The eye in the sky can spot 66% of the trees…

Its **Accuracy Depends on Image Quality!**

SPOT the Trees: Remote-sensing Based Techniques for Tree Species Classification in Northern Limpopo

PROJECT SUMMARY

The **Baobab, Leadwood, Marula, and Shepherd trees are economically and culturally significant** to the northern Limpopo region. However, climate change is destroying their natural habitats. Monitoring tree populations using field data is expensive and time-consuming. **Remote-sensing data from satellite images provides a cost-effective way to monitor and manage biodiversity** in the area. We tested two approaches to species classification and visualisation: A two-stage Support Vector Machine. And a **Convolutional Neural Network,** which **uses computer vision and eliminates the reliance on field data.** This project is meant to assist the Department of Geography, Geoinformatics and Meteorology with conservation efforts to preserve the tree populations.

METHODS

- We received two SPOT 6 satellite images and field location data collected in September 2020. **SPOT 6 images have 4 multi-spectral bands that can be used for species profiling.**
- The field data was standardised into point shapefiles, which were converted to polygons. The polygons were projected onto the satellite image to create bounding boxes around the pixels associated with each treetop. The bounded pixels were used to output average spectral values for the ML model and to extract image patches for the DL model.
- **Two-Stage Support Vector Machine:**
  - A total of 30 features were extracted. Features included spectral values, vegetation indices, and texture values.
  - *Stage 1* - A one-class SVM used to filter out any potentially unknown tree species in future applications. We used synthetic data to simulate the ingestion of unknown species data.
  - *Stage 2* - a multi-class SVM which learns each species reflectance signature (see Figure 3) and categorises the data into 1 of 4 species. We used the predictions from the first stage to validate the multi-class SVM.
- **Convolutional Neural Network:**
  - We used TensorFlow to setup the CNN with the Adam optimiser, a *Sparse Categorical Cross-entropy* loss function and a 0 dropout rate. The model uses *ReLU* activation in all but the final layer, which uses *Softmax* for multi-class classification.
  - The output dimensions are set to 4. The CNN is a 3-layer network with a learning rate of 0.001, 20 epochs and batch size of 8.

EVALUATION CRITERIA

- The models are evaluated on the Area Under the Curve (AUC), Accuracy and the macro-average F1, Precision, and Recall scores.
- We prioritise the macro-average F1 score, which balances false positives and false negatives when there is class imbalance.

RESULTS

- Between the Two-stage SVM and 3-layer CNN, the **SVM model performs the best with an overall accuracy of 93% and F1-score of 0.71.**
- The **decrease in the F1-score** against accuracy illustrates the **adverse impact of class imbalance** in the data – our rebalanced data using SMOTE performed worse and these results are not included.

MODEL NAME	F1-SCORE	ACCURACY	PRECISION	RECALL	AUC
One-class SVM	0,95	0,99	0,92	0,99	0,99
Multi-class SVM	0,71	0,93	0,78	0,68	0,98
3-layer CNN	0,60	0,66	0,61	0,60	0,82

- The **CNN shows moderate performance with accuracy 66% and F1-score of 0.60** – a smaller reduction in prediction performance compared to the SVM. Several configurations of the CNN were run, but this was the highest accuracy we could obtain.
- **Image resolution is correlated to model performance** – low spectral resolutions result in higher misclassification. There are better quality images that can be used to fine-tune the CNN – images such as WorldView3. However, these are not free to download.

DISCUSSION

- **We propose the use of the CNN to our project partners.** The CNN can be used for prediction without the need for frequent field data collection – one of the goals of this project.
- The results also show that the **CNN performs relatively well in predicting Baobabs and Leadwoods** (see Figure 5).
- **Future work**: Use higher resolution images or pre-trained networks (ResNET, VGG16) to improve predictions. Canopy size and shape, as well as tree height data could also improve the model's performance.
- **Future work**: Project predictions onto the original satellite image to visualise tree populations.

