AN AUTOMATIC MOBILE APPROACH FOR TREE DBH ESTIMATION USING A DEPTH MAP AND A REGRESSION CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Carbon credit programs finance projects to reduce emissions, remove pollutants, improve livelihoods, and protect natural ecosystems. Ensuring the quality and integrity of such projects is essential to their success. One of the most important variables used in nature-based solutions to measure carbon sequestration is the diameter at breast height (DBH) of trees. In this paper, we propose an automatic mobile computer vision method to estimate the DBH of a tree using a single depth map on a smartphone, along with our created dataset **DepthMapDBH2023**. We successfully demonstrated that this dataset paired with a lightweight regression convolutional neural network is able to accurately estimate the DBH of trees distinct in appearance, shape, number of tree forks, tree density and crowding, and vine presence. Automation of these measurements will help crews in the field who are collecting data for forest inventories. Gathering as much on-the-ground data as possible is required to ensure the transparency of carbon credit projects. Access to high-quality datasets of manual measurements helps improve biomass models which are widely used in the field of ecological simulation. The code used in this paper is publicly available on Github and the dataset on Kaggle.

1 INTRODUCTION AND MOTIVATION

Creating forest inventories is a key component of carbon accounting as it is used to estimate forestry indices like forest growing stock, basal area, biomass, and carbon stock. The tree diameter at breast height is one of the variables used in allometric models [1, 2, 3, 4] to estimate tree carbon sequestration.

In a typical ground forest inventory survey, a field worker must wrap a measuring tape [5] around a tree trunk to measure the diameter of a tree at "breast height" (1.3 meters). A measuring tape can be difficult to use in the field depending on diverse ecological and environmental factors [6]. Furthermore, measuring the DBH of trees with tape may require two people for larger trees, and is time intensive, making the work cost prohibitive. In this paper, we propose an automatic approach to estimate the DBH of a tree using a single depth map. This process can be easily integrated into a mobile application that saves field crews hours when creating forest inventories. It will also allow them to cover more surface and collect more data to optimize the carbon simulation/prediction models.

2 RELATED WORK

Researchers have been working on estimating DBH using LiDAR remote sensing data [7] or using mobile LiDAR scanning systems [8]. Some research has been done on the use of smartphone camera images to calculate dense point clouds for the estimation of a tree's DBH [9, 10]. Similar research to our own, estimation of tree DBH with the use of depth information from consumer mobile devices, has been conducted. However, this research requires multiple steps as it involves the extraction of depth maps from RGB images of the trees using a depth extraction model before calculating the DBH [11].

The novel solution we propose here, which includes the combination of a light deep learning approach and a single depth map, can be used for ground data collection and is meant to be used directly and easily on a smartphone. This single-pass neural network model provides a more accessible solution for forest inventory crews when integrated into a smartphone application.

Convolutional neural networks [12] have been used for regression tasks to estimate dimensions [13] successfully which encouraged our efforts to pursue this work.

3 DATASET

In this section, we will present the dataset **DepthMapDBH2023** that we have created for this project. We will explain the data collection process, data features, and challenges encountered while collecting the dataset. The dataset is currently available on Kaggle: `https://www.kaggle.com/datasets/earthshot/depthmapdbh2023`.

3.1 DATA COLLECTION

We have gathered 1008 trees' RGB pictures along with their corresponding 192x192x1 depth maps and tape-measured DBH values.

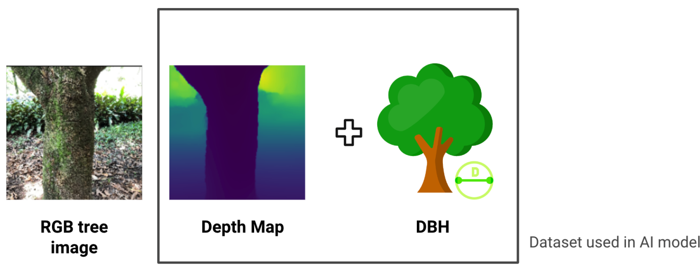

Figure 1: Dataset structure

We designed a separate test set (164 samples) with different physical trees of diameters ranging from 0 cm to 109 cm.

