Automatic Detection of Urban Trees from LiDAR Data Using DBSCAN and Mean Shift Clustering Methods in Fatih, Istanbul

Zehra Cetin [1], Naci Yastikli [1]

[1] YTU, Civil Engineering Faculty, Dept. of Geomatic Engineering, 34220 Esenler Istanbul, Turkey - zerisir@yildiz.edu.tr, ynaci@yildiz.edu.tr

Keywords: LiDAR, Classification, Segmentation, Machine Learning, DBSCAN, Mean Shift.

Abstract

Trees in green areas offer numerous benefits for the environment and human health. Up-to-date, information about trees in urban green areas is crucial for sustainable urban planning. Traditionally, the detection and inventory of urban trees have been conducted through field surveys and terrestrial measurements. However, this labour-intensive approach can be replaced with the more efficient LiDAR (Light Detection and Ranging) systems, an active remote sensing technology. Urban trees can be quickly and automatically determined using 3-dimensional (3D) LiDAR point cloud data. The objective of this study is to acquire trees in densely populated areas of large cities using raw LiDAR data. The urban study area was chosen in the Fatih district of Istanbul, which includes Sultanahmet Square, a site registered on the UNESCO World Heritage List. To detect urban trees, initially, eight classes representing the ground surface were obtained from LiDAR data with a point-based classification approach which is called hierarchical rule-based classification, and the high vegetation class was separated from the other classes. Noise points, which did not correspond to urban trees within the high vegetation class, were removed using the machine learning-based Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithm. The remaining high vegetation points were subsequently segmented using the machine learning-based Mean Shift clustering algorithm to obtain individual tree crowns. An accuracy assessment was conducted through completeness and correctness analyses, demonstrating the effectiveness of the proposed point-based approach for the automatic detection of urban trees from LiDAR data. According to the proposed Mean Shift clustering approach, the completeness was 60% and the correctness was 77.42% in test area A, while in test area B, the completeness was 62.30% and the correctness was 80.85%. The much higher completeness (78.26%) and correctness (100%) values were obtained for street trees with regular structure in test area B in comparison with the proposed Mean Shift clustering approaches.

1. Introduction

Urban trees, which are the most dominant element of green areas in cities, are of great importance for urban ecology. In addition to their critical effects such as improving air, water, and land quality; preventing noise, dust, gas, and wind damage; maintaining soil and water balance; reducing carbon accumulation; saving energy; and climate control, urban trees are fundamental elements of urban landscapes due to their socio-cultural (monumental trees, endemic species, etc.), aesthetic, and psychological functions (Pu and Laundry, 2012; Tigges et al., 2013; Li et al., 2014; Mustafa et al., 2015; Dian et al., 2016; Shojanoori et al., 2016). Besides their numerous positive effects, some urban trees can cause negative effects such as causing allergic reactions due to pollen (Xu et al., 2016), creating environmental pollution, damaging urban structures and historical texture due to excessive rooting, and disrupting the silhouette of cities due to excessive branching and growth. The tree culture in cities is one of the main activity areas for local governments in the planning of sustainable cities. Detailed and accurate information about trees is of great importance for local governments in activities such as disaster management, environmental protection, urban development policy creation, geographic information system applications, or 3D city model production (Iovan et al., 2008). In order to fulfil the functions expected from trees, actions such as planning and managing afforestation efforts must be carried out in accordance with the appropriate techniques. Therefore, first of all, the current situation of urban trees must be known well (Mustafa et al., 2015, Wallace et al., 2021).

The identification of urban trees and inventory studies are traditionally carried out by experts through fieldwork and terrestrial measurements (Wallace et al., 2021). However, fieldwork and measurements for identifying trees are timeconsuming, expensive, and often do not cover large areas comprehensively. Although using aerial photographs or satellite remote sensing images, which have the advantage of collecting data over a large area simultaneously, has emerged as an alternative method for identifying urban trees, these methods also have some limitations due to the vertical structure and complex crown structures of the trees (Pu, 2009; Pu and Landry, 2012; Moradi et al., 2016).