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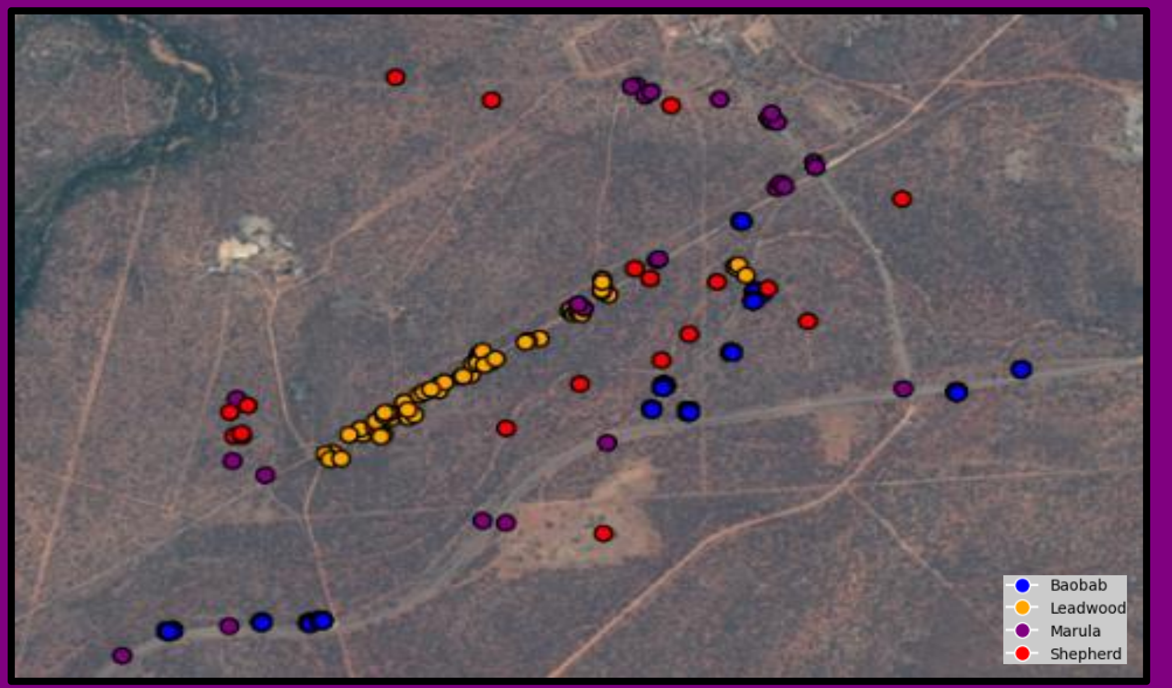

Figure 1: Spatial distribution of the tree species locations at the study site.

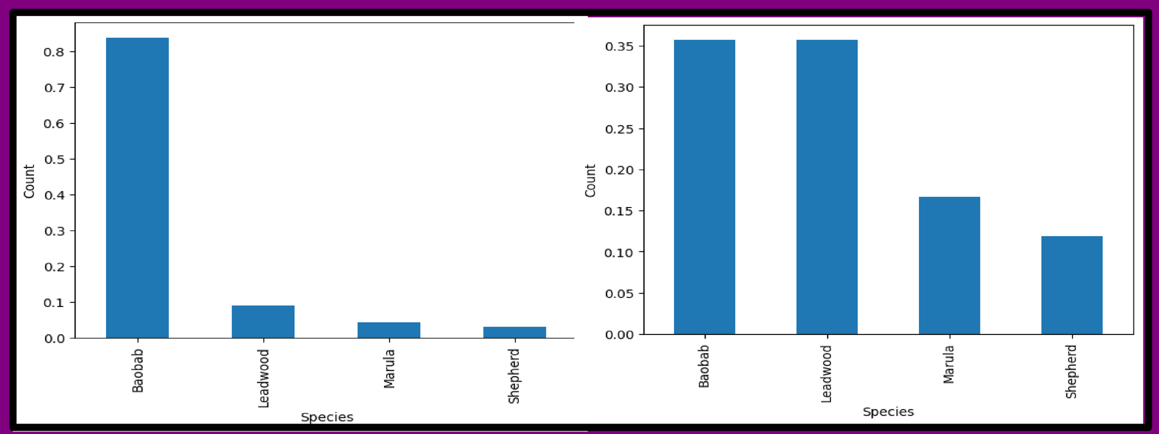

Figure 2: Original species distribution in the field data (left). Species distribution using Random Under-sampling for the CNN, with the Baobab count weighted down (right).

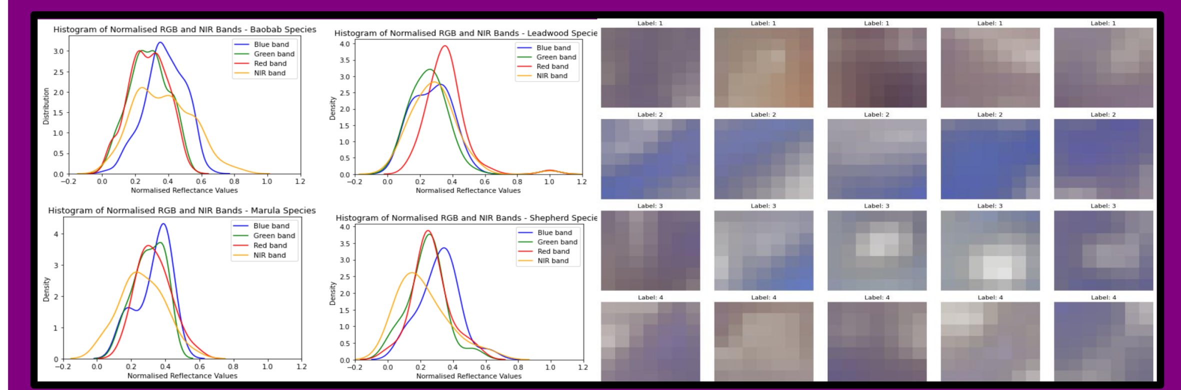

Figure 3: Spectral profiles of the four target species, used to train the two-stage SVM model (left). A sample of image patches for each species from the validation dataset used to train the CNN (right).

