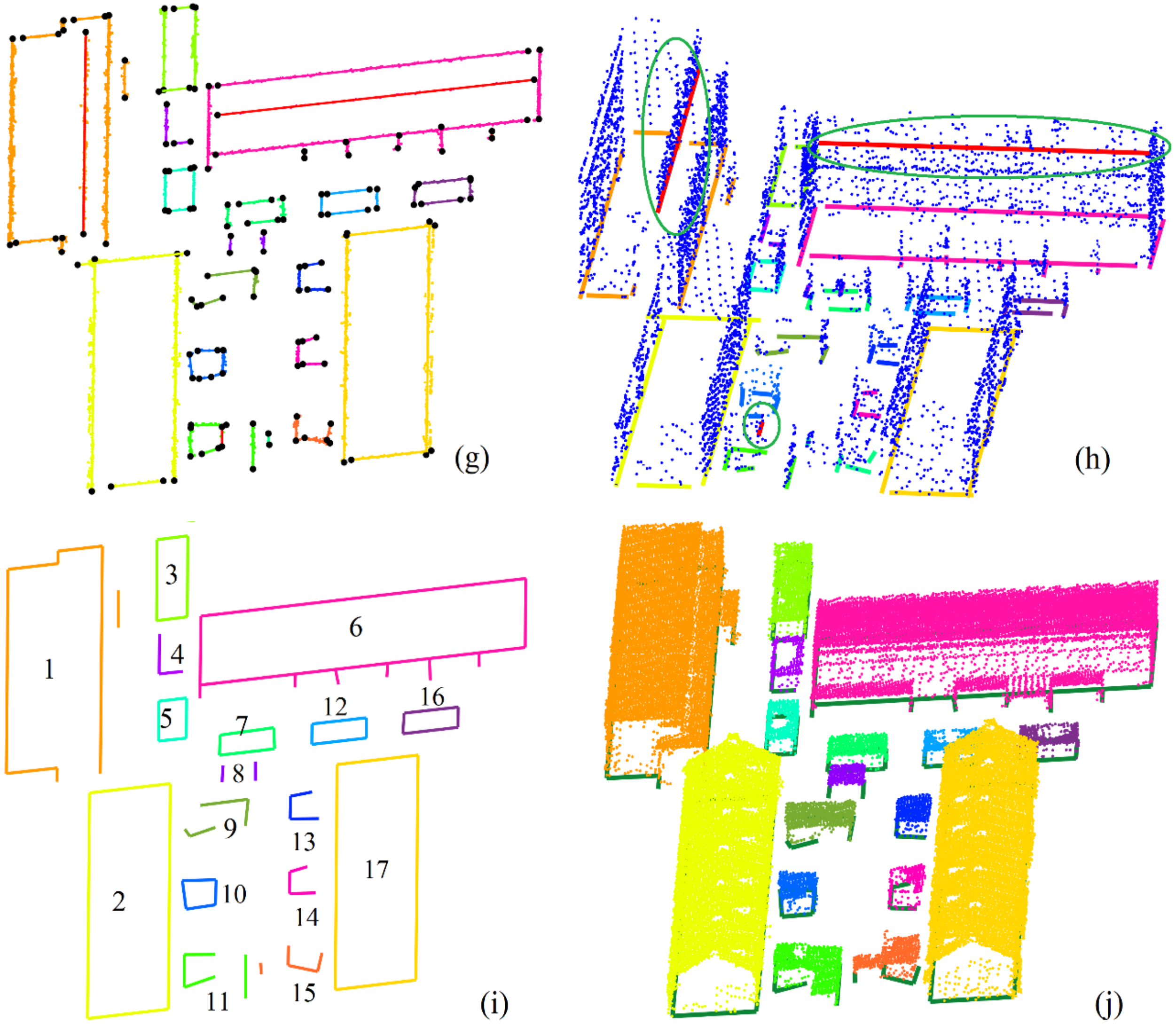


Figure. (a) Labelled AHN data set, (b) front-view of the buildings to extract footprint, (c) side-view of the buildings.