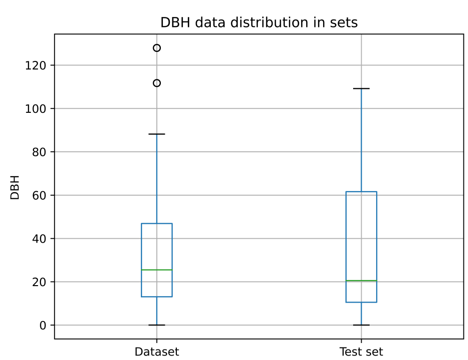

Figure 2: Plots of the distribution of the dataset (a) Dataset (b) Separate Test set

We focused our data gathering on collecting DBH values between 0 and 120 cm in a relatively even distribution. Our final DBH value distribution for the datasets is illustrated in Figure 2.

3.2 Challenges

In order to generate the depth maps required for our research, we created a special iOS application for LiDAR iPhones. The application captured the necessary information needed for building this dataset. The values in the depth maps collected are in meters (float) but a conversion to decimeters was advantageous to distribute the values more evenly in the 0-255 float space.

Our goal to create a robust model that was effective in a wide range of settings required carefully collecting a diverse variety of images that modeled the real-world scenarios in which the application could potentially be used. To achieve this purpose, we collected data from a diverse array of trees distinct in appearance, shape, number of tree forks, tree density and crowding, and vine presence.

In order to collect more data, we generated depth maps from different angles and distances for each tree. Capturing depth maps at different distances to the trees is important so that the dataset can cover a wide range of user-to-tree distances.

We also included several images with no tree to address false positive results.

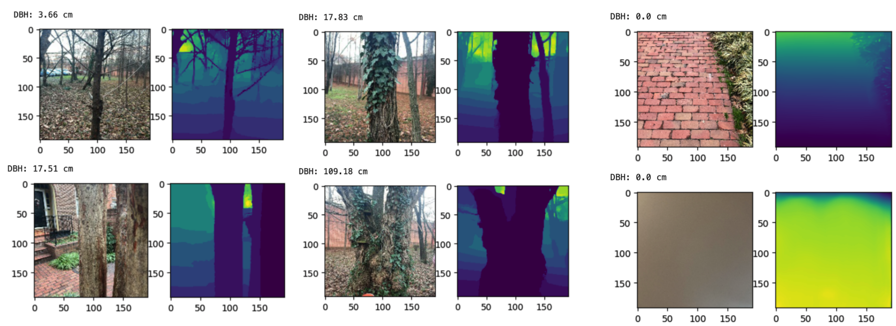

Figure 3: (a) Examples of diversity in dataset (b) Images without any trees in dataset to prevent false positive results

4 Experiments

Our model architecture is a single-channel input regression convolutional neural network (CNN). We experimented with four efficient modified convolutional neural network models (under 35MB each), all pre-trained on ImageNet [14], to solve this regression task as our final goal is to run this model on a mobile application: MobileNet [15], MobileNetV2 [16], DenseNet121 [17], and EfficientNetB0 [18]. We experimented with adding RGB data to the inputs, but the results during the preliminary tests for single-channel depth maps proved to be superior to 4 channels (RGB + Depth map). Moreover, as our future goals include implementing this model into a mobile application, where memory and computation efficiency are of high concern, we decided to continue and run all our experiments with only one channel (depth map).

We ran experiments on an NVIDIA GeForce RTX 3080 GPU with batch sizes of 8, 16 and 32, a plateau-reduced learning rate starting at 0.001, the Adam optimizer and MSE loss.

