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# Predictive Maintenance in Tree Care - TreeAngel

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**Abstract.** Ensuring the traffic safety of trees poses a significant challenge for urban authorities. Conventional manual inspection methods are both time-consuming and resource-intensive, and they are subject to human error. The following paper presents an innovative system for automated tree condition assessment using modern camera technologies and artificial intelligence (AI). As part of a feasibility study, image data generated by various camera systems was analyzed. Based on this data, a YOLOv8 model was trained, which enables precise detection of trees and damage, such as deadwood. The results of the prototype system presented are promising in terms of accuracy and efficiency, suggesting the potential to supplement or replace manual inspections with automated procedures. The results of this study lay the foundation for sustainable and scalable approaches in tree care and can contribute to increasing public safety and efficiency in urban management.

**Keywords:** Predictive Maintenance, Machine Learning, YOLO, Tree Care

## 1. Introduction

The maintenance of comprehensive tree inventories constitutes a pivotal aspect of public safety and environmental management in urban and municipal contexts. The meticulous compilation of detailed tree information in both urban and rural areas is imperative for the establishment of comprehensive tree registers, encompassing the geographical location, species, age, and health status of the trees. This comprehensive data holds significant value not only for effective green space management and urban planning, but also for ensuring road safety. Damage to trees, such as deadwood or unstable branches, harbors potential dangers that need to be minimized. The challenges in tree cadastre management are increasing considerably due to climate change [1]. More frequent storms and extreme weather events put tree populations under increased stress [2], [3] and increase the risk of damage from falling branches or toppling trees. This requires early identification and repair of the damage or proactive pruning for maintenance to ensure the safety of people and infrastructure. Conventionally, tree monitoring has been performed manually through regular and visual inspections, a process that is both time-consuming and resource-intensive, and subject to human error. Concurrently, staff shortages and mounting cost pressures exacerbate the challenges associated with manual tree monitoring. Traditional methods are reaching their limits due to their high resource requirements and inherent human error. Emerging digital technologies offer a promising solution to address these challenges, enabling efficient and seamless support. Modern technologies, such as artificial intelligence (AI) and automated image processing, hold particular promise in this regard [4], [5]. These technologies facilitate the efficient and reliable detection of damage, thereby ensuring compliance with legal regulations. The implementation of a prototype system demonstrates the capacity for innovative approaches to address the demands of safety, sustainability, and efficiency.

In the context of a development initiative, a range of camera systems were employed to generate image data concerning trees. This data served as the foundation for the conceptualization and training of an artificial intelligence (AI) model. The primary objective of the model is to automatically identify trees and accurately detect damage, with a particular focus on deadwood. This novel approach holds the promise of providing substantial support to individuals engaged in the management of urban tree populations, thereby contributing to the sustainable care and safety of tree populations in society [6].

# 2. Development process

## 2.1 Project goals

The development process of the project is outlined below, along with the objectives it seeks to achieve. The project involves the development of an automated solution for recording and evaluating the condition of trees. The objectives can be enumerated as follows:

1. In the initial phase, the focus was on analyzing the applicability of generated image data for training an AI model. The knowledge gained was used to formulate well-founded recommendations for the selection and optimization of a future prototype. To this end, various camera systems were tested and verified in parallel.
2. Subsequently, a feasibility study was conducted to assess the viability of employing automated tree condition monitoring through image recording. This study investigated the extent to which the captured image data and the AI technology derived from it are suitable for the automated assessment of tree conditions, with a particular focus on the identification of deadwood.
3. Based on the collected image data and the findings from the feasibility study, an initial functional prototype was developed. This prototype has been demonstrated to reliably detect trees and their damage, especially deadwood, in images, thereby creating an efficient and precise method for automated tree monitoring that has the potential to supplement or replace manual tree inspection in the long term.

These objectives form the basis for an innovative approach to tree care and should help to make the safety and care of trees more efficient and future-proof.