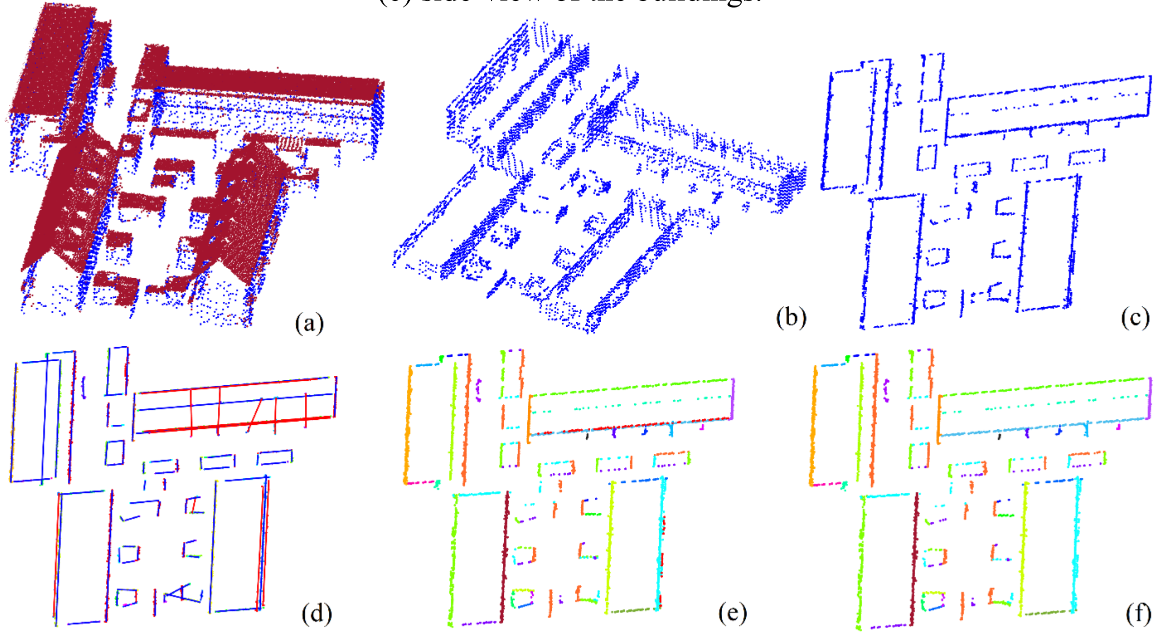


Figure. Building footprints extraction of AHN data set: (a) classification of vertical (blue) and non-vertical (maroon) surfaces, (b) 3D vertical surfaces (facades) below the roofs, (c) 2D (x, y) points for the vertical surfaces, (d) extracted lines using MSAC for the points in plot (c), (e) spatial segmentation for the 2D facades points in plot (d), (f) elimination of redundant/false (red) lines in (e); using $A_t = 5^0$, and nPT=10, (g) LTS regression lines for the points in plot (f); black dots are the end points of the lines, (h) footprint-lines for the buildings in 3D, red lines within the three green ellipses are from the hanging walls that have no ground connection, (i) final footprint-lines for the buildings, and (j) footprint (green)-lines aligned with the 3D buildings in plot (a).

Erkennung von Straßenflächen und Straßeninstallationen von mobilen Laserscanner Daten

- Road surface extraction is crucial for many applications including 3D city analysis and ensuring road safety.
- MLS (vehicle based mobile laser scanning) is the most appropriate mapping system for the road environment.
- Most of the existing methods for road surface extraction use classical approaches that do not relieve problems caused by the presence of noise and outliers.

Investigate problems of road surface extraction in the presence of noise and outliers, and to propose a statistically robust algorithm for road surface elements (road pavement, curb, divider/islands, and sidewalk) extraction using Mobile Laser Scanning (MLS) point clouds.

Vorgeschlagene Methode

Step 1:Slicing the raw point clouds along the road.

Step 2: Filtering ground and non-ground points using weighted robust regression technique.

Step 3: Slicing the stripes from Step 2 into small patches along the road width.

Step 4: Calculation of the range *Rz* of the patches, and find abnormal height values.

Step 5: Decision making using some prespecified criteria to identify road surface categories (components).

