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Ref. Ares(2025)4934035 - 20/06/2025

REFOREST

Organisation: Czech University of Life Sciences
Department: Faculty of Forestry and Wood Sciences

D4.4

Semi-autonomous Remote sensing-based AF system verification tool

Date 12.06.2025
Doc. Version 05

Funded by the European Union

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101060635 (REFOREST). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Executive Agency (REA). Neither the European Union nor the granting authority can be held responsible for them.

UK Research and Innovation

UK partners are funded by UK Research and Innovation (UKRI) under UK government's Horizon Europe funding guarantee [grant number 10039700].

Document Control Information

Settings	Value
Deliverable Title	Semi-autonomous Remote sensing-based AF system verification tool
Work Package Title	Monitoring and Verification
Deliverable number	D4.4
Description	Description of the development and testing of machine-learning algorithms utilising remotely sensed data to identify features in agroforestry systems
Lead Beneficiary	CZU
Lead Authors	CZU – Gokul Kottilapurath Surendran, Martin Mokros, Martin Lukac
Contributors	ORC
Submitted by	Martin Lukac
Doc. Version (Revision number)	05
Sensitivity (Security):	Low
Date:	12/06/2025

Document Approver(s) and Reviewer(s):

NOTE: All Approvers are required. Records of each approver must be maintained. All Reviewers in the list are considered required unless explicitly listed as Optional.

Name	Role	Action	Date
Martin Lukáč	Executive Board Member	Approved	12/06/2025
Rym Ayadi	Executive Board Member	Approved	20/06/2025
Bhim Bahadur Ghaley	Executive Board Member	Approved	20/06/2025
Eike Lüdeling	Executive Board Member	Approved	20/06/2025
Markus Hassler	Executive Board Member	Approved	20/06/2025
Julia Cooper	Executive Board Member	Approved	20/06/2025

Document history:

The Document Author is authorised to make the following types of changes to the document without requiring that the document be re-approved:

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Changes to this document are summarised in the following table in reverse chronological order (latest version first).

Revision	Date	Created by	Short Description of Changes
05	12/06/2025	CZU – Martin Lukáč	Final version
04	12/06/2025	CZU – Martin Mokroš	Minor edits
03	09/06/2025	CZU – Martin Lukáč	Technical description, text improvements
02	23/05/2026	CZU – Martin Mokroš, Kottilapurath Surendran Gokul	Update on the Results section
01	21/05/2025	CZU – Martin Lukáč	Initial version

Configuration Management: Document Location

The latest version of this controlled document is stored in https://czuvpraze.sharepoint.com/teams/fld-t-reforest/Sdilene%20dokumenty/Forms/AllItems.aspx

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ACKNOWLEDGEMENT

This report forms part of the deliverables from the ReForest project which has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 101060635. The Community is not responsible for any use that might be made of the content of this publication.

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TABLE OF CONTENTS

EXECUTIVE SUMMARY

This deliverable presents the development of a semi-autonomous system for assessing soil carbon and biodiversity in agroforestry systems using remote sensing data and machine learning. The aim is to enable scalable, rapid, and reliable verification of ecosystem services, supporting financial mechanisms such as payments for ecosystem services and biodiversity or carbon credits.

Two key outputs are described: (1) web-based applications that estimate soil organic carbon and plant species richness from Sentinel-2 imagery via convolutional neural networks (CNNs), and (2) desktop software tools—the Advanced Machine Learning Classifier and CNN Parameter Tuner—which allow users to build and optimise classification models for agroforestry-related image analysis tasks, such as tree species identification from bark images.

Validation across diverse European sites confirmed the models' ability to produce ecologically meaningful predictions, with CNNs consistently outperforming classical machine learning algorithms in accuracy and robustness. The classifier tool supports hybrid workflows combining deep feature extraction with flexible classification options, improving accessibility and interpretability.

These open-source tools, documented and available through the ReForest project's Zenodo repository, provide researchers and land managers with practical solutions for agroforestry monitoring, laying the groundwork for transparent, semi-automated ecosystem service verification at scale.

LIST OF ACRONYMS AND ABBREVIATIONS

Abbreviation	Definition
AGI	Artificial general intelligence
AI	Artificial intelligence
CNN	Convolutional neural network
ORC	Organic Research Centre
SOC	Soil organic carbon

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Agroforestry is increasingly recognised for its potential to enhance agricultural sustainability through the delivery of critical ecosystem services, including carbon sequestration, biodiversity enhancement, soil protection, and climate resilience. However, the widespread adoption of agroforestry across Europe remains limited, partly due to a lack of robust and scalable methods to monitor and verify its performance. Financial incentives such as payments for ecosystem services depend on credible, timely, and cost-effective verification mechanisms. At present, such mechanisms are either absent or prohibitively complex. Conventional tools, such as the SustainFarm Public Goods Tool developed by the Organic Research Centre, are comprehensive but rely on detailed on-farm questionnaires and manual assessments, limiting their scalability and speed.

To effectively assess the establishment and maintenance of agroforestry systems, it is essential to identify and eventually quantify key structural and compositional features. These include tree species identity, number and spacing of trees, canopy dimensions, alley width, and potential shading patterns—all of which influence microclimatic conditions, biodiversity potential, and carbon dynamics. Accurate detection of these features from remote sensing data enables not only the classification of land use as agroforestry, but also deeper insight into the functional performance of the system. For example, tree spacing and species mix can affect understorey productivity and soil moisture, while alley width and canopy structure influence shading and heat stress mitigation—critical aspects for livestock and crop health.

The description of agroforestry systems is closely linked to the verification of ecosystem service delivery, particularly carbon accumulation and biodiversity enhancement. Unlike conventional agricultural outputs such as crop yield or livestock production, these benefits are spatially heterogeneous, temporally dynamic, and often intangible. Without efficient, repeatable, and trustworthy monitoring tools, agroforestry systems risk exclusion from emerging finance streams—particularly those related to carbon markets, biodiversity credits, and sustainable investment portfolios.

This deliverable presents the development of a semi-autonomous process for monitoring agroforestry systems using remotely sensed data combined with machine learning techniques. Our approach focuses on two key variables of ecosystem service provision: carbon capture and habitat diversity. By integrating satellite and UAV imagery with ground-truth data and agroforestry system modelling, we aim to build an independent, scalable verification tool that can support policy implementation, investor confidence, and farmer decision-making.