## 2.2 Image recordings

In addition to a Ladybug5+ camera from the manufacturer TELEDYNE FLIR, combinations of GoPro Hero 9 cameras were utilized for the image recordings. For a realistic and application-oriented feasibility test, the cameras were mounted at several positions on a car, as depicted in Figure 1, among other configurations. This approach enabled the capture of data sets depicting the road and surrounding foliage while in motion. The Ladybug5+ was also combined with a GPS receiver (NL-442U) from the manufacturer NAVILOCK, enabling the recording of the GPS position during the recording and the creation of recordings at approximately regular intervals. The GoPro camera also has an integrated GPS receiver, which records the corresponding position data during recording. To ensure data stability during driving, distance and time-controlled recording was employed, thereby ensuring regular recording distances and intervals.

The Ladybug5+ offers spherical 360° imaging, enabling the creation of images that allow the viewer to orient freely. In contrast, the GoPro camera is distinguished by its particularly wide aperture angle. To implement distance or time-controlled recording, the Ladybug5+ camera was configured to take a picture approximately every ten meters. In contrast, the GoPro camera utilized the time-lapse mode, capturing an image every second or every fifth second. During the investigation, multiple car trips were conducted, and the summer period was selected to facilitate the classification and localization of deadwood. The positioning and orientation of the cameras varied across these trips. The orientation of the cameras was adjusted during the test drives, which enabled better utilization of the field of view.

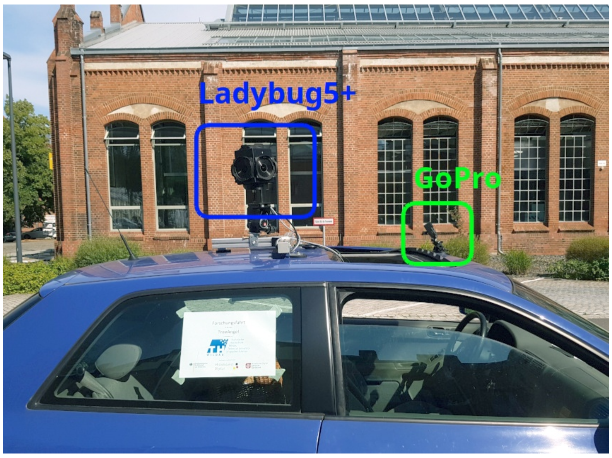



***Figure 1.*** *Camera setup on the test vehicle, with the Ladybug5+ mounted in the center and the GoPro Hero 9above the windscreen.*

# 3. Prototypical Implementation

## 3.1 AI Model selection

In this paper, the YOLOv8 model was employed as the AI model for the prototype system, with the training and evaluation processes being carried out using the Python library Ultralytics[1]. The YOLO family is distinguished by its user-friendly model approaches, which facilitate the transition between different model sizes as required. In this particular instance, the YOLOv8m model was utilized for detection. The suffix 'm' in 'YOLOv8m' denotes the model's size, measured by the number of parameters. The model selected for this study is of a medium size, a compromise that has been found to yield a satisfactory balance between accuracy and processing speed. As demonstrated in Figure 2, a comparison of the performance of different variants of the YOLO model reveals that marginal enhancements in accuracy are observed only with increasing model size. The experimental findings demonstrate that the self-trained model per-

[1] Ultralytics[7] Version 8.2.77: https://pypi.org/project/ultralytics/

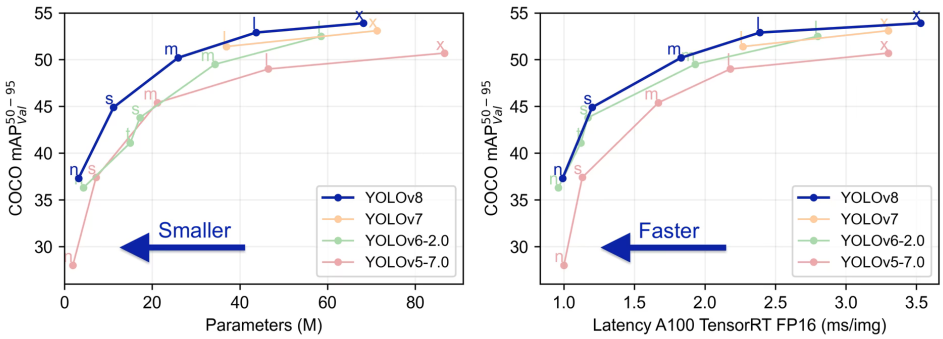



***Figure 2.*** *Performance comparison of different YOLO model variants, taken from [8].*

forms satisfactorily in comparison to the effort expended in creating the training data set used.