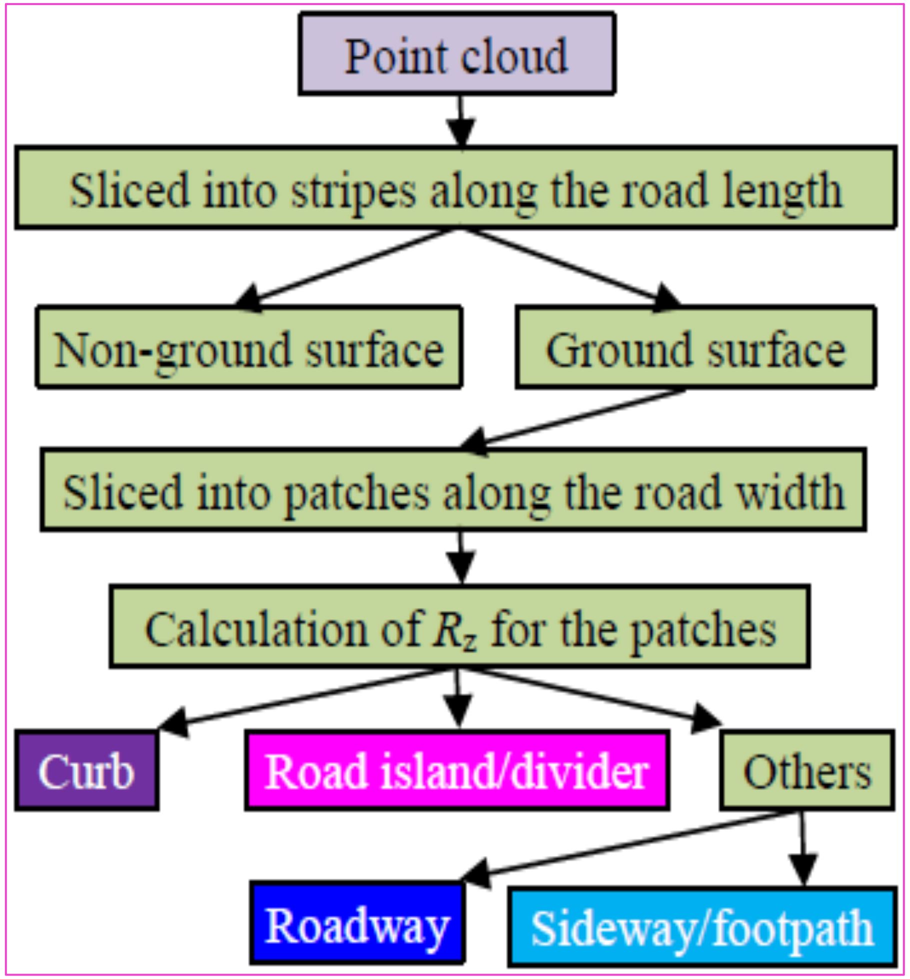


Figure: Workflow for the proposed method. *Rz* is the range of *z* (height) values within a patch points.

Versuch: Erkennung von Straßenflächen und Straßeninstallationen

MLS data:
Length = 53m
Total points: 1,112, 462
Stripes = 106, Patches = 100

Method	Point label	No. of points		Performance metrics		
		GT	D	P (%)	R (%)	MCC
Proposed method	Pavement	707,458	707,400	99.99	99.99	0.999
	Sideway	86,922	86,541	100.00	99.56	0.997
	Curb	14,928	15,346	**97.28**	100.00	**0.986**
Zhao et al. (2021)	Curb	14,928	16,663	**72.61**	81.05	**0.764**

Table. Road surface extraction results. Ground-truth (GT), and detected (D). P, R and MCC are for precision, recall and Matthews correlation coefficient, respectively.

(i) Proposed algorithm extracts road pavement, curb, road divider and sidewalk.

(ii) It produces robust results in the presence of noise and outliers.

(iii) It performs well in the presence of steep slopes, sharp edges, and corners.

(iv) It is successful for both straight and curved roads.