The primary objective of this work package is to develop a monitoring and verification capability acceptable to key stakeholders along the agroforestry value chain, including farmers, regulators, retailers, and impact investors. The process is led by the Czech University of Life Sciences (CZU) and builds on ReForest's interdisciplinary expertise in agroforestry modelling, remote sensing, artificial intelligence, and stakeholder co-design. By combining automated data processing, robust ground-truthing, and co-designed interfaces, this work aims to produce a semi-autonomous system for the monitoring and verification of agroforestry systems. The system is designed to offer:

- Reliable assessment of carbon and biodiversity indicators;
- Scalable change detection capability across diverse landscapes;

- Decision-support tools linked to site-specific data;
- Direct application to financial instruments being developed under WP5.

This deliverable, therefore, lays the technical and conceptual foundation for a new generation of verification services that will enable credible PES schemes and unlock alternative finance streams for agroforestry in Europe and beyond. The technology described in this Deliverable represents a continuous development of capabilities described in D4.1 and D4.2.

2. METHODOLOGY

2.1 BACKGROUND

This deliverable outlines the development of a semi-autonomous system for monitoring and verifying carbon and biodiversity outcomes in agroforestry systems, based on advanced remote sensing and machine learning techniques. Our approach integrates existing and newly gathered datasets that describe carbon stocks and biodiversity across both agroforestry and conventional agricultural systems. These datasets include high-resolution remote sensing imagery and field-based ecological measurements. Together, they provide both the input data and validation references required to train and evaluate machine learning models.

This work builds directly on Deliverables **D4.1 (Neural Network Training Dataset)** and **D4.2 (Predictive Tool for Carbon and Biodiversity Assessment)**. In those deliverables, we employed convolutional neural networks (CNNs) to link large, cross-European datasets on soil carbon and biodiversity with remote images of the landscapes from which these samples were taken. D4.1 provided the ecological training data, while D4.2 focused on remote image sampling and neural network optimisation. The geographic scope of the training data was then expanded, and the underlying AI models were refined to improve generalisability and predictive accuracy across varied European agroecological contexts.

This deliverable describes the next step: the development of a user-friendly software tool based on the predictive models generated in D4.2, now embedded in a web-based application. It also introduces further enhancements, including additional data sources, model tuning processes, and improvements to classification accuracy and interpretability.

The core of this system is an **Advanced Machine Learning Classifier**, a flexible computational model designed to detect complex patterns in large, multi-dimensional datasets and assign accurate classifications. Unlike conventional rule-based approaches, our classifier uses modern machine learning methods, particularly deep neural networks and ensemble techniques, to automatically extract features from diverse inputs and deliver high-precision predictive outputs. It is capable of processing varied data types, including imagery, time-series, and spatial GIS layers, making it ideal for land use classification, object detection, and environmental change monitoring.

To support automated identification and quantification of agroforestry-specific features, the classifier integrates spectral, spatial, and structural information to distinguish elements such as tree species, canopy size, spacing, alley width, and shading potential. Using deep learning architectures like convolutional neural networks for both image classification and semantic segmentation, the system is trained on labelled datasets from ground-based, UAV and satellite imagery, particularly those collected in the ReForest Living Labs, and cross-referenced with ground-truth data. This enables consistent, scalable detection of agroforestry configurations across a range of landscapes, forming the analytical backbone of the verification tool.

To ensure optimal performance, we employ a **CNN parameter tuner** that systematically adjusts key hyperparameters, such as learning rate, filter size, number of layers, batch size, and activation functions. This tuning process uses automated search strategies (e.g. grid search and Bayesian optimisation) to identify the most effective model configurations, tailored to the unique characteristics of agroforestry remote sensing data. The result is a more accurate, generalisable model for landscape feature classification.

Finally, the trained models are embedded into a prototype software tool capable of interpreting remotely sensed data to assess changes in carbon and biodiversity indicators. This computational capability is being translated into user-facing interfaces co-designed with stakeholders. These interfaces are designed to maximise usability, transparency, and integration with financial mechanisms (as developed in WP5) and agroforestry business models (WP6), supporting real-world decision-making and incentivisation of ecosystem service delivery.

2.2 Soil Carbon and Biodiversity Estimation Web Applications

The web applications developed for estimating soil organic carbon and biodiversity leverage satellite imagery from the **COPERNICUS Sentinel-2 mission**, accessed via the **Google Earth Engine (GEE) API**. Sentinel-2 provides multispectral GeoTIFF imagery across 13 spectral bands at high spatial and temporal resolution, enabling large-scale monitoring of vegetation and soil characteristics.

Users interact with intuitive web interfaces by submitting latitude and longitude coordinates within the European region. Upon submission, the system defines a 5 km × 5 km area of interest centred on the input coordinates. Cloud-masked Sentinel-2 images are automatically retrieved from GEE, and pre-processing is applied to ensure data quality and model compatibility. This includes cloud filtering, NaN pixel correction, and image resizing to meet the input specifications of the deep learning models. The core predictive models are deep convolutional neural networks (CNNs) trained on extensive, labelled datasets that combine remote sensing imagery with field-collected ground-truth data (D4.2). The soil organic carbon model classifies the AOI into discrete percentage ranges of soil carbon content, while the biodiversity model estimates plant species richness based on spectral variability and vegetation structure captured in the Sentinel-2 imagery. Both models are implemented using TensorFlow and are designed for robust generalisation across diverse European agroecological contexts.

The backend architecture for the web applications was developed in Python using the Flask web framework, which manages communication between the user interface, Google Earth Engine, and the prediction models. All stages of image processing, including cloud masking, cleaning, and rescaling, are automated within the pipeline. At runtime, the processed image is passed to the CNNs, which generate predictions in real-time. These outputs are served via RESTful APIs to the front-end applications, providing users with immediate access to carbon and biodiversity estimates for their selected location.

This modular architecture allows for future scalability, including the integration of additional models, expansion to other geographic regions, or enhancement with higher-resolution imagery from UAV platforms and other satellite missions. The result is a lightweight, scalable tool that supports evidence-based decision-making and spatially explicit monitoring of agroecosystem services.