The dataset was randomly divided into training data and validation data in a ratio of 80:20% after it was randomly shuffled. The metrics on the validation data were used to control the reduced learning rate and early stopping. For each modified regression CNN architecture, we ran several training sessions with different random shuffling seeds.

Code available on Github: `https://github.com/Earthshot-Labs/Automatic_Tree_DBH-Estimation_with_Depth_Map_Regression_CNN`

5 Results

Table 1 presents the results of the generalization performance of the models using the test data collected from different trees. We used the mean absolute error (MAE), mean square error (MSE), the root squared error (RMSE) and the R-squared value as metrics. All DBH estimations inferior to zero were set to 0 as it is impossible to get a negative DBH.

Model	MAE	MSE	RMSE	R2	batch size	seed	Model size (MB)
Modified DenseNet121	3.21	24.40	4.94	0.97	32	8809	33
Modified MobileNetV2	3.63	38.21	6.18	0.96	8	7150	14
Modified MobileNet	3.94	42.46	6.52	0.96	8	8439	16
Modified EfficientNetB0	8.17	121.63	11.03	0.88	32	3191	29

Table 1: Best performance on the test set for each modified regression CNN

All the modified models performed well on this task except the EfficientNetB0 which consistently had the lowest performance. The best model is the Modified DenseNet121 with an R2 of 0.97.

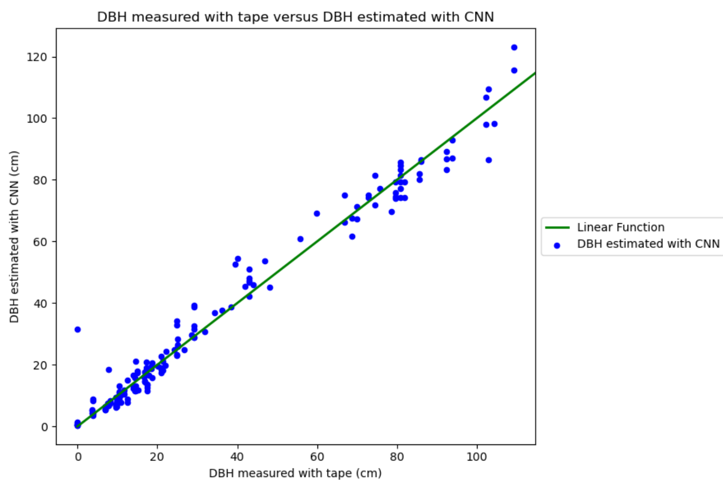

Figure 4: Scatter plot of the measured DBH (test set) values versus the estimated DBH by the best modified DenseNet121 model

However, if we consider the sizes of the models, the performance of the MobileNetV2 model with a size of only 14MB was also quite competitive.

6 Conclusion

We introduce in this paper a new dataset called **DepthMapDBH2023** consisting of 1008 training samples and 164 test samples. We have successfully demonstrated that this single channel depth map dataset contains the necessary information to estimate DBH when paired with a sufficiently sophisticated computer vision model such as a regression convolutional neural network. After training the modified CNNs on the dataset and comparing the resulting metrics on the test set, the modified DenseNet121 was selected as the optimal DBH estimation model. The modified MobileNetV2 model is a notable runner-up if the size of the model is to be taken into consideration. We have shown in this paper that using a single 192x192 depth map of a tree along with a small regression CNN gives an adequate and useful estimation of the DBH of a tree. This method also only requires a fraction of the time when compared to traditional tree-measuring methods. The goal of this project is to help crews in the field who are creating forest inventories to measure trees in a faster and more cost-efficient way.

REFERENCES

[1] Bin Liu, Wensheng Bu, and Runguo Zang. "Improved allometric models to estimate the aboveground biomass of younger secondary tropical forests". In: *Global Ecology and Conservation* 41 (2023), e02359. ISSN: 2351-9894.

