USING MULTISPECTRAL IMAGERY FROM UAV TO DERIVE SELECTED FOREST INVENTORY PARAMETERS

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Abstract

The following article deals with the usage of Unmanned Aerial Vehicles in the forest inventory. The main goal is to obtain general information about certain forest areas based on deriving data from UAV captured multispectral images. Parameters like the number of individual trees plus their species classification and health condition evaluation are obtained via the usage of deep learning techniques. Additional parameters, like crown diameter, are calculated too based on the segmentation of the digital elevation model. Used techniques are described, evaluated and further development proposed.

Keywords: UAV, Forest, Deep Learning, Tree Crown Segmentation

INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become a common way of data acquisition in many branches based on their wide availability, detail of captured data, and relatively low prices. One of them is forestry, where the UAVs can provide not only an overview of particular forest areas, but allow us to derive additional parameters. Some of the tasks that are commonly solved are the number of trees, species composition, health conditions, crown segmentation, and volume calculation. Those factors led to the utilization of UAVs for forest application in Stora Enso where the UAVs have already proved their usefulness for mill inventory [13]. This article will further focus on the usage of multispectral data acquired by MicaSense RedEdge MX (mounted on DJI Phantom 3 Pro) or DJI Phantom 4 Pro Multispectral devices and techniques used for deriving additional information. The presented approach is designed as a fully automated solution for obtaining selected forest parameters across many countries. Acquisition of data for further analysis is done by various forest experts in a uniform and most efficient way to cover large areas with satisfactory precision and detail concerning user-friendliness.

TREETOPS, TREE HEALTH, AND TREE SPECIES DETECTION

For forest inventory on a single tree level, we work with individual trees' location, health conditions, and species. For getting these parameters various techniques can be used [1,6,9,10,14]. We have decided to utilize deep learning techniques [2,7], which can produce precise results [4] and it is possible to adjust trained models anytime we need to in a short period.

The most time-consuming part was data labelling for the model training. There had been marked over 87k trees on various multispectral datasets. The main problem is that the training sample must reflect the diversity of the forest, as Stora Enso is operating in many countries all around the world. For that purpose, many datasets over the countries with various forest compositions were acquired.

As we are using multispectral sensors which are collecting images in five bands (red, green, blue, red edge, near-infrared). We can derive orthophoto classification for tree health and tree species. With the data captured by the MicaSense device, we can distinguish four classes related to tree species: spruce, pine, broad-leaf, other. Unfortunately, with data captured by DJI P4 Multispectral, we can properly distinguish just between two categories: spruce and other trees. The reason is that the orthophotos derived from DJI P4 Multispectral images suffer a larger amount of image artefacts (blurred areas, spectral bands mismatch) than orthophotos based on MicaSense images. In tree health status, for now, we identify only for spruces which are classified into three categories: healthy tree, infested (stressed) tree, dead tree.

For each model, the training was realized in the Azure Databricks platform (using all the captured bands) with the usage of the PyTorch library. The model itself is based on U-Net convolutional neural network. In total 3 models were created, first for single tree localization, the second for health classification, and the third for tree species classification. Based on labels for single tree localization, we are creating image masks with point size 3px, so we can apply standard segmentation methods. During the training phase, we erase “bad” areas from input images, where even a human eye is not able to recognize if the object is a tree or something else like bushes. Once we have the locations of trees, we can classify them. We are creating a window 60px wide around each tree top and training the network in that window. If you are interested in more details about the developed solution, please, contact one of the authors.

With different cameras, more models must be trained. Based on initial testing, the usage of models trained on MicaSense camera showed poor quality results on datasets acquired by DJI P4 Multispectral due to a slightly different wavelength for the same bands. Models for MicaSense devices are already in use since 2019. Models for Phantom Multispectral devices were trained and tested recently. For the DJI P4 Multispectral model testing, one dataset from Sweden (Boreal zone) and two from Finland (Southern boreal zone) were chosen and over 300 points for tree health and over 900 points for tree species were manually labelled on orthophoto image and precision was calculated.