2.3 Machine learning classifiers and datasets

To support flexible, user-driven classification tasks in agroforestry and related land use systems, we have used two modular software solutions for building and optimising machine learning models. These tools are designed to accommodate a wide variety of data sources and applications, from high-resolution UAV imagery to standard camera-based inputs, and allow users to train custom classifiers tailored to their specific landscapes and management needs.
The first tool, the **Advanced Machine Learning Classifier (version 2.0.0)**, enables users to construct classification models using various supervised learning algorithms. It supports a range of use cases, including:

- Tree species identification from UAV-generated orthomosaics based on crown morphology;
- Land use classification (e.g. pasture, cropland, silvopasture);
- Crop type or livestock identification from aerial or ground-based imagery;
- Disease detection in trees or crops from simple camera inputs.

The classifier provides a user-friendly pipeline for uploading image data, labelling samples, selecting a model architecture (e.g. decision trees, random forests, support vector machines, or CNNs), and generating predictions.

As a demonstration, we present an example workflow for **tree species classification using bark images**, chosen for its simplicity and ease of data acquisition. This use case allows farmers to rapidly use the tool with minimal setup, using standard digital cameras or smartphones to capture datasets. The same approach can be extended to other classification tasks where image data is available, such as identifying shrubs, pasture features, crops or assessing tree health.

The second tool, the **CNN Parameter Tuner (version 3.0.0)**, complements the classifier by enabling systematic optimisation of convolutional neural network (CNN) hyperparameters. This step is intended for model developers only, who can define ranges for key parameters, such as learning rate, number of layers, filter sizes, batch size, and activation functions, and the tuner will automatically explore the parameter space using techniques such as grid search or Bayesian optimisation. This results in models that are better adapted to the specific characteristics of the dataset, with improved classification accuracy and generalisability.

Both tools are implemented in Python and fully documented. Comprehensive user handbooks are available via the **ReForest project repository on Zenodo**, with direct links provided in Appendix 1.

Advanced Machine Learning Classifier 2.0.0

The Advanced Machine Learning Classifier 2.0.0 is a standalone desktop application designed to facilitate efficient image classification through an accessible interface backed by advanced machine learning functionality. It integrates deep feature extraction using CNNs with a selection of widely used machine learning algorithms, enabling users to experiment with different model architectures and optimise performance for a variety of classification tasks. The tool is suitable for both novice and experienced users and has been developed with flexibility and reproducibility in mind.

Key features of the application include:

- Support for importing and preprocessing labelled image datasets;
- Customisable image resizing and augmentation options (e.g. flipping, rotation, normalisation);
- An embedded CNN module for feature extraction from input images;
- A choice of classification algorithms including Random Forest, Support Vector Machines (SVM) with customisable kernels, AdaBoost, Gradient Boosting, Decision Trees, and Naïve Bayes;
- Train-test-validation split configuration and support for performance-enhancing techniques such as bagging.

The classification workflow begins with loading labelled image folders into the interface and defining preprocessing and CNN feature extraction settings. Once features are extracted, users select a preferred classifier and initiate training. Throughout the process, a command prompt panel provides real-time feedback on data loading, parameter settings, and model progress. Upon training completion, the application presents a suite of results to support model evaluation. These include confusion matrices, classification reports, misclassification summaries, and per-image class probabilities. To support reproducibility and further development, the full workflow can be exported as a Python Jupyter Notebook script, allowing for custom modifications or publication-ready documentation.

CNN Parameter Tuner 3.0.0

The Tuner is a companion desktop tool designed to support the optimisation of CNN architectures for image classification tasks. The tuner provides a graphical user interface that enables users to explore the effect of various hyperparameters on model performance, offering an efficient and transparent way to improve accuracy and generalisability.
The tool supports:

- Import of labelled image folders in standard formats (e.g., JPG, PNG);
- Preprocessing functions including resizing, normalisation, standardisation, and data augmentation;
- Custom construction of CNN architectures, with user-defined layer depths, filter sizes, dropout rates, and activation functions;
- Automated tracking of parameters and intermediate processing steps via an integrated command prompt.
-

The user workflow involves loading image datasets, selecting preprocessing steps, and designing the CNN structure. Training is initiated within the interface, and the application provides real-time logs and visual feedback on training progress. Upon completion, users can review interactive results including confusion matrices, classification metrics (precision, recall, F1-score), and training accuracy graphs. As with the classifier tool, the entire workflow can be exported as a Python Jupyter Notebook, supporting both publication and integration into larger analytical pipelines.

Workflow for Implementing Image-Based Classifiers

To illustrate the implementation of these tools, we present a representative workflow for tree species classification using bark images, based on a study published in ***Ecological Informatics*** **(Surendran et al., 2025)**. The process was divided into four stages: fieldwork, preprocessing, model training/post-processing, and accuracy assessment (Figure 1).

The methodology explores optimal classification workflows for tree species identification using both classical machine learning and deep learning approaches. A grid search strategy was employed to optimise hyperparameters across multiple algorithms, including k-Nearest Neighbour (k-NN), Gaussian Naïve Bayes, Decision Trees, Random Forest, Gradient Boosting, Support Vector Machines (SVM), Multilayer Perceptron (MLP), and CNNs.

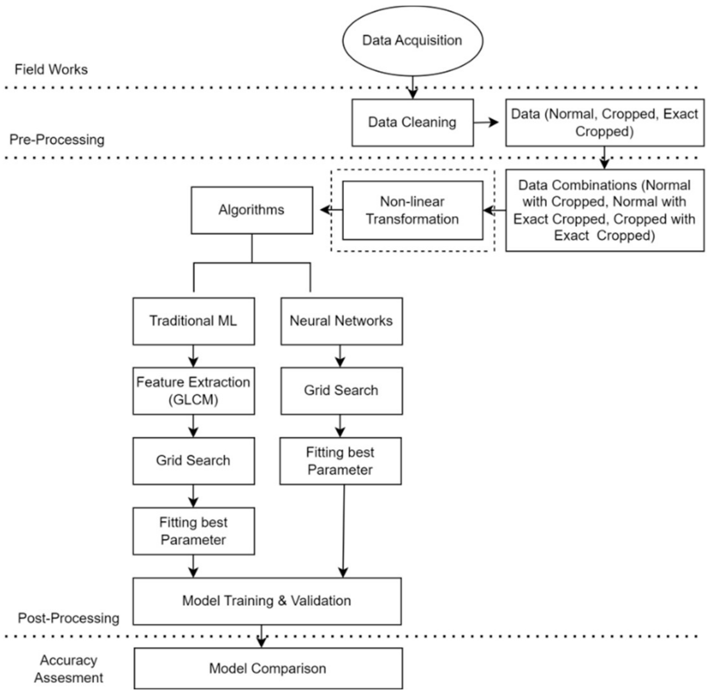


Figure 1: Research architecture workflow diagram (Surendran et al., 2025).