[2] Chuankuan Wang. "Biomass allometric equations for 10 co-occurring tree species in Chinese temperate forests". In: *Forest Ecology and Management* 222.1 (2006), pp. 9–16. ISSN: 0378-1127. DOI: `https://doi.org/10.1016/j.foreco.2005.10.074`.

[3] Thomas G. Cole and John J. Ewel. "Allometric equations for four valuable tropical tree species". In: *Forest Ecology and Management* 229.1 (2006), pp. 351–360. ISSN: 0378-1127. DOI: `https://doi.org/10.1016/j.foreco.2006.04.017`.

[4] Shem Kuyah et al. "Allometric equations for estimating biomass in agricultural landscapes: II. Belowground biomass". In: *Agriculture, Ecosystems Environment* 158 (2012), pp. 225–234. ISSN: 0167-8809. DOI: `https://doi.org/10.1016/j.agee.2012.05.010`.

[5] Hanieh Saremi et al. "Impact of local slope and aspect assessed from LiDAR records on tree diameter in radiata pine (Pinus radiata D. Don) plantations". In: *Annals of forest science* 71.7 (2014), pp. 771–780.

[6] Ruyi Zhou et al. "A Levenberg–Marquardt Backpropagation Neural Network for Predicting Forest Growing Stock Based on the Least-Squares Equation Fitting Parameters". In: *Forests* 9.12 (2018). ISSN: 1999-4907. DOI: `10.3390/f9120757`.

[7] Wei Yao, Peter Krzystek, and Marco Heurich. "Tree species classification and estimation of stem volume and DBH based on single tree extraction by exploiting airborne full-waveform LiDAR data". In: *Remote Sensing of Environment* 123 (2012), pp. 368–380. ISSN: 0034-4257.

[8] Alexander Proudman, Milad Ramezani, and Maurice Fallon. "Online Estimation of Diameter at Breast Height (DBH) of Forest Trees Using a Handheld LiDAR". In: (2021), pp. 1–7. DOI: `10.1109/ECMR50962.2021.9568814`.

[9] Maria Immacolata Marzulli et al. "Estimating tree stem diameters and volume from smartphone photogrammetric point clouds". In: *Forestry: An International Journal of Forest Research* 93.3 (Dec. 2019), pp. 411–429. ISSN: 0015-752X. DOI: `10.1093/forestry/cpz067`.

[10] Yongxiang Fan et al. "Estimating tree position, diameter at breast height, and tree height in real-time using a mobile phone with RGB-D SLAM". In: *Remote Sensing* 10.11 (2018), p. 1845.

[11] Xinmei Wu et al. "Passive measurement method of tree diameter at breast height using a smartphone". In: *Computers and Electronics in Agriculture* 163 (2019), p. 104875.

[12] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. "Deep learning". In: *nature* 521.7553 (2015), pp. 436–444.

[13] Jianlong Zhang et al. "Pig Weight and Body Size Estimation Using a Multiple Output Regression Convolutional Neural Network: A Fast and Fully Automatic Method". In: *Sensors* 21.9 (2021). ISSN: 1424-8220.

[14] Jia Deng et al. "Imagenet: A large-scale hierarchical image database". In: (2009), pp. 248–255.

[15] Andrew G. Howard et al. "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications". In: (2017). DOI: `10.48550/ARXIV.1704.04861`. URL: `https://arxiv.org/abs/1704.04861`.

[16] Mark Sandler et al. "MobileNetV2: Inverted Residuals and Linear Bottlenecks". In: (2018). DOI: `10.48550/ARXIV.1801.04381`. URL: `https://arxiv.org/abs/1801.04381`.

[17] Gao Huang et al. "Densely Connected Convolutional Networks". In: (2016). DOI: `10.48550/ARXIV.1608.06993`. URL: `https://arxiv.org/abs/1608.06993`.

[18] Mingxing Tan and Quoc V. Le. "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks". In: (2019). DOI: `10.48550/ARXIV.1905.11946`. URL: `https://arxiv.org/abs/1905.11946`.