# Object-Guided Tree Species Classification Using Deep Learning

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Dataset

## Motivation

**Goal**

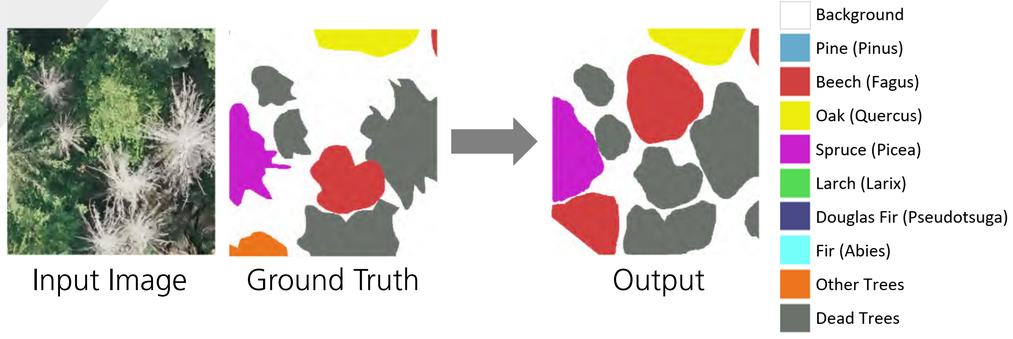
- Optimize the classification of individual tree species.
- Minimize the impact of overlapping canopies and dense regions with mixed tree species.

**Problems**

- Tree-level classification limited by noise despite high-detail data.
- Minority classes are difficult to learn accurately.
- Use of very high-resolution imagery remains underexplored.

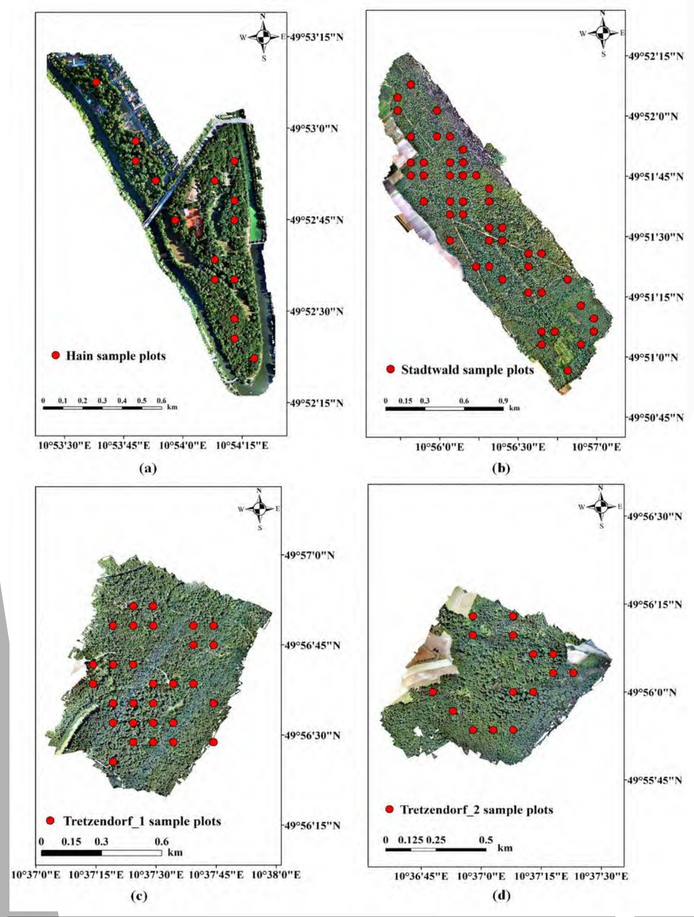
**Contributions**

- Develop a model for pixel-based tree species classification (10 classes).
- Combine semantic and individual tree crown (ITC) segmentation.




## Methodology

### Bamforest Benchmark Dataset [2]

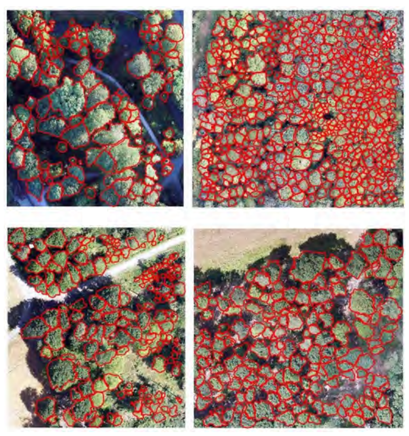



**Ground Sampling Distance**

- Hain: 1.82 cm (a)
- Stadtwald: 1.7 cm (b)
- Tretzendorf: 1.79 cm (c,d)