Today, LiDAR (Light Detection and Ranging), an active remote sensing laser technology, provides a significant advantage over field measurements and many other remote sensing technologies in urban tree identification and inventory studies due to its detailed 3D location data (Cao et al., 2016). LiDAR enables automatic, fast and cost-effective collection of 3D point cloud data of urban trees without the need for field studies (Wu et al., 2013). The ability of LiDAR to directly provide threedimensional information, its high capability to receive multiple return signals from vegetation, and its ability to collect intensity data have made LiDAR data a significant alternative to aerial photographs and satellite imagery (Moradi et al., 2016).

Accurate individual tree segmentation is an important basis for many applications that involve trees. In recent years, significant advancements have been observed in tree detection and segmentation (Xie et al., 2019; Wan et al., 2023; Li et al., 2023). While many individual tree segmentation methods have been developed, it remains a challenging task especially for LiDAR data (Yang et al., 2020). Selecting an appropriate algorithm for individual tree segmentation is very important for accurate tree detection results. Summaries and comparisons of some existing methods for segmenting individual trees can be found in Kaartinen et al. (2012) and Eysn et al. (2015). A major drawback of many segmentation methods is the loss of information caused by interpolating the initial 3D point cloud into a grid structure (Vega et al. 2014; Yastikli and Cetin, 2021; Cetin and Yastikli, 2023).

In this study, it is aimed to automatically detect urban trees in densely populated areas from 3D raw LiDAR point cloud data. To this end, firstly, a point-based classification approach, called hierarchical rule-based classification, is proposed for automatic classification of point cloud to obtain ground, low vegetation, medium vegetation, high vegetation, building, low point, air point and default classes. The high vegetation class has been separated from other classes, and noise points that do not belong to urban trees within this class have been removed using the machine learning-based Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithm. In the next step, a point-based segmentation approach using the machine learning-based Mean Shift clustering algorithm has been proposed to obtain individual tree crowns from high vegetation points. Finally, an accuracy assessment has been conducted using completeness and correctness analyses to evaluate the performance of the proposed point-based approach for the automatic detection of urban trees from LiDAR data.

Figure 1. Urban study area, Sultanahmet, Istanbul (2013).

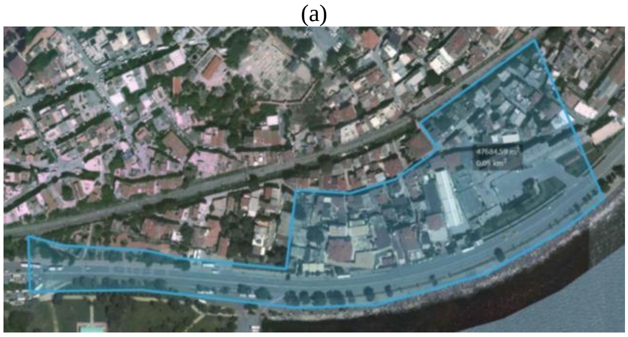
2. Study Area and Dataset

Sultanahmet, situated in the Fatih district of Istanbul and registered on the UNESCO World Heritage List, was chosen as the urban study area (Figure 1). Sultanahmet is a very dense urban area with several complex structures, roads, pavements, trees, etc. Test area A and test area B were used to obtain individual urban trees in the dense urban study area (Figure 2).

LiDAR data, obtained from the Istanbul Metropolitan Municipality and acquired in September 2013, was used for this study. The LiDAR data was obtained with a "Riegl LSMQ680i" laser scanner, which mounted on an "Eurocopter AS350" helicopter. The used full-waveform LiDAR data is in Log ASCII Standard (LAS format) with an average point density of 16 points/m².

Trees obtained using field measurements and panoramic street views of 2013 were taken as reference data. For the reference data collection in the field, a data collection application was developed using the API library provided by the Istanbul Metropolitan Municipality City Map for all users. On the frontend, the City Map API was used, while the back-end utilized the Django and NGINX web application frameworks.

(a)



(b)

Figure 2. Test area A (a) and test area B (b) in urban study area.

3. Materials and Methods

In this study, the point-based processing steps in order to obtain individual urban trees are divided into two groups as classification and segmentation (Figure 3).