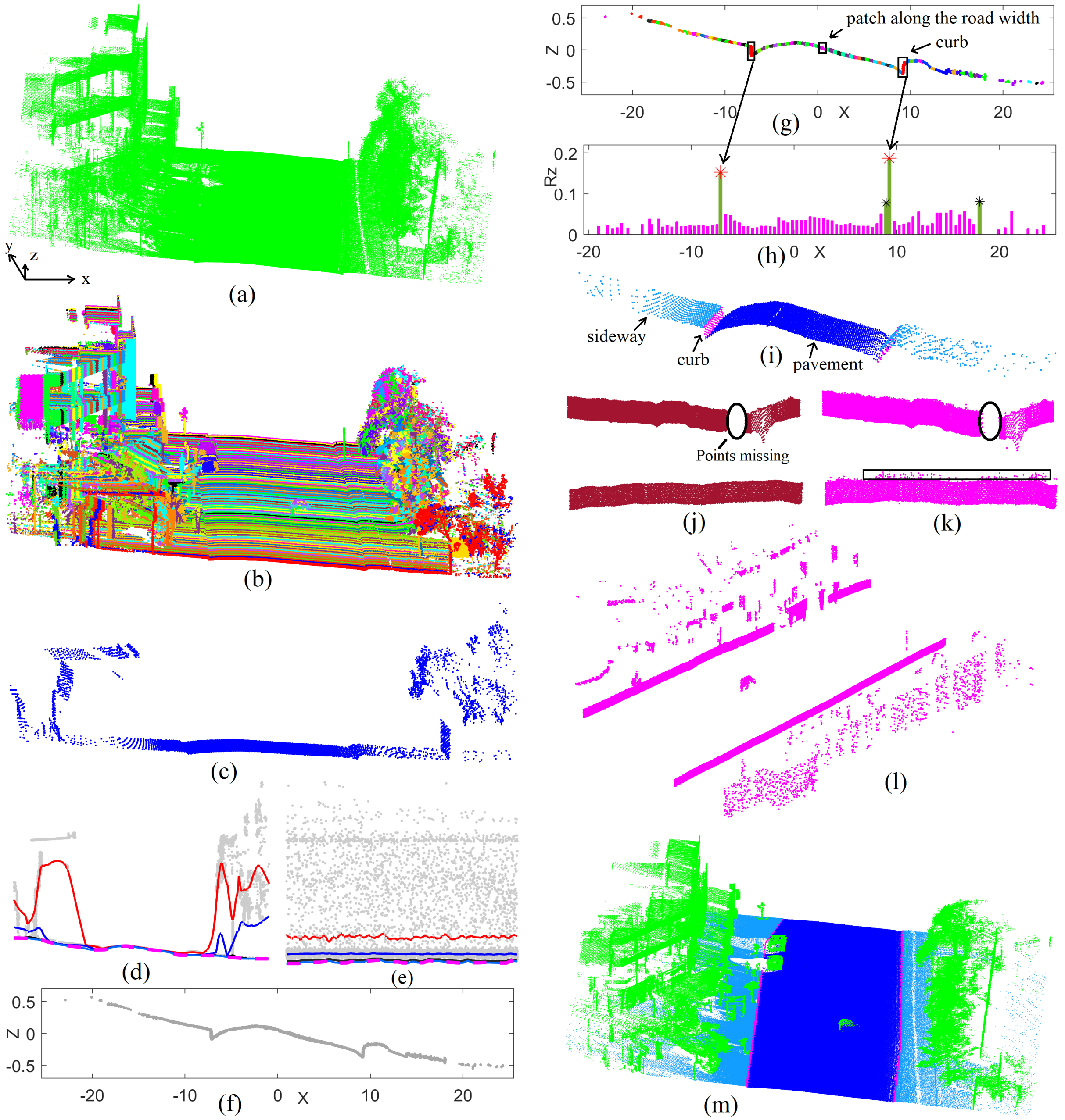
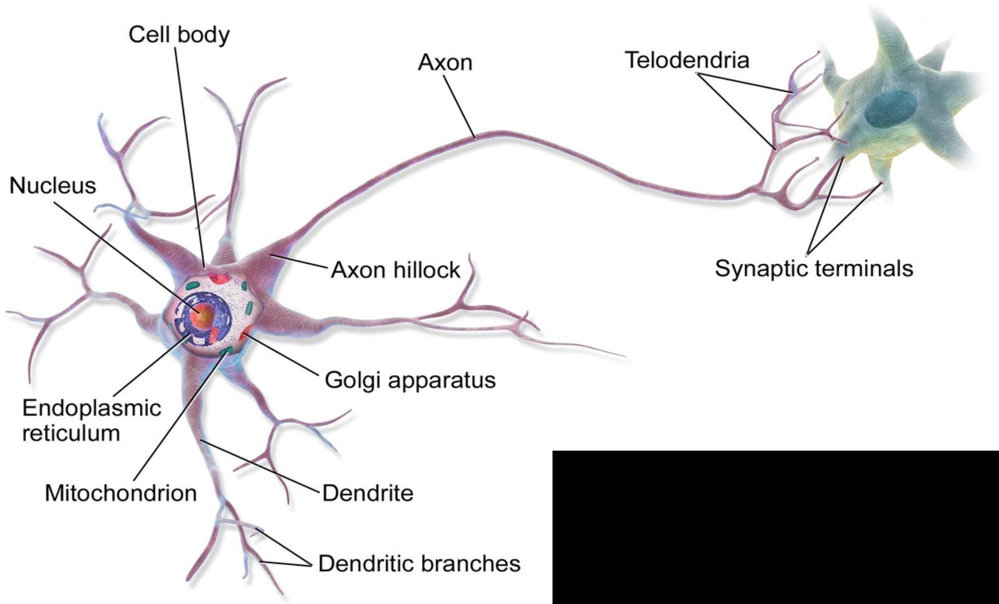