Three datasets were used:

1. Field-collected bark images from Slovakia;
2. Field-collected images from CZU (Czech Republic);
3. A synthetically augmented dataset with non-linear transformations.

Images were taken using standard digital cameras at approximately 0.5 m distance. Manual segmentation was used to eliminate artefacts such as moss or glare. Two subsets were created: “normal” (larger, unprocessed segments) and “exact” (cropped, clean sections), to evaluate the impact of input precision on classification outcomes. To further stress-test the models, synthetic distortions (e.g., swirl transformations) were applied.

Feature extraction was carried out using Gray-Level Co-occurrence Matrix (GLCM) metrics, including contrast, dissimilarity, homogeneity, correlation, and energy. Models were trained and validated using cross-validation techniques (e.g., 3-fold and 15-fold), and performance was assessed using precision, recall, F1-score, and overall classification accuracy.
This workflow demonstrates the flexibility and scalability of the tools developed, which can be applied to a wide range of agroforestry image classification challenges with minimal technical overhead.

3. RESULTS

3.1 Soil Carbon and Biodiversity Estimators

The soil carbon and biodiversity estimation web applications were tested across a range of locations within Europe to assess both predictive performance and user experience. These applications utilised preprocessed Sentinel-2 satellite imagery and trained deep learning models to generate rapid, spatially explicit estimates of key ecosystem attributes. The goal of this evaluation was to verify that the outputs are consistent with known environmental conditions and suitable for integration into agroforestry monitoring and management workflows.

Soil Carbon Estimation

The Soil Carbon Estimator classifies soil organic carbon (SOC) content into discrete percentage categories, ranging from 0–1% up to >10%, based on multispectral satellite imagery processed through the application's automated pipeline. Predictions were tested across several agroecologically diverse regions of Europe.

For example, in the Black Forest region of Germany (48.0°N, 8.0°E), the model predicted SOC content within the 3–4% range, aligning well with the region's known organic-rich soils and mixed forest-agriculture land use systems. This suggests that the model can effectively identify carbon-rich soils in heterogeneous landscapes.

Another test was conducted in the vicinity of the Czech University of Life Sciences, Prague, where users input geographic coordinates to generate predictions. Figure 2 illustrates the user interface and the prediction output for this location, showcasing the system's ability to deliver relevant localised results via a simple, interactive interface.

Biodiversity Estimation

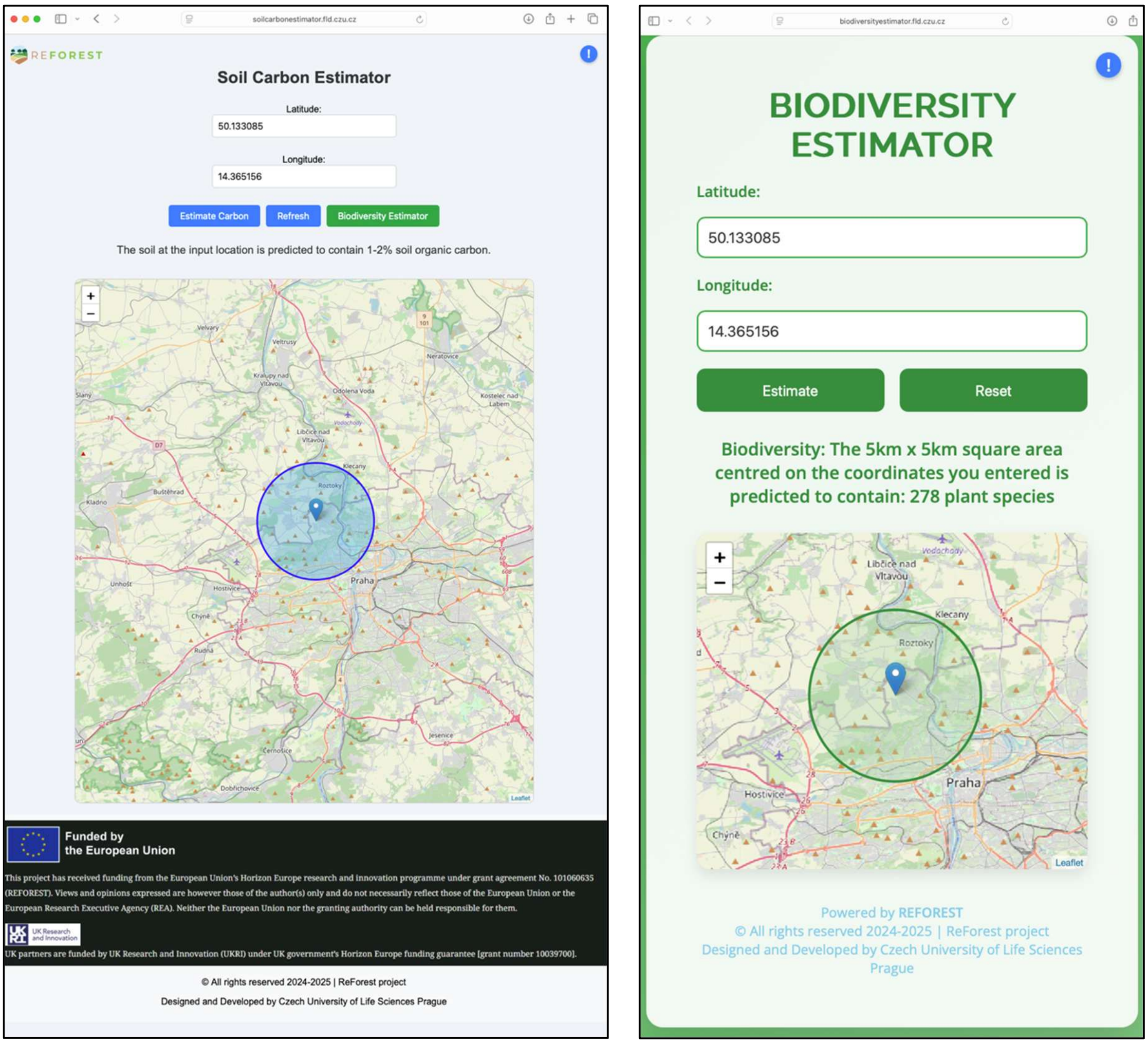
The Biodiversity Estimator uses spectral variability from Sentinel-2 data to estimate plant species richness over a 5 km × 5 km area centred on user-defined coordinates. This provides rapid, non-invasive assessments of biodiversity potential across landscapes.