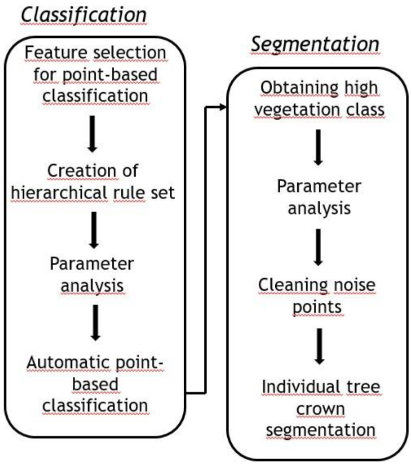


Figure 3. Point-based processing steps to obtain individual urban trees.

3.1 Point-based Classification

Point-based classification methods which use LiDAR points aim to assign an object class to each individual laser point (Yastikli and Cetin 2016). Various point-based classification techniques including both machine learning- and rule-based approaches are available for classifying LiDAR point clouds (Cetin and Yastikli, 2023). In the rule-based classification algorithms, terrain surface information is converted into a series of rules (Mehta et al. 2014, Gevaert et al. 2018). Classification is then carried out based on these predefined sequential rules (Cetin and Yastikli, 2022). The classification rules are created with different classification features according to terrain characteristics such as height features, eigenvalues, surfacebased features, local plane features, multiple returns features, echo amplitude, echo width, etc. which are calculated for all individual LiDAR points (Chehata and Bretar, 2008; Mallet et al., 2011; Kim and Sohn, 2013).

In this study, the proposed hierarchical rule-based classification of LiDAR point cloud was performed to obtain high vegetation points. A hierarchical rule set was created using the selected geometric features for point-based classification, and after conducting parameter analysis, the ground, low, medium, and high vegetation, building, low point, air point, and default classes were obtained using the defined parameters (Table 1). The high vegetation class was separated from the other classes. The point-based classification was conducted using TerraScan module of Terrasolid software.

Point-based classification	
Rules	**Classes**
By class	Default
Low points	Low point
Ground	Ground
Below surface	Low point
Air points	Air point
By height from ground 1	Ground
By height from ground 2	Low vegetation
By height from ground 3	Medium vegetation
By height from ground 4	High vegetation
Building	Building
By height from ground 5	Air point
Multiple returns	Building

Table 1. Hierarchical rule set and obtained classes.

3.2 Point-based Segmentation

Point-based segmentation approaches divide data into groups by using the individual characteristics of the points. Point-based methods primarily segment data based on geometric features (Che et al., 2019). Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Mean Shift, which are unsupervised machine learning clustering methods, can be used in point-based segmentation applications. The DBSCAN algorithm evaluates points within a specified neighbourhood around a random point and initiates a cluster if there is sufficient density of points in that neighbourhood. Otherwise, the point is labelled as noise (Nasiboglu et al. 2019). Mean Shift clustering, a widely used segmentation method, is a nonparametric, iterative technique that shifts each data point according to the local maximum density function (Wen and Cai, 2006). The Mean Shift algorithm begins by selecting a random point from the dataset as the initial cluster center (Du et al., 2019), and then updates the cluster center candidates to be the average of the points within a specified region.

After the point-based classification of the LiDAR data with hierarchical rule-based classification method, noise points, which did not correspond to urban trees within the high vegetation class, were removed using DBSCAN clustering algorithm. The LiDAR points remaining in the high vegetation class were segmented with the widely used Mean Shift clustering algorithm. The Mean Shift segmentation process was performed after a thorough parameter analysis to achieve the best segmentation results. The 2D tree segmentation, aimed at detecting individual urban trees, was implemented using the Python programming language (Python 3.6.4) in Jupyter Notebook.