Table 1. Description of selected datasets acquired by DJI P4 Multispectral and average accuracy of applied deep learning models

	Dataset 1 (SWE)	Dataset 2 (FI)	Dataset 3 (FI)
Number of images	390	1065	1794
Area (ha)	1.7	7.2	9.3
Number of detected trees	987	3537	5927
Tree health accuracy (%)	97	92	73
Tree species accuracy (%)	86	83	93

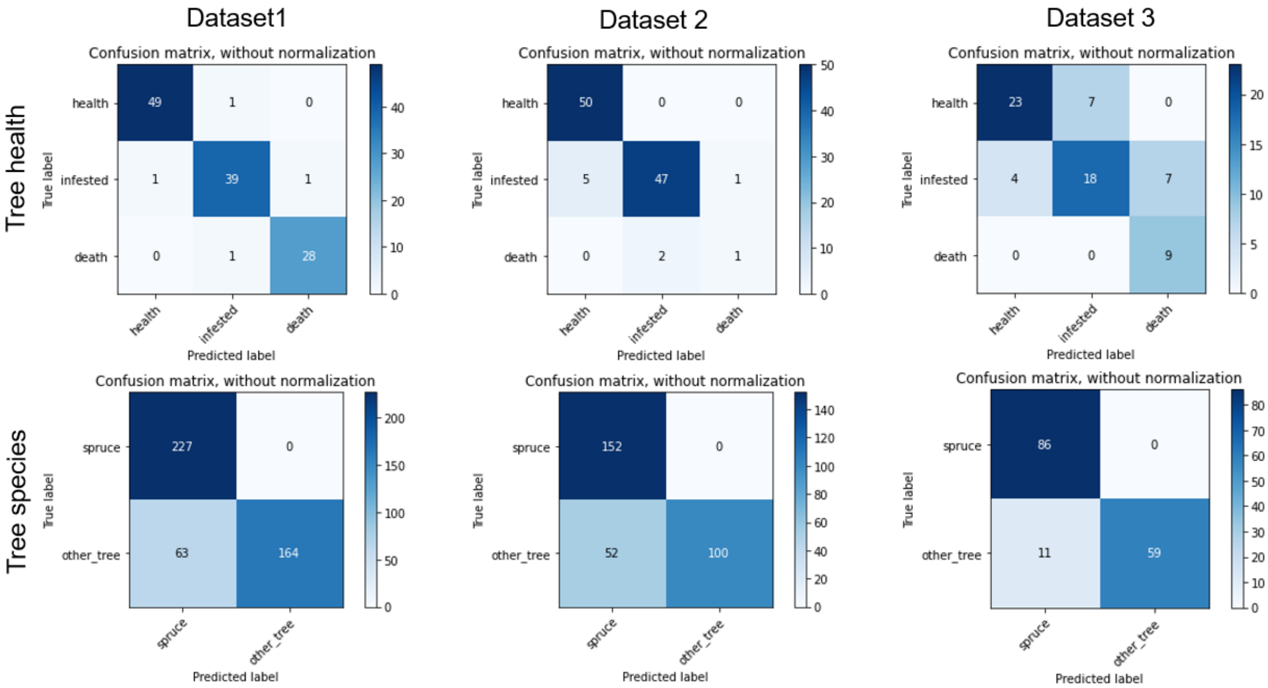

Fig 1. Confusion matrix of tree species and tree health models for each dataset acquired with DJI P4 Multispectral

Table 1 portrays the accuracy results of used models on tree testing datasets. We can state the model for tree health produced satisfactory results but the model for tree species still needs some improvements. As was described before, we are now dealing with errors coming with DJI P4 Multispectral camera to be able to distinguish the same tree species as with the MicaSense camera. This problem also affects results for tree health classification as you can see in dataset 3, which has quite many of the previously described artefacts in the image.

In comparison to other studies, we achieved very high accuracy for tree health classification. A similar accuracy of 86% was achieved [6] but distinguish only two categories (infested, not infested). Related to tree species classification our model results were not so precise. The higher classification accuracy was achieved by other studies [6], [7], however their precision was tested on small sites [6] or neighbouring areas [7].

Table 2. Comparison of studies dealing with tree health and tree species classification on data from UAV

	Data type	Technique	Tree health		Tree species		Location	Year
			Accuracy	Classes	Accuracy	Classes		
[1]	RGB, Multispect.	OBIA	78%	1	78%	4	Jablunkov, Czechia	2018
[6]	Multispect.	OBIA	86%	2	96%	5	Austria	2019
[9]	RGB	Residual neural network	-	-	80%	3	Ontario, Canada	2019
[14]	RGB	ITCD algorithm	77%	4	83%	7	Stolby, Russia	2019
[2]	RGB, Multispect.	U-NET	-	-	85%	8	Guangxi, China (forest farm)	2020
[7]	RGB	U-Net, ResNet50	-	-	94%	2	Jamagatana, Japan	2020
[15]	RGB, Multispect.	machine learning classifier	-	-	81%	8	Yunnan, China	2020
[10]	RGB	computer vision techniques	40%	1	72%	3	Yamaga, Japan	2021
Prop.	Multispect.	U-Net	87%	3	87%	2	Finland, Sweden	2022

TREE CROWN SEGMENTATION

Based on the previously mentioned data, we can achieve other information such as tree crown diameters. Those calculations are commonly performed on LiDAR data [5,12,16], which can provide comprehensive datasets. Unfortunately, LiDAR sensors for UAVs are still quite expensive to be widely used, hence we have decided to utilize photogrammetrically derived data.