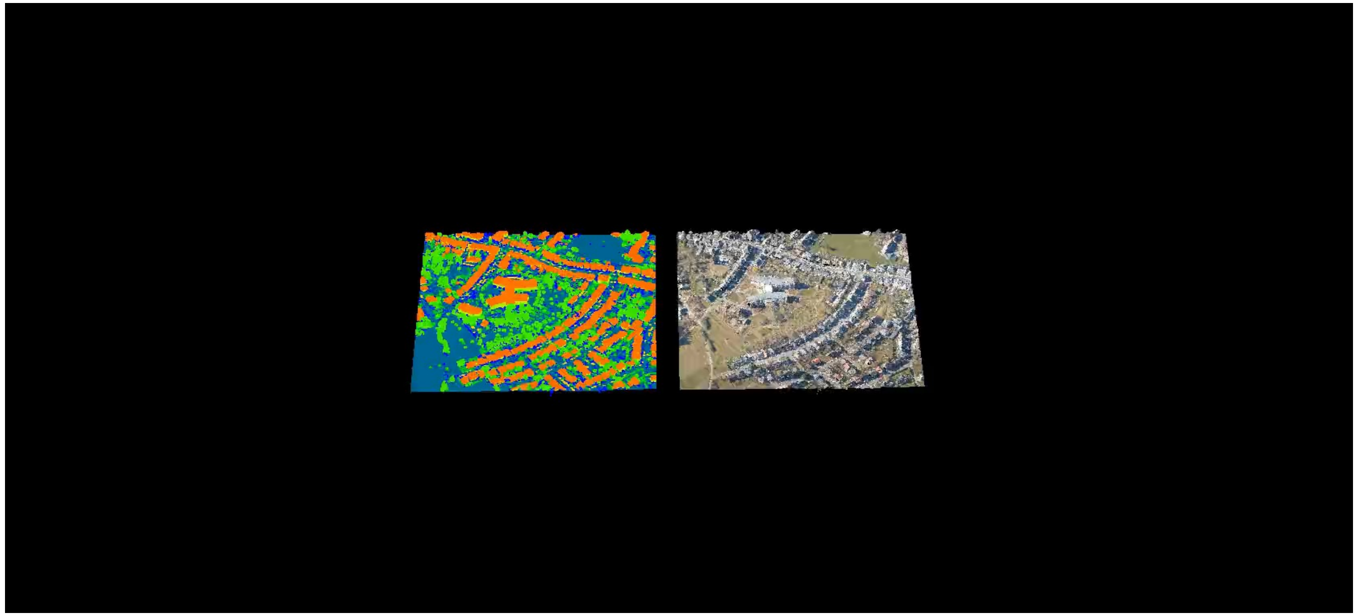
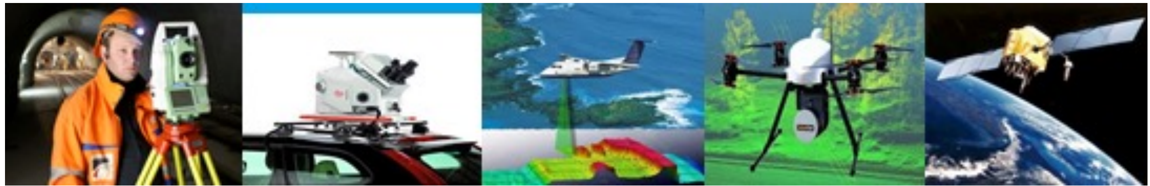