3.3 Accuracy Assessment

Accuracy assessment is an important part of information extraction applications and determines the quality of the resulting products. In this study, the accuracy assessment of the proposed segmentation methods was conducted based on detection rates, which is completeness and correctness analyses. The equations for completeness and correctness are given as follows:

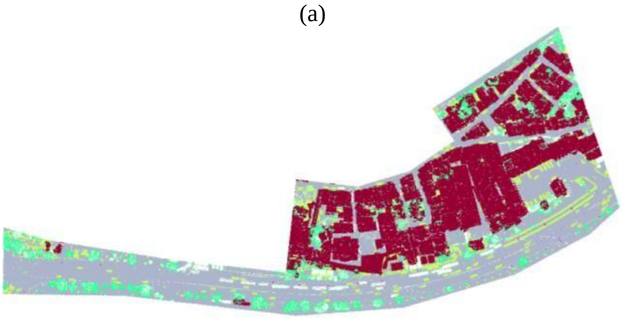
$$\text{Completeness} = (TP)/(TP+FN) \tag{1}$$
$$\text{Correctness} = (TP)/(TP+FP) \tag{2}$$

TP (True Positive), FP (False Positive), and FN (False Negative) represent perfect segmentation, over segmentation, and under-segmentation, respectively (Li et al., 2012; Cetin and Yastikli, 2023). TP refers to the entities that were correctly segmented, FP denotes the entities that appeared in the segmentation but do not correspond to any entity in the ground truth data, and FN refers to the entities present in the ground truth data but not identified in the segmentation process (Yastikli and Cetin, 2020; Cetin and Yastikli, 2023).

4. Result and Discussion

The automatic 3D point-based classification results of the LiDAR point cloud in the test area A and test area B, based on geometric features within the hierarchical rule set (see Table 1), are shown in Fig. 4. The high vegetation points, separated from the other terrain classes, are displayed in Fig. 5. It is clear from the classification results (see Fig. 4 and Fig. 5) that the high vegetation points are accurately identified for tree crown segmentation of individual trees in the urban study area.

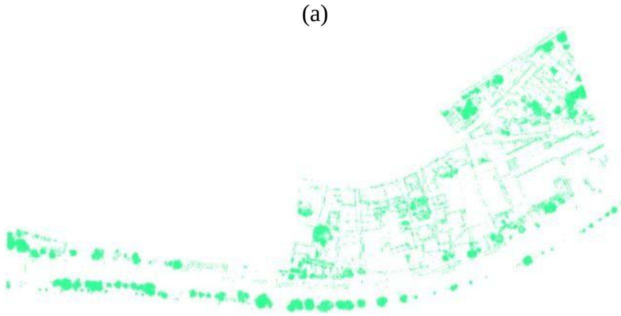
(a)



(b)

Figure 4. Classification result of test area A (a) and test area B (b) with hierarchical rule set.

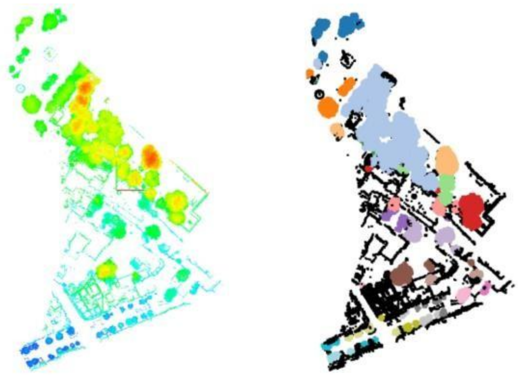
(a)



(b)

Figure 5. High vegetation points in test area A and test area B.

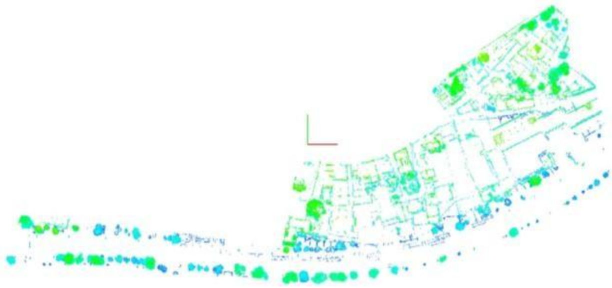
The results of removing noise points, which do not belong to urban trees in the high vegetation class, using the machine learning-based DBSCAN clustering algorithm are provided for test area A and test area B in Fig. 6 and Fig. 7, respectively. After the removal of noise points, the 2D segmentation results of individual tree crowns in the high vegetation class, obtained using the Mean Shift clustering algorithm, are given in Fig. 8 and Fig. 9 for test area A and test area B, respectively.