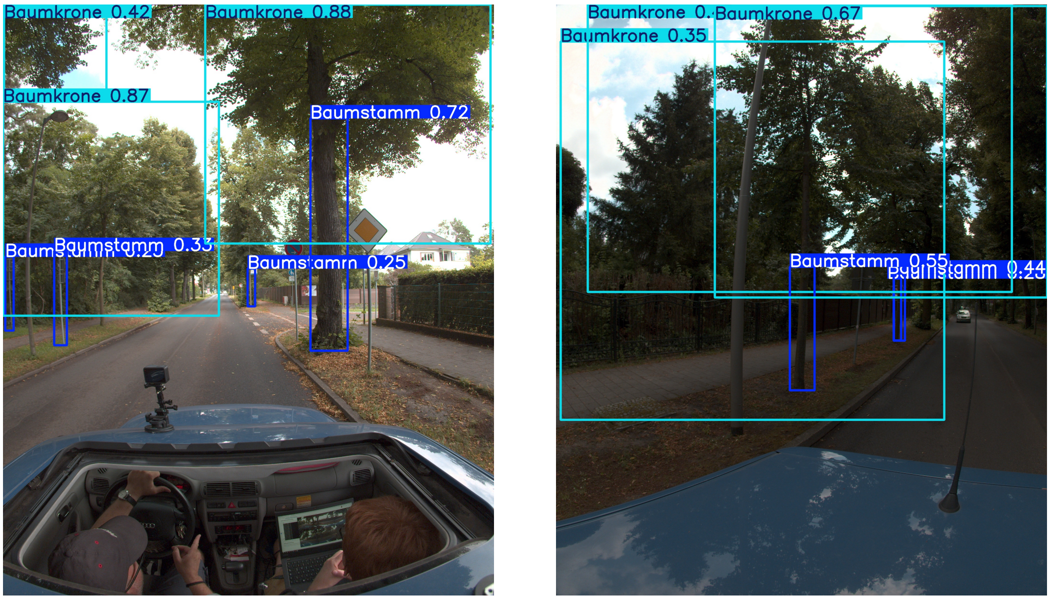
### 3.2 Assessment of the Image Data

The present study assesses the suitability of the image data for use in an AI model. The assessment is based on a pre-trained model (YOLOv8m), which was refined using an existing data set. The data set used for this purpose comprises a series of images of trees that were available from a preliminary study and were taken with a smartphone camera in the Adlershof region of Berlin. In contrast to the images taken with the test vehicle, this data set has a different perspective. Notwithstanding the discrepancies mentioned above, an initial evaluation of the suitability of the new image recordings is conducted by subjecting the images from the data set to a preliminary test. Subsequently, the trained model was evaluated using a set of images from unseen trips, excluding those utilized during the training data set. The outcomes of this evaluation were encouraging, though not fully satisfactory. This outcome was anticipated due to two factors: the modest size of the training data set and the varied perspectives. Consequently, the data set was augmented with additional recordings from various trips. Initially, a selection of 17 images from the Ladybug5+ data set was compiled, encompassing 102 individual images[2]. In the subsequent stage, the augmented training data set was utilized to retrain the original YOLOv8 model, yielding encouraging results. This enabled the formulation of a preliminary prototype based on the model approach. The outcomes from the initial training methodologies are demonstrated as illustrations in Figures 3a and 3b. The application of the adapted model to new image data enables an initial assessment of the extent to which the collected image data offers sufficient quality and variation to serve as a training basis for automated tree condition detection.

### 3.3 Training the AI model

As part of the implementation of the prototype, the image data is annotated in detail to create a valid basis for the subsequent evaluations. In this step, the classes relevant for the subsequent application of the model are defined again, using the criteria already known. The classes used initially comprise the categories tree trunk, tree crown, tree number and a specific class for damage. The latter category was constrained in this instance to dead wood or to areas in the tree crowns that were devoid of foliage at the time the images were captured. The images were annotated using the web application

[2] $17$ Aufnahmen $\times$ $6$ Kameras $=$ $102$ Einzelbilder




*(a) Example 1* *(b) Example 2*

***Figure 3.*** *Examples of the detection results after the first training of the model.*

***Table 1.*** *Overview of training datasets*

| Model | Dataset | Images | Composition | Epochs |
|---|---|---|---|---|
| version 1 | pre-study | 100 | smartphone (100) | 30 |
| version 3 | dataset 1 | 202 | pre-study (100) + Ladybug5+ (102) | 50 |
| version 4 | dataset 2 | 225 | dataset 1 (202) + GoPro (23) | 100 |

CVAT[3], which provides efficient management of the datasets and the corresponding annotation tools. Examples of the annotation and the interface used are demonstrated in Figure 4.