In the Loire Valley, France (47.3°N, 0.9°E)—an area characterised by a mosaic of hedgerows, small woodlots, and organic farms—the model predicted moderate to high species richness, which is consistent with field observations and ecological expectations. These preliminary results support the model's utility for mapping habitat diversity in structurally complex landscapes.

Validation and Usability

Initial validation against field data and agroforestry models indicates that the applications are capable of producing ecologically meaningful and spatially consistent predictions. While additional validation and calibration are ongoing, current results suggest strong potential for these tools to support: e.g. ecosystem monitoring and verification schemes; agroforestry system planning; or integration into incentive frameworks such as payments for ecosystem services. Both applications demonstrated good usability, with minimal technical requirements for users. Once geographic coordinates are entered, the systems automatically retrieve and process satellite imagery, returning results within seconds. This supports fast, scalable, and user-friendly monitoring of key ecological indicators.

Figure 2: Examples of Soil Carbon (left) and Biodiversity Estimators using screenshots of the websites when the position near the Czech University of Life Sciences is used (50.1330855, 14.365156).



3.2 An application of CNN Parameter Tuner and Advanced Machine Learning Classifier

Extensive testing was conducted to evaluate the performance of various machine learning algorithms and datasets using the Advanced Machine Learning Classifier and CNN Parameter Tuner. The experiments focused on bark-based tree species classification, assessing how dataset quality, segmentation precision, and model selection influence classification accuracy.

Dataset Influence and Classical Algorithm Performance

Multiple datasets were created and tested (see Table 1), including labelled image sets from Slovakia and CZU (Czech Republic), as well as a synthetically altered dataset designed to test model robustness under nonlinear distortions. Across all experiments, dataset quality and segmentation precision proved to be key determinants of model performance. In particular, "exact" cropped images, focused on clean, anomaly-free bark segments, consistently outperformed “normal” crops that included background variation and artefacts (see Figure 3).

Figure 3: Example of the bark images used in the experiment. Slovak (A) and Czech (B) datasets (Surendran et al., 2025).

Among classical machine learning algorithms, Random Forest and Gradient Boosting delivered the highest accuracies (up to 86%) when combined with appropriate feature scaling. In contrast, Support Vector Machines (SVM) and Gaussian Naïve Bayes showed poor performance unless scaled, and Decision Trees exhibited clear signs of overfitting on smaller datasets. These findings underscore the importance of both preprocessing and parameter optimisation in classical classification workflows.

CNN Superiority and Robustness

Convolutional Neural Networks (CNNs) consistently outperformed all classical models, particularly when trained on the exact cropped datasets. Fine-tuned CNNs achieved classification accuracies exceeding 90%, demonstrating high precision and generalisability across bark texture variations.

Testing on the CZU dataset, which featured fewer samples and additional species diversity, confirmed these trends. CNNs again reached up to 93% accuracy, while classical models struggled with overlapping textures and limited intra-class variance. Multilayer Perceptron (MLP) models benefited from scaling but still trailed CNNs in both performance and robustness.

A synthetically distorted nonlinear dataset was used to evaluate algorithm resilience to real-world image imperfections. CNNs maintained high accuracy (>90%), whereas classical models performed inconsistently, with marked overfitting. Notably, SVM accuracy improved significantly from 42% to 77% when scaling was applied but still fell short of CNN benchmarks. These results highlight CNNs' inherent capacity to capture complex visual patterns and maintain stability under challenging conditions.

Overall, the experiments underscored that CNNs are the most suitable models for bark-based tree species classification, though they require careful parameter tuning, motivating the development of the accompanying CNN Parameter Tuner software (Figure 4).