(a) (b)

Figure 6. The noisy high vegetation points color-coded by height (a), and the noise points (in black) and the remaining high vegetation points (b) in test area A.

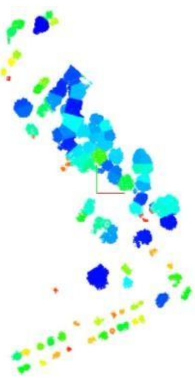
https://doi.org/10.5194/isprs-archives-XLVIII-M-6-2025-95-2025

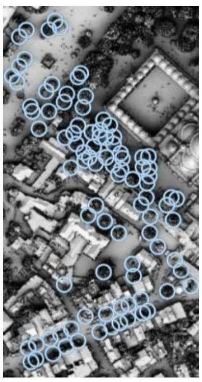


(a)

(b)

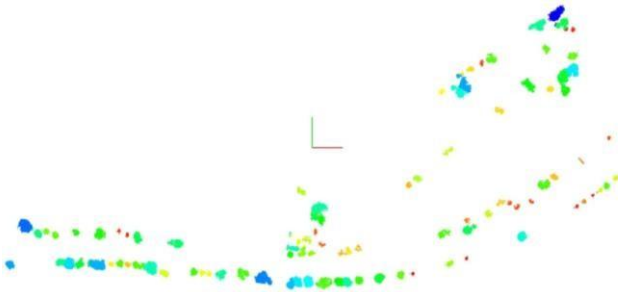
Figure 7. The noisy high vegetation points color-coded by height (a), and the noise points (in black) and the remaining high vegetation points (b) in test area B.



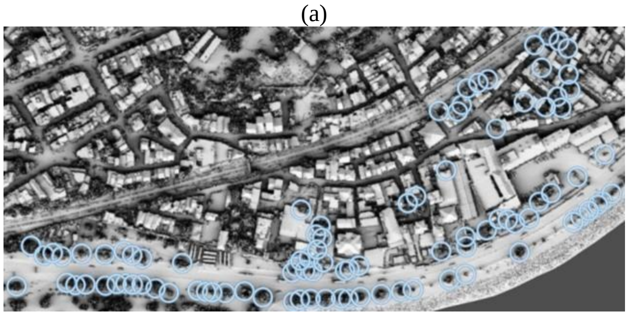


(a) (b)

Figure 8. Individual urban trees segmented using the Mean Shift clustering algorithm (a) and Individual urban trees overlaid with grayscale DSM (b) in test area A



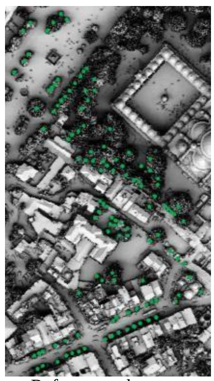
(a)

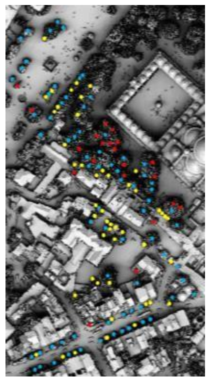


(b)

Figure 9. Individual urban trees segmented using the Mean Shift clustering algorithm (a) and individual urban trees overlaid with grayscale DSM (b) in test area B.

In Fig. 10 and Fig. 11, the reference urban trees, along with the TP, FP, and FN values obtained using the Mean Shift clustering algorithm, are presented as the results of the accuracy assessment for the detected trees in Test Area A and Test Area B, respectively. In addition, the reference urban street trees, along with the TP, FP, and FN values obtained using the Mean Shift clustering algorithm, are presented for the detected street trees in Test Area B in Fig. 12.





Reference urban trees TP FP FN

(a) (b)

Figure 10. Reference urban trees (a) and TP, FP, and FN trees (b) overlaid with grayscale DSM in test area A.