As part of the prototype implementation, it is initially planned to extract additional image data from the existing images in order to expand the training basis of the model. The images correspond to a greater extent to the later use case and serve to sensitize the model to the envisaged scenario. Particular emphasis was placed on a balanced representation of healthy trees and trees with visible damage, in order to optimize the model's ability to differentiate between these states. Subsequently, two additional datasets were generated based on the image quality evaluation dataset. The first dataset comprises 100 additional individual images of the Ladybug5+, which originate from an existing journey, and the second dataset was supplemented by 23 additional images recorded with a GoPro camera. An overview of the composition of the datasets used can be found in Table 1.

The models are trained using the aforementioned Python library Ultralytics. Except for the number of epochs, the standard parameters of the library were utilized. The number of epochs employed in this study is indicated in the overview provided in Table 1. Subsequently, the models were trained using the extended datasets, which resulted in two additional trained models that can be compared. The primary focus was on analyzing the model's capacity to reliably identify trees and damage features such as

[3]Computer Vision Annotation Tool – Community

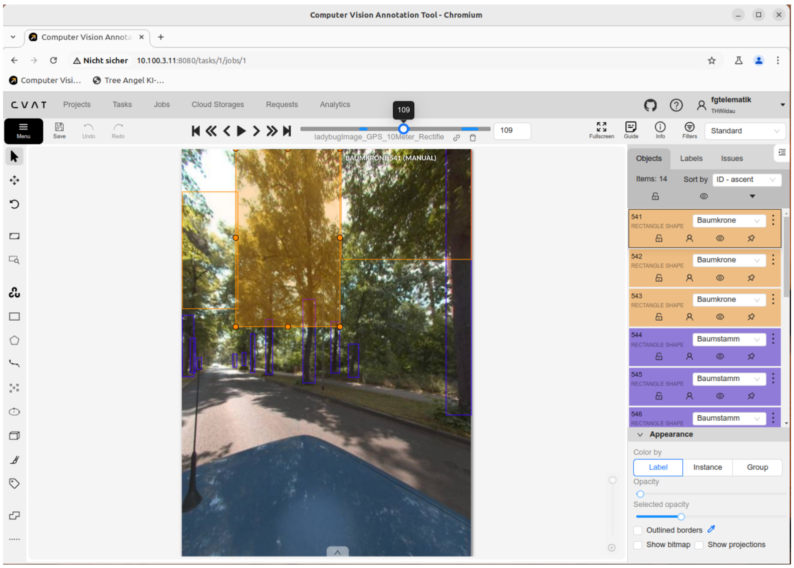



***Figure 4.*** *Annotation view in CVAT*

deadwood. The results of the study provide valuable insights into the applicability of the method in practice, as well as potential further adjustments or optimizations.

### 3.4 Implementation as demo application

The capabilities of the trained models are evaluated and demonstrated using a bespoke demonstration application for automated tree condition detection. The prototype is implemented as a straightforward web application in Python using the Flask framework, with particular attention paid to the integration of the trained models during implementation. The objective was to offer users the opportunity to upload their own images and to visualize the results of the models directly. The user interface has been designed to facilitate the comparison of the results obtained from both models with the original image, thereby enabling the visual interpretation of the differences in the detection and classification of tree features. A sample result from the web application is shown in Figure 5.

