How to create a state-of-the-art LiDAR tree species classification model using deep-learning? Lessons learned from the FOR-species data-science competition.

Julian Frey[1], Zoe Schindler[1], Katja Kröner[1], Thomas Seifert[1]
[1] *Chair of Forest growth and dendroecology, University of Freiburg*

The species identity of individual trees is a key information in forest management for timber production, retention, conservation, biodiversity protection and carbon storage assessments. While many other important metrics like tree diameters or heights have been extensively studied and successfully measured using modern survey technology like light detection and ranging (LiDAR), the classification of species has been shown to be a difficult candidate for automated surveys. Deep learning techniques like convolutional neural networks have shown promising results on image data acquired from unmanned aerial vehicles (Schiefer *et al.*, 2020; Ecke *et al.*, 2024) or handheld devices (Carpentier *et al.*, 2018) to solve this task. The assessment using UAV-RGB data has the downside that individuals might be completely occluded from above and might therefore be overlooked. Pictures acquired from handheld devices are extremely difficult to localize in the forest and are therefore of limited use to create management relevant information. The tree species classification on LiDAR data could solve these problems since point clouds typically contain the real-world locations. Other forest metrics like the trees' diameter and height can be derived from the same data source with little effort. Nevertheless, the species classification based on point clouds has yielded non satisfactory results (Puttonen *et al.*, 2010) or required extensive feature extraction to yield reasonable results on a very limited set of species (Åkerblom *et al.*, 2017) based on parametric or classic machine learning models. Deep learning models have so far been hindered by a lack of training data which generalises over a wide set of acquisition scenarios, spatial extend and species groups (Xi *et al.*, 2020; Seidel *et al.*, 2021).

Within the EU cost action 3DforEcoTec a reference dataset containing more than 20,000 single tree point clouds of 33 species from close range LiDAR acquisitions (terrestrial mobile and static as well as UAV surveys) from a broad set of sensors has been collected (Puliti *et al.*, 2024a). Contributions to this dataset span a wide geographical extend including Oceania and the north American continent, but were mainly from Europe. However, what looks like the perfect dataset for AI training contains actually various challenges. The dataset is heavily imbalanced in multiple dimensions. Small trees are much more abundant than large ones, static terrestrial scanning was used by magnitude more often than other platforms, and while *Pinus sylvestris* has more than 3,000 specimens in the dataset, *Prunus avium* has only about 50. As expectable in such a diverse dataset, also the level of detail and scanning artefacts vary greatly and while some trees are represented by millions of points, some only contain less than a hundred.

This means that the split into a training and validation dataset is already challenging, since a random sample would most likely omit various species-size-sensor combinations if the sample is too small. If the sample is larger, it is likely that not enough training data for the rare options persist. We therefore sampled this parameter space by a farthest point sampling (FPS) algorithm (Eldar *et al.*, 1994) to generate a tiny but representative validation dataset. For this, we normalized all parameters (tree height, species-id and platform-id) and drew 800 samples using the FPS algorithm. Since this includes all extremes (largest and smallest trees per species and sensor), we split this dataset in half randomly and assigned the first half back to the training data to ensure that the model encounters some of the extremes during training. Since the FPS is a deterministic algorithm it is not suitable as a training sampler. We implemented a weight function taking the relative abundance of species, tree height in 5m height bins and platform as the basis for a weighted random sampler for the training dataset instead.

For the application of tree species classification, there were mainly two families of deep learning architectures used and compared in the literature. Point based methods, taking the point cloud directly as an input, and image based methods, taking a projection of the point cloud as an input, have shown diverging performances in the literature (Xi *et al.*, 2020; Seidel *et al.*, 2021). The image based methods profit from the vast body of research and the large number of foundation models in the field (Kattenborn *et al.*, 2021), but the projection of the points is associated with a loss of information. This can be minimized by the parallel pass of multiple projections from different sides taking the distance to the projection plane as a raster value (depth maps). Nevertheless, the aggregation of points to raster cells also comes with a loss in spatial accuracy (Allen *et al.*, 2022). Contrary, point based methods require to store the full point cloud in the computing memory of the neural network, usually the graphics card memory, which might also require downsampling and the usage of small data types with limited precision (Xi *et al.*, 2020; Seidel *et al.*, 2021) due to limitations in computational resources.