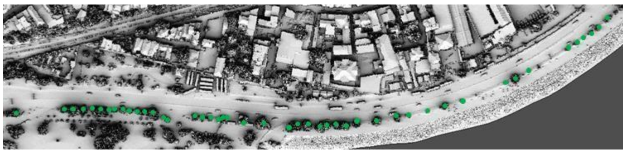
● Reference urban trees

(a)

● TP ● FP ● FN

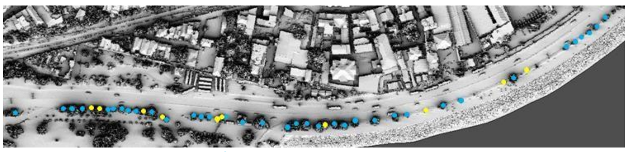
(b)

Figure 11. Reference urban trees (a) and TP, FP, and FN trees (b) overlaid with grayscale DSM in test area B.



● Reference urban trees

(a)



● TP ● FP ● FN

(b)

Figure 12. Reference urban street trees (a) and TP, FP, and FN street trees (b) overlaid with grayscale DSM in test area B.

In test area A, 72 clusters were correctly segmented as individual urban trees (TP), 21 clusters were incorrectly identified as individual urban trees (FP), and 48 urban trees could not be segmented as individual tree clusters (FN) using the Mean Shift segmentation. Based on this, the completeness was 60% and the correctness was 77.42% according to the Mean Shift segmentation in test area A (Table 2). The completeness value was relatively lower than the correctness value due to the segmentation of overlapping, complex crownshaped trees as single trees using the proposed segmentation approach in test area A.

76 clusters were correctly segmented as individual urban trees (TP), 18 clusters were incorrectly identified as individual urban trees (FP), and 46 urban trees could not be segmented as individual tree clusters (FN) using the Mean Shift segmentation in test area B. The results of the segmentation were 62.30% completeness and 80.85% correctness for Mean Shift clustering algorithm (Table 2). Similar to the results in test area A, the completeness value is lower than the correctness value in test area B.

In test area B – street trees, 36 clusters were correctly segmented as individual urban street trees (TP), no clusters were incorrectly identified as individual urban street trees (FP), and 10 urban street trees could not be segmented into individual tree clusters (FN) using the Mean Shift clustering algorithm. The completeness was 78.26% and the correctness was 100% according to the Mean Shift segmentation in test area B – street trees (Table 2). In the case of street trees with a discrete, regular structure, the completeness value is lower than the correctness value. However, both the completeness and correctness values are significantly higher than those in test area A and B.

	Mean Shift Segmentation	
	Completeness	**Correctness**
Test area A	60%	77,42%
Test area B	62,30%	80,85%
Street trees in Test area B	78,26%	100%

Table 2. Completeness and correctness values.

5. Conclusion

In this study, an approach has been proposed for the automatic detection of urban trees using airborne LiDAR data. Raw LiDAR point cloud data has been classified using a point-based classification method with hierarchical rules. Noise points in the high vegetation class, which do not correspond to urban trees, were removed using the DBSCAN clustering algorithm. In test area A and test area B, high vegetation points, cleared of noise, were segmented using the Mean Shift clustering approach to obtain individual urban trees. An accuracy assessment has been performed based on the detection rate of individual urban trees.

In test area A, the completeness was 60% and the correctness was 77.42% according to the Mean Shift clustering approach. The completeness was 62.30% and the correctness was 80.85% in test area B according to the Mean Shift clustering approach. Finally, the completeness was 78.26% and the correctness was 100% according to the Mean Shift clustering approach in test area B – street trees. Due to the segmentation of overlapping, complex crown-shaped trees as single trees using the proposed segmentation approach, the completeness values were relatively lower than the correctness values. However, in the case of street trees with a discrete, regular structure, both the completeness and correctness values are quite high. For better results, different features can be used during the segmentation of individual urban trees, or different clustering algorithms can be tested. The urban trees obtained with the proposed approach can be easily used in various studies, such as disaster management, urban planning, environmental protection, or urban development policy formulation.

Acknowledgements

This study was supported by Yıldız Technical University Scientific Research Projects Coordination Unit (YTU BAP) within the scope of the project titled “Parameter Analysis and Optimum Classification Feature Detection in Automatic Detection of Tree species by Machine Learning Using LiDAR Data (Project No: FBA-2023-5425)”.

References

Cao, L., Coops, N., Innes, J.L., Dai, J., Ruan, H., She, G., 2016. Tree species classification in subtropical forests using smallfootprint full-waveform LiDAR data. *Int. J. Appl. Earth Obs.*, 49, 39–51.