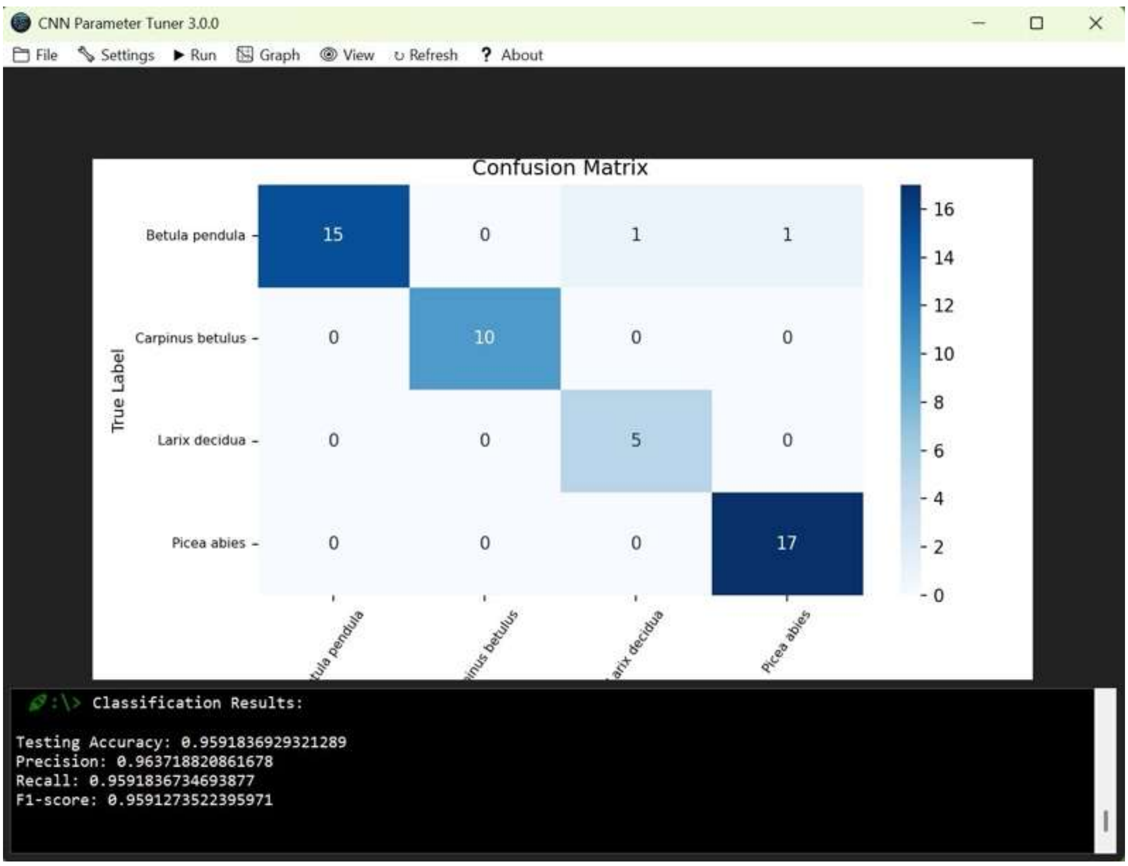


Figure 4: Screenshot of a result table from the CNN Parameter Tuner 3.0.0

The Role of the Advanced Machine Learning Classifier

The insights gained from these experiments led to the development of the Advanced Machine Learning Classifier—a tool that enables users to combine CNN-based deep feature extraction with a suite of classical supervised learning algorithms. This hybrid approach provides flexibility for users who wish to experiment with different classifiers while benefiting from the representational power of deep learning. The tool allows for seamless integration of deep feature extraction via embedded CNNs; Classification using Random Forest, AdaBoost, Gradient Boosting, SVM, or other models; and comparative analysis of end-to-end CNNs vs. hybrid architectures.

In terms of performance, the hybrid approach achieved strong results. On the Slovak dataset, CNN-only models reached >90% accuracy, while the hybrid approach using deep features with ensemble classifiers yielded slightly lower but still robust accuracies in the 84–87% range. Importantly, these results were consistent across all datasets, including the CZU and nonlinear datasets, validating the generalisability of the hybrid workflow. This approach also demonstrates that classical classifiers can benefit from CNN-derived features even in the absence of large training datasets, offering a practical balance between model interpretability and computational complexity.

Usability and Practical Value

The graphical user interface (GUI) of the Advanced Machine Learning Classifier plays a crucial role in making these capabilities accessible. An example output is shown in Figure 5, demonstrating how the tool can be used for research, education, and applied agroforestry management. These results confirm the value of the classifier not only as a high-performing analytical engine but also as a practical tool for researchers.

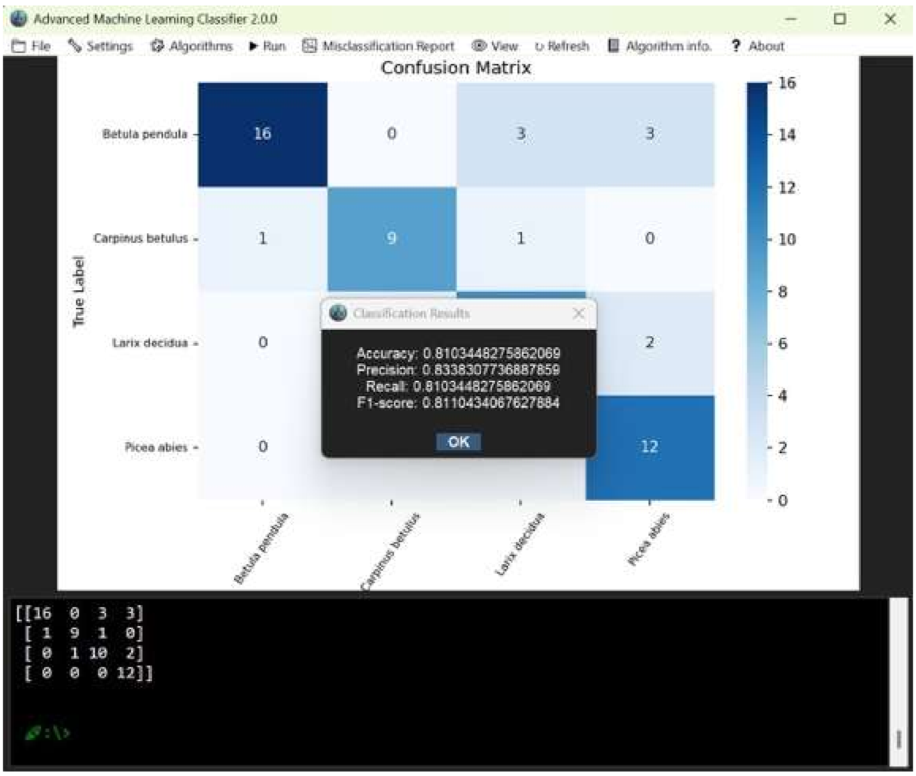


Figure 5: Screenshot of a result table from the Advanced Machine Learning Classifier 2.0.0

The confirmation of the relevance and interest in both solutions and their usability can be demonstrated through the views and downloads of both software, exceeding 500 downloads for the Advanced Machine Learning Classifier (Figure 6) and reaching almost one thousand downloads for the CNN Parameter Tuner (Figure 7).