### 3.5 Determination of the tree position

The determination of the tree position is dependent upon the calibration of the camera system, which allows for the derivation of the geo-positions of the trees from the image data. The trees are localized with the aid of the recorded image data and image processing methods, with the simultaneous recording of GNSS data by the two cameras used enabling triangulation to calculate the geo-positions of the trees. This process requires, for example, the recognition of the tree trunk from two positions. The integrated multi-view functionality and the factory calibration of the Ladybug5+ camera facilitate triangulation from a single image, thereby simplifying the determination of the tree position.In instances where a tree is captured from two viewing directions and the tree trunk is recognized by the AI, for instance, these can be assigned to the two images by selecting suitable pixels on the tree trunk. Three-dimensional information can be captured in two different ways. The first method involves the movement of the camera, a process known as Structure from Motion[9]. The second method utilizes the fixed reference of the internal sensors to each other, a capability inherent in the Ladybug5+ camera, to achieve multi-view geometry[9]. The information obtained through these

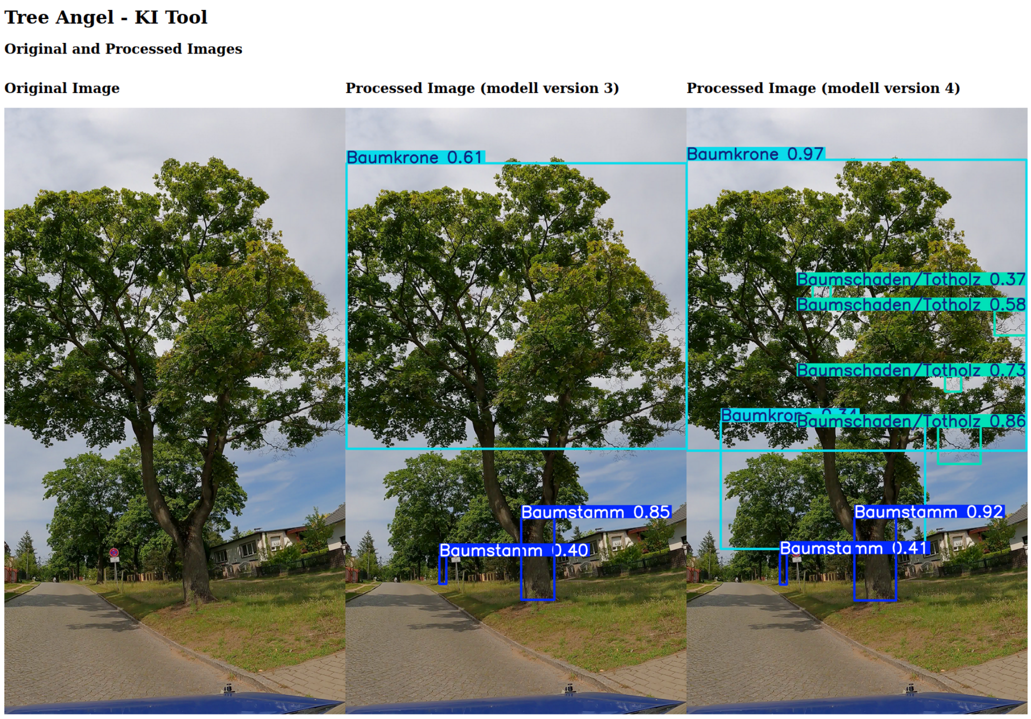
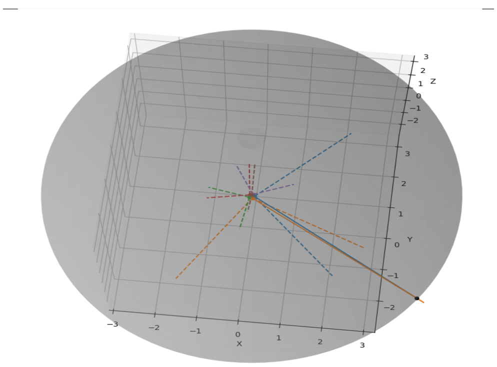



***Figure 5.*** *Comparison of the results from the application of the trained models in the demo application.*

methods can then be used to compare the geo-position with the tree register, facilitating the assignment of information to a specific tree. For a more detailed overview of this subject, please refer to Figure 6b.



