NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

ASE22012 – One-shot learning for dictionary classification of tropical rainforest species

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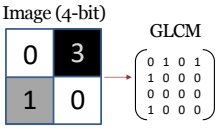
1. Introduction

One-shot learning refers to classification with little data. Random Forest was used in various studies for tree species classification [1],[2]. Previous years for this project has shown only up to <60% accuracy for Random Forest, but only with 5 species [3]. This project's goal is to (i) further increase the accuracies by obtaining good data and (ii) classify more tree species. We used Gray-Level Co-Matrix (GLCM), as a key component generating our features for classification.

Gray-Level Co-Matrix

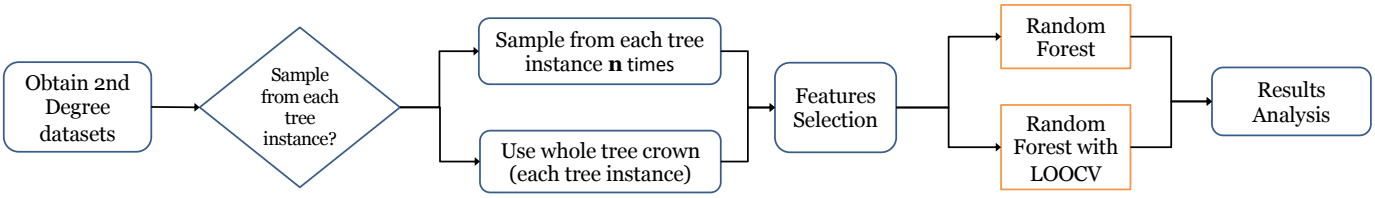
A matrix that shows the distribution of co-occurring grayscale values of each pixel in an image. It is commonly used for texture analysis.



The matrix is then used to generate textual features e.g.: Contrast, Homogeneity, Mean and gives us a single value in the end, which is fed into our Random Forest.

2. Methods

Classifying tree species using Random Forest and Random Forest with Leave One Out Cross Validation (LOOCV).



2.1 Study Area

We studied tree species at Chestnut Nature Park, Singapore. We have Dec 2020 (33 tree instances) and May 2021 (34 tree instances), both with 19 tree species.

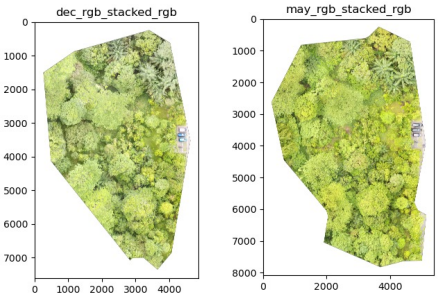


Figure 1 RGB images (left: December, right: May) of Chestnut Nature Park, Singapore.

2.2 Raw Datasets

Red (R), Green (G), Blue (B), Red Edge (RE), Near Infra-Red (NIR) spectral bands taken from LIDAR cameras.

We take the bounding boxes of each tree instances.

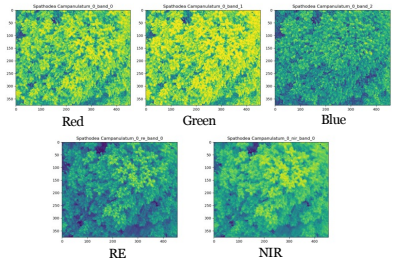


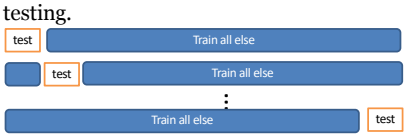
Figure 2 R,G,B,RE,NIR images of tree species *Spathodea Campnulatum*, instance 0.

2.3 Second degree datasets

- Windowed GLCM: Sliding across the image, with a window to calculate the GLCM and its respective features.
- Whole-crown GLCM: Instead of a window of pixels, we slide a pixel across the image.

2.4 Random Forest and LOOCV

Taking inspiration from two research papers [5],[6], we explored a Leave One-Out Cross Validation algorithm, where each sample is left out once in training and testing.



3. Results/ Findings

Using whole tree crown data:

1. Normal Random Forest: 22.3% peak accuracy (10 features)
2. Random Forest with LOOCV: 26.8% peak accuracy (40 features)

4. Conclusion/ Discussion

- Will be a challenge to transfer the model to different forest.
- Leave-One-Out Classification is computationally expensive and should be carefully implemented in large datasets.
- Searching for additional textual features that are spatial invariant
- Run the model on smaller trees and larger trees.

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References

[1]M. Pal, "Random forest classifier for remote sensing classification," International journal of remote sensing, vol. 26, no. 1, pp. 217–222, 2005, doi: 10.1080/01431160412331269698.
[2] R. Hologa, K. Scheffczyk, C. Dreiser, and S. Gärtner, "Tree species classification in a temperate mixed mountain forest landscape using random forest and multiple datasets," Remote Sensing, vol. 13, no. 22, p. 4657, 2021.
[3] C. Seriadharma, "Tree Crown Classification using Grey-Level Correlation Matrix," Proceedings of the URECA@NTU 2021-22.
[4] M. Hall-Beyer, "GLCM texture: A tutorial V. 3.0 March 2017," PRISM Test, 01-Mar-2017. [Online]. Available: https://prism.ucalgary.ca/handle/1880/51900. [Accessed: 28-Mar-2023].
[5] C. Sothe et al., "Tree Species Classification in a Highly Diverse Subtropical Forest Integrating UAV-Based Photogrammetric Point Cloud and Hyperspectral Data," Remote Sensing, vol. 11, no. 11, p. 1338, Jun. 2019, doi: 10.3390/rs11111338.
[6] M. Dalponte, L. Bruzzone, and D. Gianelle, "Fusion of hyperspectral and Lidar Remote Sensing Data for classification of complex forest areas," IEEE Transactions on Geoscience and Remote Sensing, vol. 46, no. 5, pp. 1416–1427, 2008.