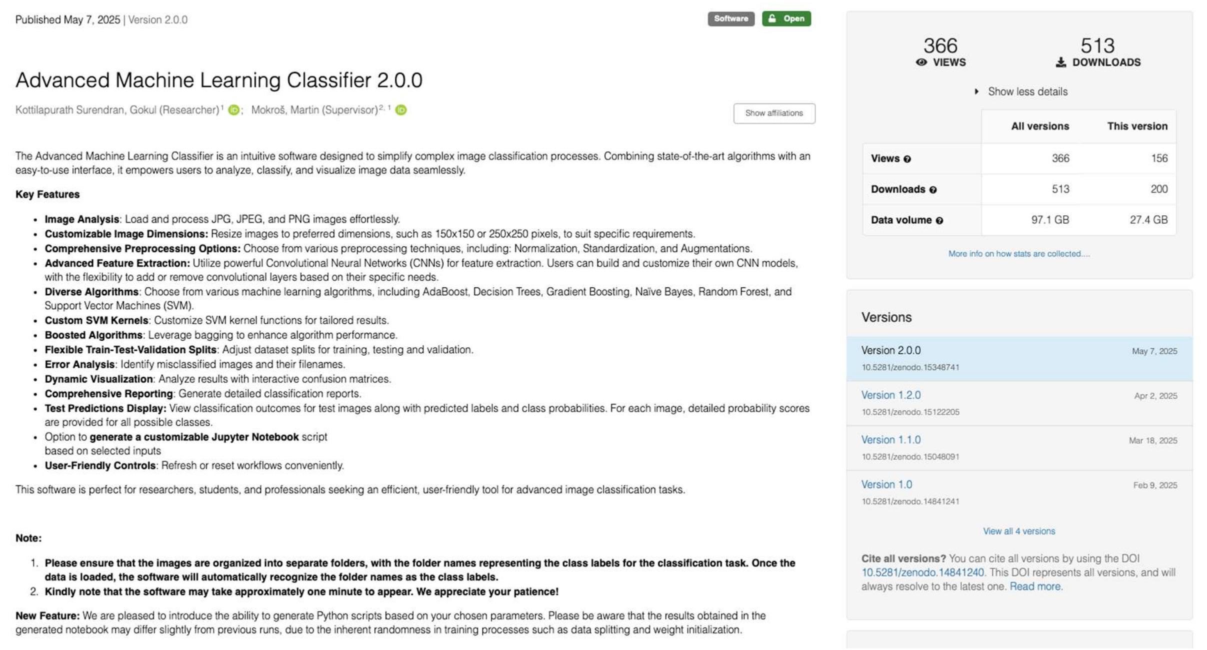


Figure 6: Advanced Machine Learning Classifier 2.0.0 webpage shows the main information, but also the number of views and downloads.

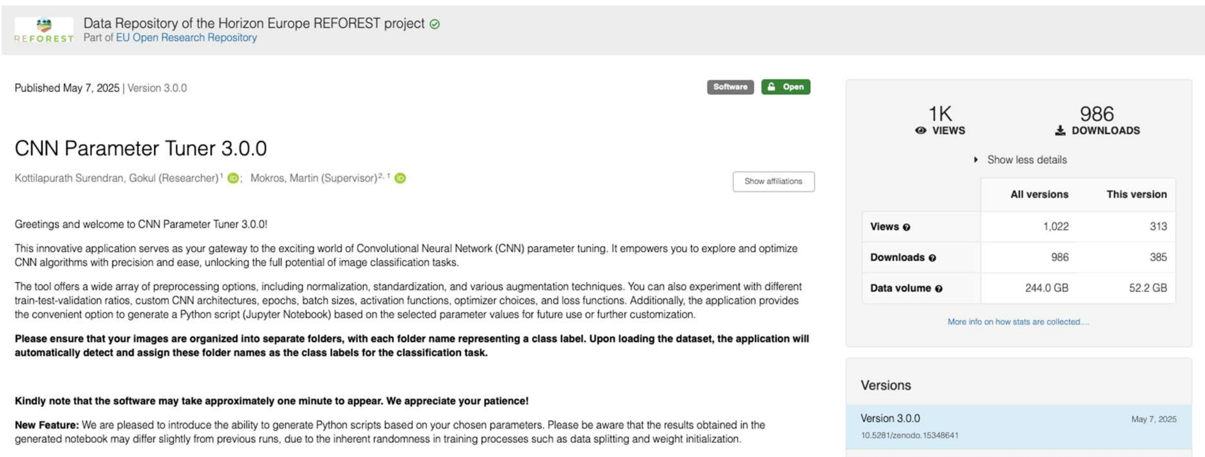


Figure 7: The CNN Parameter Tuner 3.0.0 webpage shows the main information, but also the number of views and downloads.

The second publication on the classification with booster support vector machines using bagging and feature selection techniques was undergoing the second round of reviews in Ecological Informatics at the time of writing this report.

3.3 Open datasets

All datasets that were used for the experiments focusing on the tree species classification using various algorithms and software solutions are published as open data in the Zenodo (*Table 1*).

Datasets	Details
Slovak exact cropped extended dataset https://zenodo.org/records/14800379	consisting of 1367 images of 4 tree species, *Fagus sylvatica*, *Quercus petraea*, *Picea abies*, *Abies alba.*
Slovak normal cropped dataset https://zenodo.org/records/14228004	consisting of 1369 images of 4 tree species, *Fagus sylvatica*, *Quercus petraea*, *Picea abies*, *Abies alba*.
Nonlinear dataset https://zenodo.org/records/14221584	consisting of 527 images of 4 tree species, *Fagus sylvatica*, *Quercus petraea*, *Picea abies*, *Abies alba.*
CZU exact cropped dataset https://zenodo.org/records/14221740	consisting of 386 images of 4 tree species, *Fagus sylvatica*, *Tilia platyphyllos*, *Acer platanoides*, *Pinus sylvaltica*.
CZU normal cropped dataset https://zenodo.org/records/14221890	consisting of 386 images of 4 tree species, *Fagus sylvatica*, *Tilia platyphyllos*, *Acer platanoides*, *Pinus sylvaltica*.

Table 1: The list of all datasets - all are open and available through Zenodo.

3.4 Improving classification and UAV applications.

The classification accuracy of the machine learning algorithms is the most crucial part for a wide range of applications in the agroforestry sector. Figure 8 shows the accuracy development of the approaches mentioned in previous chapters, regarding the machine learning algorithms. The last part is the MOKROS-NET, which is an ongoing experiment - **M**odular **O**ptimised **K**ernel-based **R**epresentation for **O**bjective **S**ystems. It is proposing a novel fusion algorithm combining multiple methods that are helping to increase the validation accuracy to 96%.