***(a)*** *Illustration of the viewing areas of the cameras (dashed lines) and the two projected 3D rays, as well as their intersection point (black). The gray circle/sphere describes the spherical surface on which the intersection point is located.*

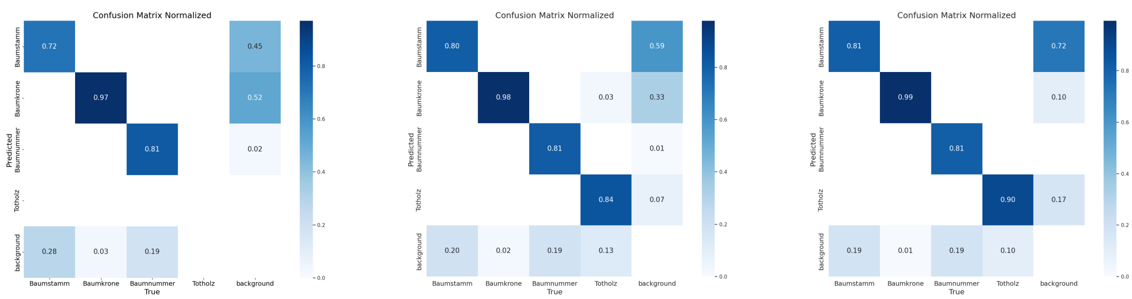

***(b)*** *Representation of the position of the vehicle/camera (red dot) and the determined tree position (blue dot) based on the intersection of the two rays from the adjacent figure. The underlying map was taken from OpenStreetMap.*

***Figure 6.*** *Illustration of how the geo-position of a tree can be determined from the GNSS position of the camera using triangulation. Figure 6a shows the rays that correspond to the mapping of a specific image point on two neighboring camera sensors of the Ladybug5+. The intersection of these two rays then corresponds to the 3D position of the pixel, which represents the position of the tree.*

## 4. Discussion

The procedure delineated in this study establishes the foundation for the development of a system that automates and optimizes the evaluation of the traffic safety of trees. A key innovation is the ability to collect data during existing work processes, such as the utilization of municipal vehicles. This facilitates cost-efficient integration into everyday operations and enables comprehensive recording through existing daily routines and route sequences. The analysis demonstrates the technical feasibility of precise detection of deadwood using a YOLOv8 model and delivers promising results. This assertion is further substantiated by the training outcomes, as illustrated by the confusion matrices depicted in Figure 7. These matrices elucidate that augmenting the training basis enhances the efficacy of the system. The assessment of tree damage and health, a dimension hitherto unexplored in this feasibility study, is rendered possible by the diverse perspectives afforded by the changing seasons and growth periods throughout the year. To assess and train accordingly, further investment of time is required, which would, however, significantly improve the training results.In the context of the predictive maintenance approach, this results in various approaches for ensuring traffic safety, as well as for shaping and maintenance pruning, which could be planned shortly after the winter break or before the bird protection season.

The findings and other research work, e.g. [10], demonstrate that AI-based methods are a future-proof solution for the challenges in tree care that are being exacerbated by climate change.In the long term, AI models could not only identify damaged areas, but also support predictive simulations for planning maintenance and safety measures, emphasizing the importance of further research and development in this area. The incorporation of additional data sources, such as the infrared spectral range, as demonstrated in [11], holds promise for enhancing the depth and scope of condition assessment.




***(a)** Confusion matrix of the first model based on the pre-study training dataset (see Table 1).*

***(b)** Confusion matrix of the second model based on dataset 1 (see Table 1).*

***(c)** Confusion matrix of the fourth model based on dataset 2 (see Table 1).*

***Figure 7.** Normalized confusion matrices of the different models.*

## 5. Summary

The feasibility study demonstrates the potential of automated systems for tree condition assessment, in particular by combining image data, AI models and GNSS information. The study shows that suitable camera systems can be used to efficiently record trees on roadsides as well as freestanding trees. In addition, the study demonstrates that their positions can be precisely determined using the recorded GNSS data and thus reliably assigned to the inventory data.

The development of a YOLOv8 model for damage detection, particularly of deadwood, lends further credence to the viability of these approaches. While further refinement of the training data is necessary, the outcomes of the prototype system provide a substantial foundation for the automation of tree inspection.

The implementation of such systems has the potential to augment or supplant manual inspections in the long term, thereby conserving resources and enhancing efficiency. This project signifies a substantial advancement towards a sustainable, scalable approach to tree care in both urban and rural contexts.