**Dataset Specifications**

- Data acquisition: Summer 2022
- 27,160 trees delineated
- RGB imagery
- Bamberg area
- Tree species determined

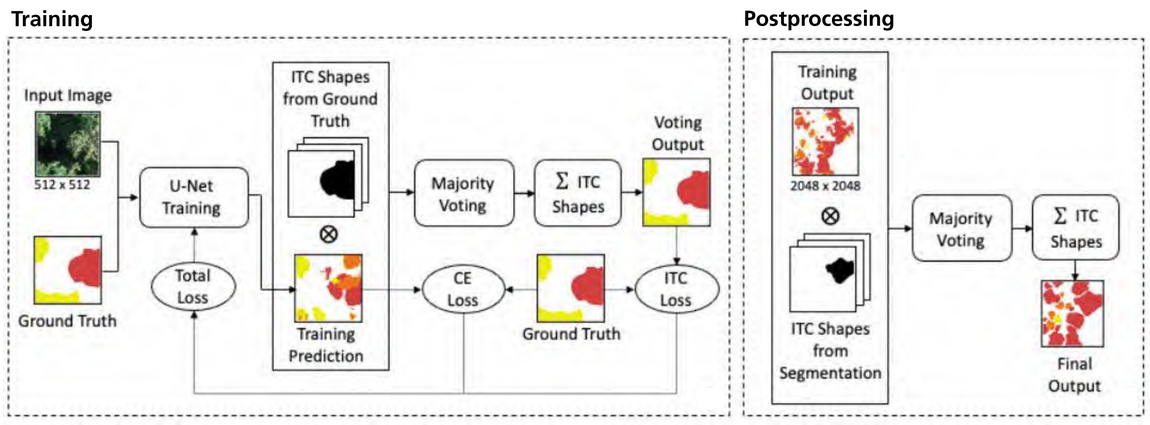


| Region | Size | Sample plots | Tree numbers |
|---|---|---|---|
| Hain | 50ha | 15 | 1.978 |
| Stadtwald | 150ha | 46 | 15.477 |
| Tretzendorf_1 | 50ha | 29 | 6.898 |
| Tretzendorf_2 | 50ha | 15 | 2.814 |

| Dataset | Image numbers | Tree numbers |
|---|---|---|
| Train | 367 | 16.124 |
| Test | 255 | 7.722 |
| Validation | 226 | 6.391 |

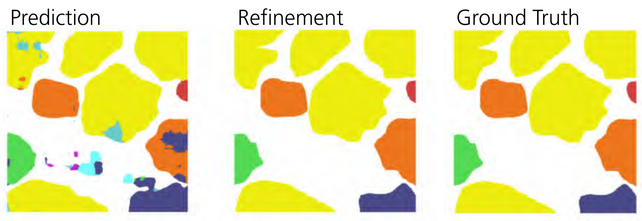
### ITC-Based Tree Species Classification [3]

- Use the features of tree crowns for species classification.
- Combine pixel-based and ITC-based segmentation approaches.
- Pixel-based segmentation performed using U-Net.
- ITC-based segmentation applied post hoc [1].
- Two-step method for improving segmentation:
  - Incorporation of a second loss function during U-Net training.
  - Postprocessing with ITC-based segmentation to refine crown shapes.
- Combination improves both accuracy and biological realism of results.




**Majority Voting**: Using the ITC shape to refine the results during the training and creating a loss ($L_{ITC}$) of the comparison of false predictions in comparison of total predictions:

$$L_{ITC} = \frac{\text{Number of False Predictions}}{\text{Total Number of Predictions}}$$




Prediction output from training.

Refinement from shaping and voting.

Ground truth for refinement and to calculate the loss ($L_{ITC}$).

## Experiment

**Key Results** [3]

- Input patches (512 × 512) yield better segmentation accuracy than 2048 × 2048 patches.
- Consistent improvement in both F1 Score and IoU across most classes.