We built a compromise between those limitations by utilizing a projection-based approach where we added an additional projection of a detail view of the trunk to cover high detail of the bark structure (Figure 1). In total we added 4 side views, one from the top, one from the bottom and one covering the points between 1 and 1.5 m height. Since the true scale is lost in the projections we also used the tree height as an input. Every projection depth raster gets processed by a network branch with a DenseNet (Huang *et al.*, 2017) backend and the outputs of the single branches get concatenated with the tree height information. These outputs get classified to a species after two further linear network layers. To increase the ability of the model to generalize, we implemented point-based augmentations prior to the projection step using random horizontal (max 22.5°) and vertical rotations (max 180°) as well as random point dropping (max 10%).

With this setup, we reached an overall accuracy of 0.79, precision 0.81, recall 0.79, and an F1-score of 0.79 on the test dataset from the data science competition (https://github.com/stefp/FOR-species) where

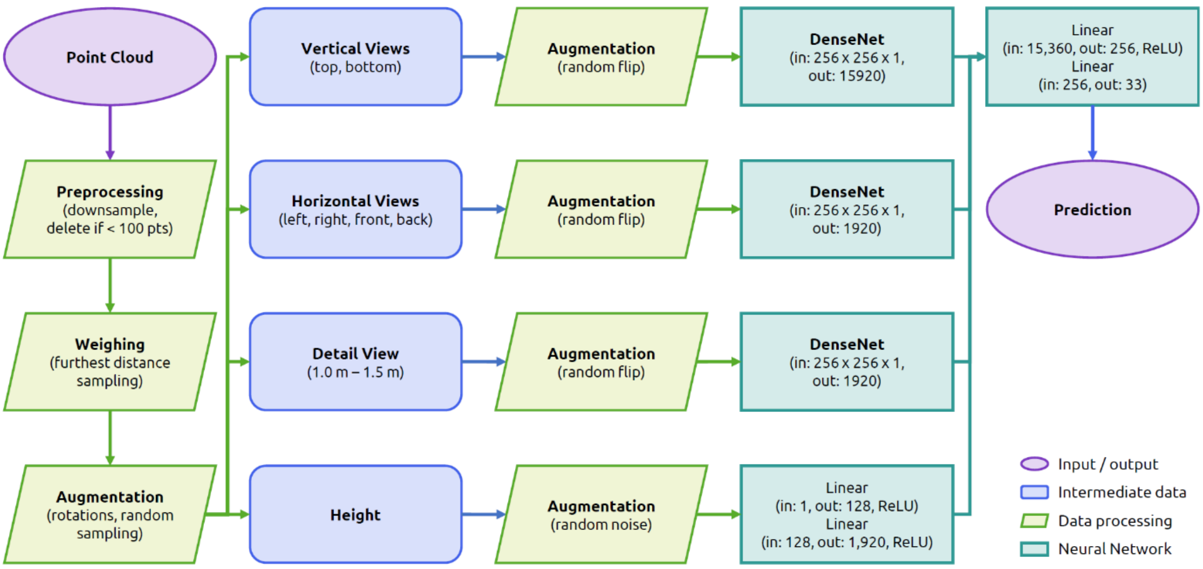

Figure 1: Illustration of the model structure of the DetailView deep learning model for tree species classification from LiDAR data.

the actual distribution of tree species and platforms was unknown to us (Puliti *et al.*, 2024b). Within the competition, our model slightly outperformed other projection-based approaches but was clearly superior to all point-based approaches. We see great potential to use this technology for forest research and practice, especially with fine-tuned local models only incorporating locally relevant species. Together with fully automated single tree segmentation and forestry parameter information extraction, the species classification closes the last bit in the workflow from a scan to a single tree-based inventory. This potentially enables us to build detailed information driven digital twins as a basis for an evidence-based forest management and an enhanced data provision for forest research.

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