## Data availability statement

The data recorded as part of the project is currently not publicly accessible. The reason for this is the sensitive information, which is subject to data protection.

## Author contributions

Richard Fiebelkorn: Conceptualization, Data curation, Investigation, Methodology, Software, Writing - original draft

Rafael Kugel: Conceptualization, Investigation, Writing - review & editing

Norman Günther: Project administration, Funding acquisition, Writing - review & editing

Jörg Reiff-Stephan: Supervision, Funding acquisition, Writing - review & editing

## Competing interests

The authors declare that they have no competing interests.

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## References

[1] M. Jonsson, J. Bengtsson, J. Moen, and T. Snäll, "Tree damage risk across gradients in tree species richness and stand age: Implications for adaptive forest management," *Ecosphere*, vol. 15, no. 11, e70071, 2024. DOI: https://doi.org/10.1002/ecs2.70071. eprint: https://esajournals.onlinelibrary.wiley.com/doi/pdf/10.1002/ecs2.70071. [Online]. Available: https://esajournals.onlinelibrary.wiley.com/doi/abs/10.1002/ecs2.70071.

[2] D. Haase and R. Hellwig, "Effects of heat and drought stress on the health status of six urban street tree species in leipzig, germany," *Trees, Forests and People*, vol. 8, p. 100 252, 2022, ISSN: 2666-7193. DOI: https://doi.org/10.1016/j.tfp.2022.100252. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666719322000590.

[3] L. Portoghesi, E. Masini, A. Tomao, and M. Agrimi, "Could climate change and urban growth make europeans regard urban trees as an additional source of danger?" *Frontiers in Forests and Global Change*, vol. 6, Apr. 2023, ISSN: 2624-893X. DOI: 10.3389/ffgc.2023.1155016. [Online]. Available: http://dx.doi.org/10.3389/ffgc.2023.1155016.

[4] B. Prell, S. Wilbers, N. Günther, and J. Reiff-Stephan, "Will my job be automated? fathoming current and persisting impediments for automation," in *Smart Technologies for a Sustainable Future*, M. E. Auer, R. Langmann, D. May, and K. Roos, Eds., Cham: Springer Nature Switzerland, 2024, pp. 155–166, ISBN: 978-3-031-61891-8.

[5] D. Gugutishvili, S. Kalyazina, and J. Reiff-Stephan, "Identification and classification of the effects of digital transformation on business," in *Algorithms and Solutions Based on Computer Technology*, C. Jahn, L. Ungvári, and I. Ilin, Eds., Cham: Springer International Publishing, 2022, pp. 391–401, ISBN: 978-3-030-93872-7.

[6] J. Reiff-Stephan, "Humanity-centered production - automatisierung für die gesellschaft," in *Tagungsband der Konferenz der Mechatronik Plattform Österreich 2024: Smart Technologies in Mechatronics*, Nov. 2024, p. 36.

[7] G. Jocher, A. Chaurasia, and J. Qiu, *Ultralytics yolov8*, version 8.0.0, 2023. [Online]. Available: https://github.com/ultralytics/ultralytics.

[8] U. Inc. "Ultralytics yolov8," Accessed: Nov. 29, 2024. [Online]. Available: https://docs.ultralytics.com/de/models/yolov8/#can-i-benchmark-yolov8-models-for-performance.

[9] R. Hartley and A. Zisserman, *Multiple View Geometry in Computer Vision*, 2nd ed. New York, NY, USA: Cambridge University Press, 2003, ISBN: 0521540518.

[10] A. Jahani and M. Saffariha, "Tree failure prediction model (tfpm): Machine learning techniques comparison in failure hazard assessment of platanus orientalis in urban forestry," *Natural Hazards*, vol. 110, no. 2, pp. 881–898, Aug. 2021, ISSN: 1573-0840. DOI: 10.1007/s11069-021-04972-7. [Online]. Available: http://dx.doi.org/10.1007/s11069-021-04972-7.

[11] D. Vidal and R. Pitarma, "Infrared thermography applied to tree health assessment: A review," *Agriculture*, vol. 9, no. 7, 2019, ISSN: 2077-0472. DOI: 10.3390/agriculture9070156. [Online]. Available: https://www.mdpi.com/2077-0472/9/7/156.