**Visual Outputs** [3]

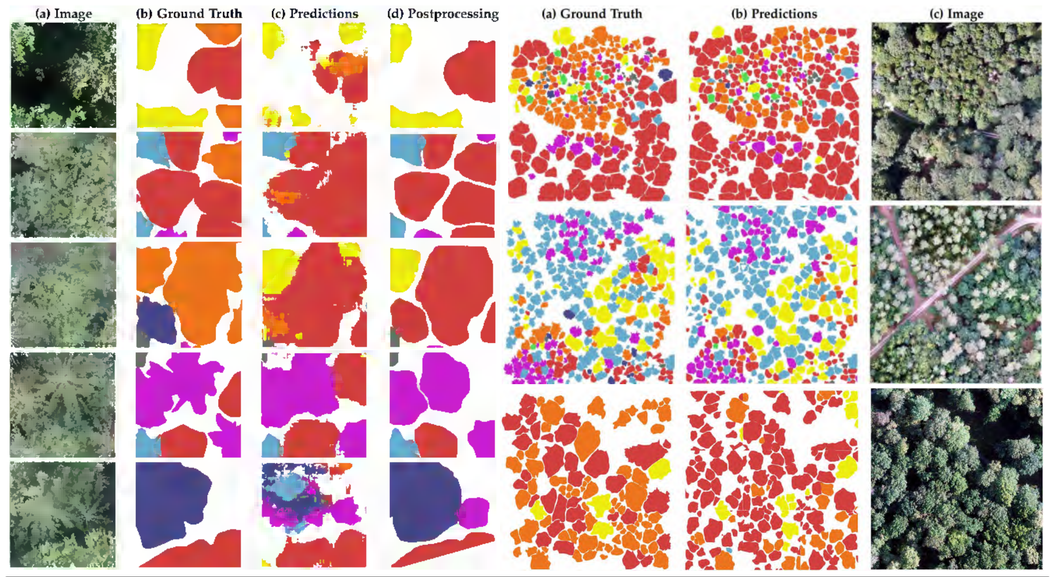
- For the postprocessing, clear qualitative improvement using ITC approaches: Sharper tree boundaries, fewer false positives, and one species per ITC.

**Conclusion**

- Combining pixel-based segmentation with ITC-based segmentation enhances both precision and interpretability.
- Supports forest inventory, species mapping, and biodiversity monitoring at high resolution.

**Future Directions**

- Apply approach to additional datasets and diverse forest types.
- Train with more annotated data to improve performance for more tree species and regions.




| Class Name (Latin Name) | Test-1 CE Loss [%] | Test-1 CE + ITC Loss [%] | Test-1 Postprocessing [%] | Test-2 CE Loss[%] | Test-2 CE + ITC Loss[%] | Test-2 Postprocessing[%] |
|---|---|---|---|---|---|---|
| Background | 59.56 | 58.21 | **64.44** | 62.47 | 64.96 | **65.28** |
| Pine (Pinus) | **00.04** | 00.02 | 00.00 | 50.22 | 50.78 | **50.96** |
| Beech (Fagus) | 11.25 | 21.24 | **29.05** | 32.83 | 35.24 | **38.58** |
| Oak (Quercus) | 23.99 | 19.52 | **29.68** | 33.24 | 32.40 | **37.62** |
| Spruce (Picea) | 00.04 | **00.06** | 00.00 | 23.73 | 23.31 | **24.72** |
| Larch (Larix) | 00.55 | **00.59** | 00.52 | 10.38 | **11.03** | 10.06 |
| Douglas Fir (Pseudotsuga) | 00.00 | 00.00 | 00.00 | **00.97** | 00.21 | 00.27 |
| Fir (Abies) | 00.00 | 00.00 | 00.00 | 00.00 | 00.00 | 00.00 |
| Other Trees | **23.52** | 14.53 | 16.25 | 09.72 | 09.63 | **10.18** |
| Dead Trees | 01.25 | 01.01 | **01.32** | **17.34** | 13.86 | 16.72 |
| Mean Score | 15.46 | 17.33 | **20.93** | 42.03 | 42.79 | **44.39** |

## References

[1] Tian, J., D. Panangian, W. Fan, B. Siegmann, and X. Yuan (2025). "Deep learning based individual tree crown delineation from panchromatic aerial imagery". In: ISPRS Geospatial Week 2025.
[2] Troles, J., U. Schmid, W. Fan, and J. Tian (Jan. 2024). "BAMFORESTS: Bamberg Benchmark Forest Dataset of Individual Tree Crowns in Very-High-Resolution UAV Images". In: Remote Sensing 16.11. Number: 11 Publisher: Multidisciplinary Digital Publishing Institute, p. 1935. issn: 2072-4292. doi: 10.3390/rs16111935. url: https://www.mdpi.com/2072-4292/16/11/1935 (visited on 07/22/2024).
[3] Weishaupt, M., W. Fan, J. Troles and J. Tian (2025). "Individual Tree Crown Based Tree Species Classification from Very High-Resolution UAV Images". IGARSS 2025. Accepted paper.

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