Che, E., Olsen, M.J., Parrish, C.E., Jung, J., 2019. Pavement marking retro-reflectivity estimation and evaluation using mobile lidar data. *Photogramm. Engr. Remote Sens.*, 85(8), 573583.

Chehata, N., Bretar, F., 2008. Terrain modelling from lidar data: hierarchical K-means filtering and Markovian regularization. *15th IEEE International Conference on Image Processing*, 1900-1903, San Diego, CA.

Chehata, N., Guo, L., Mallet, C., 2009. Airborne LiDAR Feature Selection For Urban Classification Using Random Forests. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, 39 (Part 3/W8), 207–212.

Cetin, Z., Yastikli, N., 2022. The Use of Machine Learning Algorithms in Urban Tree Species Classification. *ISPRS Int. J. Geo-Inf.*, 11, 226.

Cetin, Z., Yastikli, N., 2023. Automatic detection of single street trees from airborne LiDAR data based on pointsegmentation methods. *International Journal of Engineering and Geosciences*, 8(2), 129-137.

Dian, Y., Pang, Y., Dong, Y., Li, Z., 2016. Urban tree species mapping using airborne LiDAR and hyperspectral data. *Journal of the Indian Society of Remote Sensing*, 1–9, 2016.

Du, Y., Sun, B., Lu, R., Zhang, C., Wu, H., 2019. A method for detecting highfrequency oscillations using semi-supervised Kmeans and mean shift clustering. *Neurocomputing*, 350, 102-107.

Eysn L., Hollaus M., Lindberg E., Berger F., Monnet J.M., Dalponte M., Kobal M., Pellegrini M., Lingua E., Mongus D., Pfeifer, N., 2015. A benchmark of lidar-based single tree detection methods using heterogeneous forest data from the alpine space. *Forests*, 6(5), 1721-1747.

Gevaert, C.M., Persello, C., Nex, F.C., Vosselman, G., 2018. *A Deep Learning Approach to DTM Extraction from Imagery Using Rule-Based Training Labels. ISPRS J. Photogramm. Remote Sens.*, 142, 106–123.

Iovan, C., Boldo, D., Cord, M., 2008. Detection, Characterization, and modeling vegetation in urban areas from high-resolution aerial imagery. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, 1(3), 206-213.

Kaartinen H., Hyyppä J., Yu X., Vastaranta M., Hyyppä H., Kukko A., Holopainen M., Heipke C., Hirschmugl M., Morsdorf F., Næsset, E., Pitkänen, J., Popescu, S., Wolf, B. M., Wu, J., 2012. An international comparison of individual tree detection and extraction using airborne laser scanning. *Remote Sens.*, 4(4), 950-974.

Kim, H.B., Sohn, G., 2013. Point-Based Classification of Power Line Corridor Scene Using Random Forests. *Photogramm. Engr. Remote Sens.*, 79, 821–33.

Li, D., Ke, Y., Gong, H., Chen, B., Zhu, L., 2014. Tree species classification based on WorldView-2 imagery in complex urban environment. *Third International Workshop on Earth Observation and Remote Sensing Applications (EORSA)*, 326330.

Li, R., Sun, G., Sheng, W., Tan, T., Xu, F., 2023. Tree trunk detection in urban scenes using a multiscale attentionbased deep learning method. *Ecological Informatics*, 77.

Li, W., Guo, Q., Jakubowski, M., Kelly, M., 2012. A New Method for Segmenting Individual Trees from the Lidar Point Cloud. *Photogramm. Engr. Remote Sens.*, 78, 75-84.

Mallet, C., Bretar, F., Roux, M., Soergel, U., Heipke, C., 2011. Relevance Assessment of Full-Waveform Lidar Data For Urban Area Classification. *ISPRS J. Photogramm. Remote Sens.*, 66(6), 71–S84.

Mehta, A., Dikshit, O., Venkataramani, K., 2014. Integration of high-resolution imagery and LiDAR data for object-based classification of urban area. *Geocarto Int.*, 29, 418–432.