The tree crown segmentation algorithm is generally based on digital elevation model local maxima identification [5,12]. Tree centres identified on the orthophoto by the previously described deep learning model are not usually corresponding with the local maxima on the digital elevation model, especially when the data from UAV is acquired without ground control points. Therefore, the search area is defined around each tree centre where the local maximum is found. The segmentation process then passes through each pixel in turns beginning at the local maxima and evaluating if the pixel should be a part of the crown or not. This is judged based on several factors like pixel value and coherence with neighbouring pixels classified as a part of the tree crown. The process is a fully automatic solution developed in the Python language with the use of libraries NumPy, SciPy, and GDAL/OGR.

The last part of the process is to obtain additional tree parameters in the area of interest, such as diameter at breast height, tree height, and wood volume. Those parameters are calculated by standard forestry equations and are currently available only for datasets from Finland.

Table 3. Difference of manual measurement and algorithm derived crown diameter mean value

(m)	Whole dataset	Dataset without extremes
Mean	0.46	0.33
Min	0	0
Max	2.3	0.87
StDev	0.48	0.21
RMSE	0.66	0.39

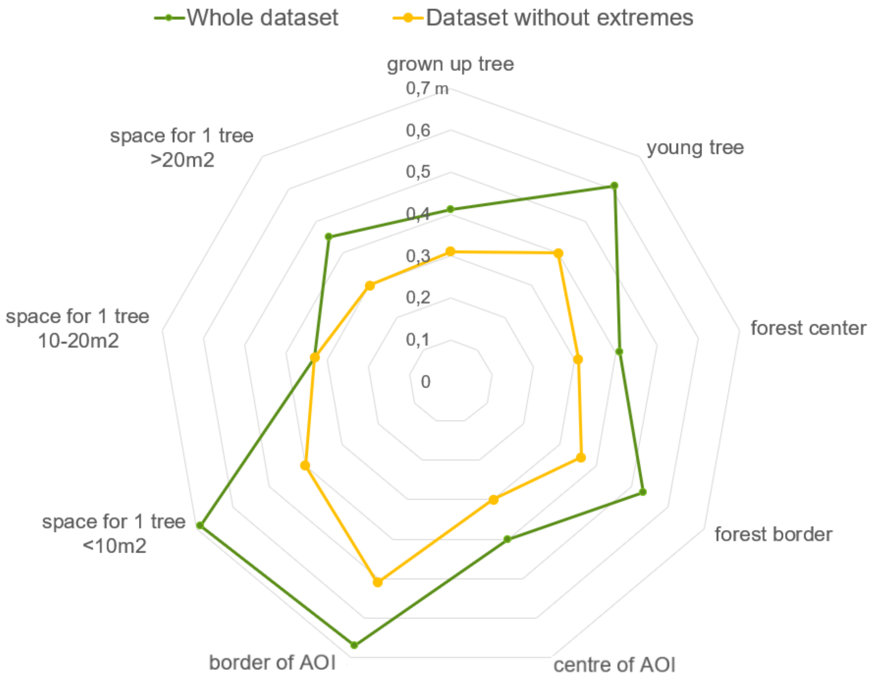

Fig. 2. Graph of the mean difference between manual measured and algorithm derived crown diameter with selected key factors influencing the accuracy

Results from the developed algorithm we compared to the manual measurement performed on various datasets where 1142 crowns had been manually measured in total. Overall results (Table 3) showed the difference between manually measured and algorithm-derived crown diameter around 0.46 m. In case the known extreme areas were excluded (too close to the border of orthophoto, visually identifiable problems like blurred areas, etc.), the difference was about 0.33 m. The mean pixel size of created digital elevation models was about 0.25 m. In the graph (Fig. 2) the key factors affecting the precision plus their effect on the result are portrayed.

In comparison to other studies where the overall accuracy was about 70% (67% [11], 70% [3], 73% [8]), our result achieved very promising results with an overall accuracy of 86% (without extremes 91%).

CONCLUSION

The described approach provides valuable data and helps to get an overall preview of certain forests areas. Information about the number of trees and their classification to species and health categories is a crucial part of forest site investigation and via this approach can be easily obtained in a quite short time. Except for the standard inventory, the data about tree health can provide early warning about pests like bark beetle, etc. Despite some difficulties, related to the quality of images acquired with DJI P4 Multispectral camera that need to be solved to derive much more realistic results, the overall classification accuracy of tree species, tree health and overall accuracy of tree crown segmentation appears satisfying in comparison to other studies. Therefore, we can consider the proposed approach as suitable for forest experts.

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