Figure. Road surface extraction: (a) road point cloud, (b) different stripes in different colors, (c) one selected stripe along the road length, (d) iterative fitting for ground filtering using RLWR on the *x*-*z* profile, (e) iterative fitting for ground filtering using RLWR on the *y*-*z* profile , (f) filtered ground points for plot (c), (g) patches along the road width, (h) bar diagram for the R_z values for the patches of plot (g), (i) classified road surface points for plot (c), (j) ground truth curb surface, (k) curb extracted by the proposed method, (l) curb extracted by Zhao et al. (2021), and (m) classified road and non-ground surfaces for the full data set.



Danke für Ihre Aufmerksamkeit!





Published Papers

[1] Nurunnabi, A., Teferle, N., Balado, J., Chen, M., Poux, F., Sun, C., 2022. Robust techniques for building footprint extraction in aerial laser scanning point clouds. This will be presented in *Urban Geoinformatics 2022*, 1-4 November, Beijing, Chaina, and will be published in *The Int Arc Photogramm Remote Sens and Spat Info Sci.*

[2] Nurunnabi, A., Teferle, N., Laefer, D., Remondino, F., Karas, I., Li, J., 2022. *k*CV-B: Bootstrap with Cross-Validation for deep-learning model development, assessment and selection. This will be presented in *The 7th Samart city Applications*, 19-21 October, and will be published in *The Int Arc Photogramm Remote Sens and Spat Info Sci.*

[3] Nurunnabi, A., Lindenbergh, R., Teferle, N., 2022. Deep learning for ground and non-ground surface separation: A feature-based semantic segmentation algorithm for point cloud classification. *GIM International; GIM - Issue 4 - 2022.*

[4] Nurunnabi, A., Teferle, N., Lindenbergh, R., Li, J., Zlatanova, S., 2022. Robust approach for urban road surface extraction using mobile laser scanning 3D point clouds. *The Int Arc Photogramm Remote Sens and Spat Info Sci.,* XLIII-B1-2022, pp. 59-66.

[5] Nurunnabi, A., Teferle, N., 2022. Resampling methods for a reliable validation set in deep learning based point cloud classification. *The Int Arc Photogramm Remote Sens and Spat Info Sci.,* Vol., XLIII-B2-2022, pp. 617-624.

[6] Nurunnabi, A., Teferle, N., Laefer, D., Lindenbergh, R., Hunegnaw, A., 2022. A two-step feature extraction algorithm: application to deep learning for point cloud classification. *The Int Arc Photogramm Remote Sens and Spat Info Sci.*, Vol. XLVI-2/W1-2022, pp. 401-408.

[7] Nurunnabi, A., Teferle, N., Li, J., Lindenbergh, R., Parvaz, S., 2021b, Investigation of PointNet for semantic segmentation of large-scale outdoor point clouds. *The Int Arc Photogramm Remote Sens and Spat Info Sci.*, Vol. XLVI-4/W5-2021-ISPRS TC IV(WG IV-1), pp. 397-404.

[8] Nurunnabi, A., Teferle, N., Li, J., Lindenbergh, R., Hunegnaw, A., 2021a. An efficient deep learning approach for ground point filtering in aerial laser scanning point clouds. *The Int Arc Photogramm Remote Sens and Spat Info Sci.,* Volume XLIII-B1-2021. pp. 31-38.

Two journal papers are nearly completed for journal submission!