Moradi, A., Satari, M., Momeni, M., 2016. Individual Tree of Urban Forest Extraction from Very High Density LiDAR Data. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLI-B3, 337–343.

Mustafa, Y.T., Habeebb, H.N., Steinc A., Sulaimanb, F.Y., 2015. Identification and Mapping of Tree Species in Urban Areas Using WORLDVIEW-2 Imagery. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 175-181.

Nasiboglu, R., Tezel, B.T., Nasibov, E., 2019. Learning the stress function pattern of ordered weighted average aggregation using DBSCAN clustering. *International Journal of Intelligent Systems*, 34, 477-492.

Pu, R., 2009. Broadleaf species recognition with in situ hyperspectral data. *Int. J Remote Sens.*, 30, 2759–2779.

Pu, R., Landry, S., 2012. A comparative analysis of high spatial resolution IKONOS and WorldView-2 imagery for mapping urban tree species. *Remote Sens. Environ.*, 124, 516–533.

Shojanoori, R., Shafri, H.Z.M., Mansor, S., Ismail, M.H., 2016. The Use of WorldView-2 Satellite Data in Urban Tree Species Mapping by ObjectBased Image Analysis Technique. *Sains Malaysiana*, 45(7), 1025–1034.

Tigges, J., Lakes, T., Hostert, P., 2013. Urban vegetation classification:Benefits of multitemporal RapidEye satellite data. *Remote Sens. Environ.*, 136, 66-75.

Wallace, L., Sun, C., Hally, B., Hillman, S., Both, A., Hurley, J., San Martin Saldias, D., 2021. Linking urban tree inventories to Remote Sensing Data for individual tree mapping. *Urban Forestry and Urban Greening*, 61. 127106.

Wan, H., Fan, Z., Yu, X., Kang, M., Wang, P., Zeng, X., 2022. A real-time branch detection and reconstruction mechanism for harvesting robot via convolutional neural network and image segmentation. *Comput. Electron. Agricult.*, 192, 106609.

Wen, Z.Q., Cai, Z.X., 2006. Mean shift algorithm and its application in tracking of objects. *Proceedings of 5th*

International Conference on Machine Learning and Cybernetics, Dalian, 4024-4028.

Wu, B., Yu, B., Yue, W., Shu, S., Tan, W., Hu, C., Huang, Y., Wu, J., Liu, H., 2013. A Voxel-Based Method for Automated Identification and Morphological Parameters Estimation of Individual Street Trees from Mobile Laser Scanning Data. *Remote Sens.*, 2013(5), 584-611.

Xie, Q., Li, D., Yu, Z., Zhou, J., Wang, J., 2019. Detecting trees in street images via deep learning with attention module. *IEEE Trans. Instrum. Meas.*, 69, 5395–5406.

Xu, J., Cai, Z., Wang, T., Liu, G., Tang, P., Ye, X., 2016. Exploring Spatial Distribution of Pollen Allergenic Risk Zones in Urban China. *Sustainability*, 8, 978.

Vega, C., Hamrouni, A., El Mokhtari, S., Morel, J., Bock, J., Renaud, J.P., Bouvier, M., Durrieu, S., 2014. Ptrees: A Point-Based Approach to Forest Tree Extraction from Lidar Data. *Int. J. Appl. Earth Obs. Geoinf.*, 33, 98–108.

Yang, J., Kang, Z., Cheng, S., Yang, Z.,. Akwensi, P.H., 2020. An Individual Tree Segmentation Method Based on Watershed Algorithm and Three-Dimensional Spatial Distribution Analysis From Airborne LiDAR Point Clouds. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, 13, 1055-1067.

Yastikli, N., Cetin, Z., 2016. Classification of LiDAR data with point based classification methods. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, 41(B3), 441–445.

Yastikli, N., Cetin, Z., 2020. Detection of Individual Trees in Urban Areas Using the Point Cloud Produced by Dense Image Matching Algorithms. *In Proceedings of the FIG Working Week 2020*, Amsterdam, The Netherlands.

Yastikli, N., Cetin, Z., 2021. Classification of raw LiDAR point cloud using point-based methods with spatial features for 3D building reconstruction. *Arabian Journal of Geosciences*, 14, 146.