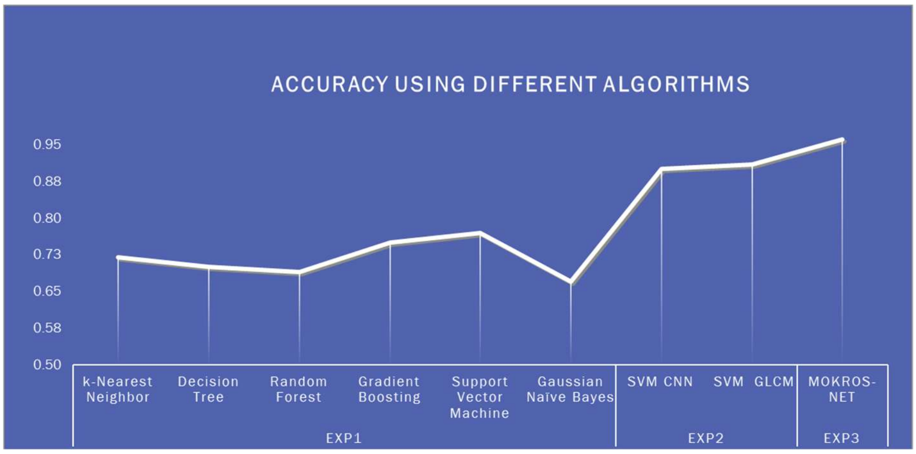


Figure 8: Accuracy development made through all three experiments.

The experiments and proof-of-concept of both software solutions have been demonstrated on the classification of tree species using the bark images. The software solution can be used on a variety of different applications. One of them is the data from UAV imagery. For example, to use delineated crowns of individual trees with labels and create a classification model for tree species, crown infestation or level of tree mortality. An example of such data is on Figure 9. This is a database of deadtrees.earth which is collecting data from across the globe of individually delimited trees that have been assessed as dead.

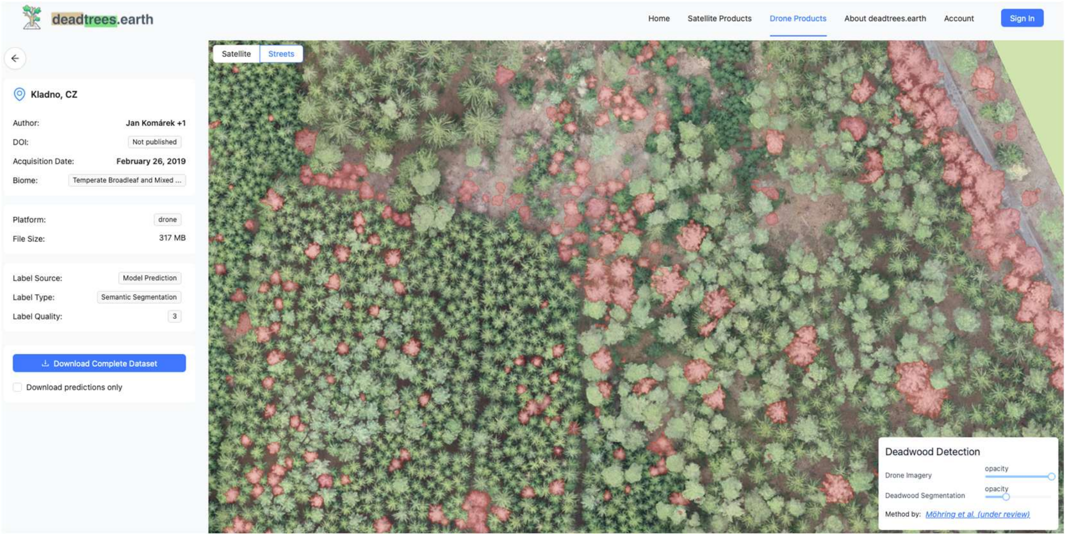


Figure 9: Deadtree.earth example of drone data with selection of individual tree crowns that belong to dead trees.

The pipeline of such implementation would consist of the following steps: planning and data collection, processing images to orthomosaic, automatic delineation of individual crowns, labelling, applying the CNN parameter tuner, evaluation and transferring the model to practice. Planning and data collection are well-established practices within various sectors. It depends on the UAV type, and it is usually automatic, where the operator draws a segment where the data collection should be done, and the UAV planning software will plan the flight accordingly. After data collection, the pipeline is also well established to get a georeferenced orthomosaic. Usually, Agisoft or Pix4D software is used for such processing. The next step is crown delineation where we use the dectree2, which is available here: https://github.com/PatBall1/detectree2. An example of the resulting data is on Figure 10.
In summary, the next step in the ReForest project is to test the use of a combination of these technologies to enable semi-automated assessment of existing AF systems in support of a consultancy model. This work is being undertaken by WP6 in Task 6.5.

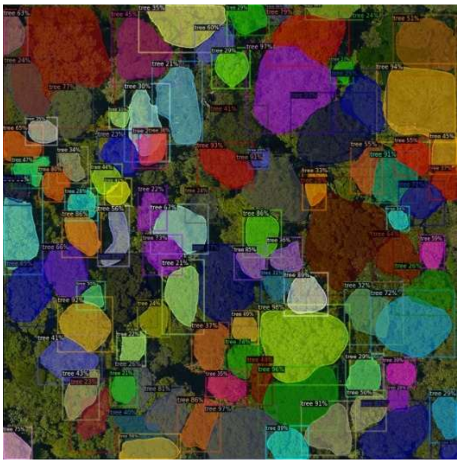


Figure 10: Example of the detectree2 algorithm results from https://github.com/PatBall1/detectree2

APPENDIX: REFERENCES AND RELATED DOCUMENTS

ID	Reference or Related Document	Source or Link/Location
1	Advanced Machine Learning Classifier V 2.0.0 Handbook.pdf	https://zenodo.org/records/15348741
2	CNN Parameter Tuner Handbook V 3.0.0.pdf	https://zenodo.org/records/15348641
3	Shannon, C.E. 1948. A mathematical theory of communication. Bell System Technical Journal 27:379–423	https://doi.org/10.1002/j.1538-7305.1948.tb01338.x
4	Surendran, G. K., Lukac, M., Vybostok, J., & Mokros, M. (2025). A forestry investigation: exploring factors behind improved tree species classification using bark images. Ecological Informatics, 85, 102932.	DOI: 10.1016/j.ecoinf.2024.102932
5	Advanced Machine Learning Classifier 2.0.0	https://zenodo.org/records/15348741
6	Slovak exact cropped extended dataset	https://zenodo.org/records/14800379
7	Slovak normal cropped dataset	https://zenodo.org/records/14228004
8	Nonlinear dataset	https://zenodo.org/records/14221584
9	CZU exact cropped dataset	https://zenodo.org/records/14221740
10	CZU normal cropped dataset	https://zenodo.org/records/14221890