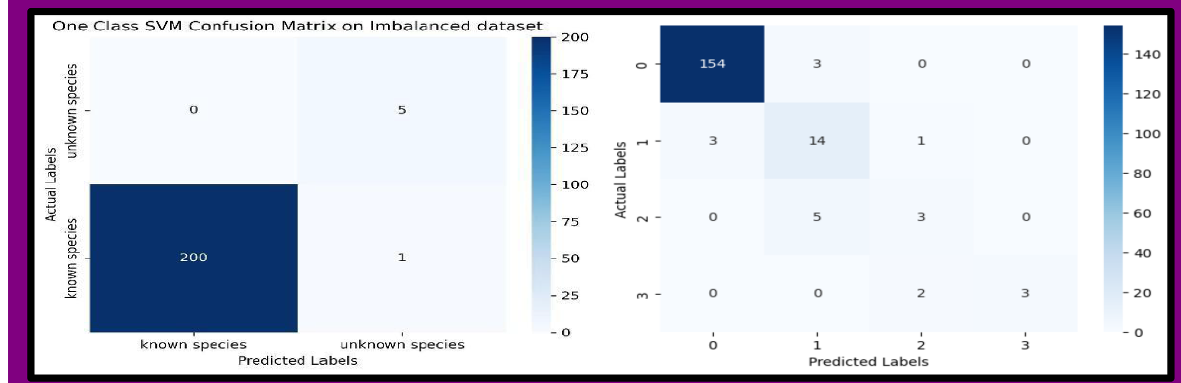

Figure 4: Confusion matrices from the Two-stage SVM model. Label encoding: 0 = Baobab, 1 = Leadwood, 2 = Marula, 3 = Shepherd.

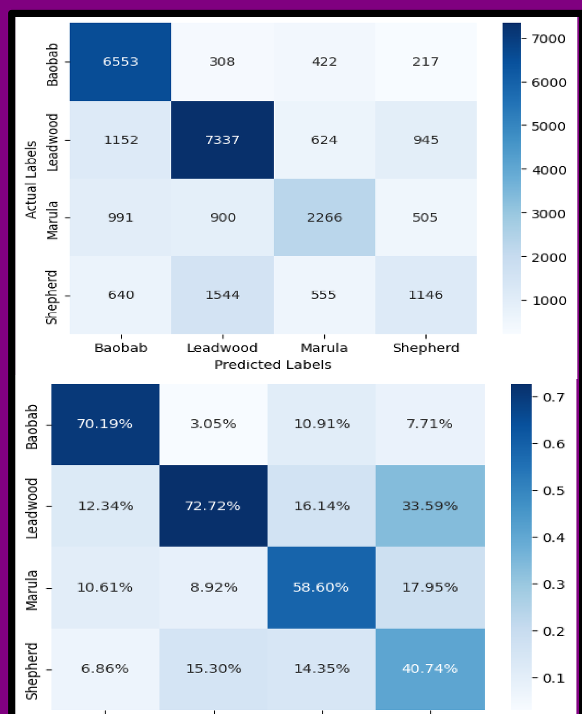

Figure 5: Confusion matrices for the 3-layer CNN. The model performs well in predicting the Baobab and Leadwood trees.

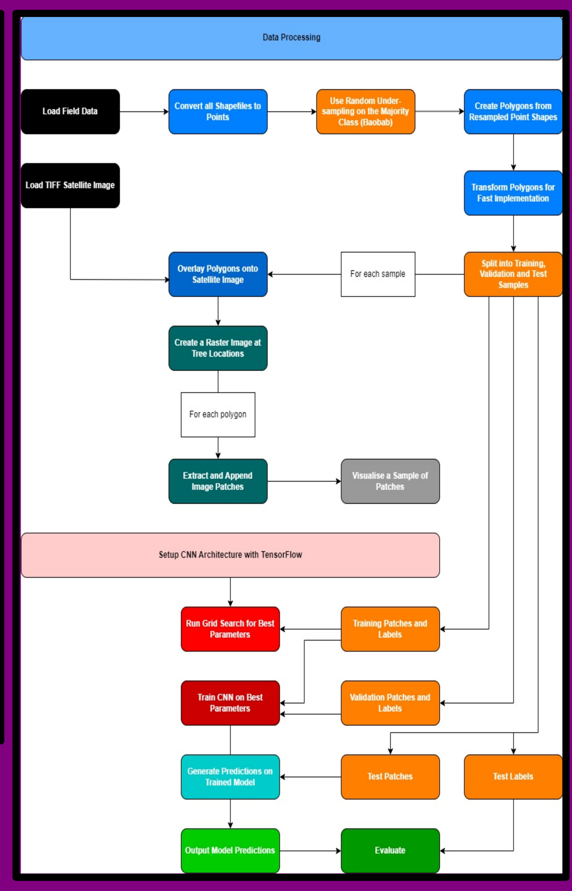

Figure 6: Our proposed deep learning pipeline to train and evaluate a CNN.

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