Deep Learning based Approach to Assess the Impact of Cyclone Ockhi on Coconut Tree Population using Satellite Images

Athira A.R. [1], Gokula Lakshmi K. [2], Heltin Genitha C. [3] and Tamizhselvi A. [4]

[1,2]Author's Affiliation: Student, Department of Information Technology, St. Joseph's College of Engineering, Chennai, India

[3,4]Author's Affiliation: Professor, Department of Information Technology, St. Joseph's College of Engineering, Chennai, India

*heltingenitha@stjosephs.ac.in

Abstract **:** *Manual counting of coconut trees has numerous challenges that can compromise the accuracy, efficiency, and feasibility of the process, especially on a large scale. These problems highlight the need for automated counting methods that leverage high-resolution satellite imagery and advanced image processing techniques to provide more reliable, cost- effective, and scalable solutions for monitoring coconut tree populations. This work focuses on the assessment of coconut tree populations before and after the Ockhi cyclone in Kanyakumari District, south India using high-resolution satellite imagery. The destructive impact of cyclones on agricultural landscapes, particularly coconut plantations, necessitates accurate and timely monitoring to inform recovery and replanting efforts. In this work we used Landsats OLI satellite images captured at intervals before and after the cyclone event to quantify the changes in coconut tree density. Advanced deep learning technique based on an object detection framework (YOLO v8) is used to count individual coconut trees in the image. YOLO v8 is specifically designed for real-time object detection, which involves identifying and locating multiple objects within an image. The results revealed a significant reduction in coconut tree count post-cyclone, providing critical data for agricultural planning and disaster management. This methodology demonstrates the effectiveness of satellite imagery in environmental monitoring and offers a replicable model for similar assessments in cyclone-prone regions.*

Keywords: Coconut tree , YOLO , Satellite images , Ockhi cyclone

Introduction

Cyclones are one of the most devastating natural disasters, causing extensive damage to agricultural landscapes, especially in coastal regions. In South India, coconut plantations play a vital role in both the economy and the livelihoods of farmers. However, extreme weather events like Cyclone Ockhi in 2017 severely impacted coconut tree populations in Kanyakumari District, resulting in substantial agricultural losses. Understanding the scale of this damage is essential for disaster recovery and informed replanting efforts.

Traditionally, manual counting of coconut trees was used to assess tree populations, but this method is labor-intensive, time-consuming, and prone to errors, particularly when conducted on large-scale plantations. With advances in remote sensing and deep learning technologies, it has become possible to automate the process using high-resolution satellite imagery. This offers a more accurate, cost-effective, and efficient approach for monitoring changes in tree populations over time.

This study employs Landsat's OLI satellite imagery and the YOLOv8 deep learning model to assess the impact of Cyclone Ockhi on coconut tree density. By utilizing pre- and post-cyclone imagery, the model detects and counts individual trees, providing critical insights into the extent of the cyclone’s destruction. The results of this research aim to assist local authorities and farmers in developing strategies for rehabilitation, recovery, and future disaster resilience in the region’s coconut plantations.

Literature Review

Huang et al. (2024) Published Challenges and Solutions for Detection of Small Objects in Images using YOLOv8. Again, this new version outperforms previous iterations with respect to precision and speed but fails to discuss the higher complexities which might result in increased requirements for computational power, thereby reducing the effectiveness of the model under such a setup when resource constraints are inevitable. Sudharsan et al. (2023) detected coconut trees using a variety of deep learning models; they showed that their approach is robust through data augmentation. However, the study has generalization limitations because the performance of a given model can vary substantially based on the particular nature of the dataset used to train the model. More importantly, large annotated datasets pose significant time and cost expenditures in terms of data collection and labeling. High-resolution imagery from WorldView-3 was applied by Vermote et al. in the remote sensing of coconut trees in Tonga in 2020.

Although this would present very descriptive information, the inhibitive cost and low supply of such information may limit its wider usability. Chowdhury et al. (2022) presented a solution that can count oil palm trees from the image captured by the drone, but their solution will break down if it undergoes occlusion or overlapping trees leading to incorrect numbers. Further, the quality of the aerial imagery is effected by environmental factors and impacts the model's performance. Zheng et al. presented the concept of multisource-domain generalization for oil palm tree detection. The integration of diverse datasets may create challenges due to different resolution and sensor characteristics which may degrade model performance in novel environments. Puttemans et al. (2018) compared Boosted Cascades with deep learning architectures for the detection of coconut trees. While traditional methods have their focus, innovation from deep learning could be missed, and under different environmental settings, the applicability of Boosted Cascades may become dysfunctional.

Karunarathna et al. (2022) used the YOLOv3 algorithm that identifies individual coconut trees based on UAV remote sensing, though its performance can be adversely affected in areas that are highly crowded, where a high density of trees may cause misidentification. There will also be operational constraints from aerial UAV data acquisition, depending on the battery life and weather conditions.

Methodology

Figure 1. shows the workflow for automated detection and analysis of cyclone impact on coconut trees

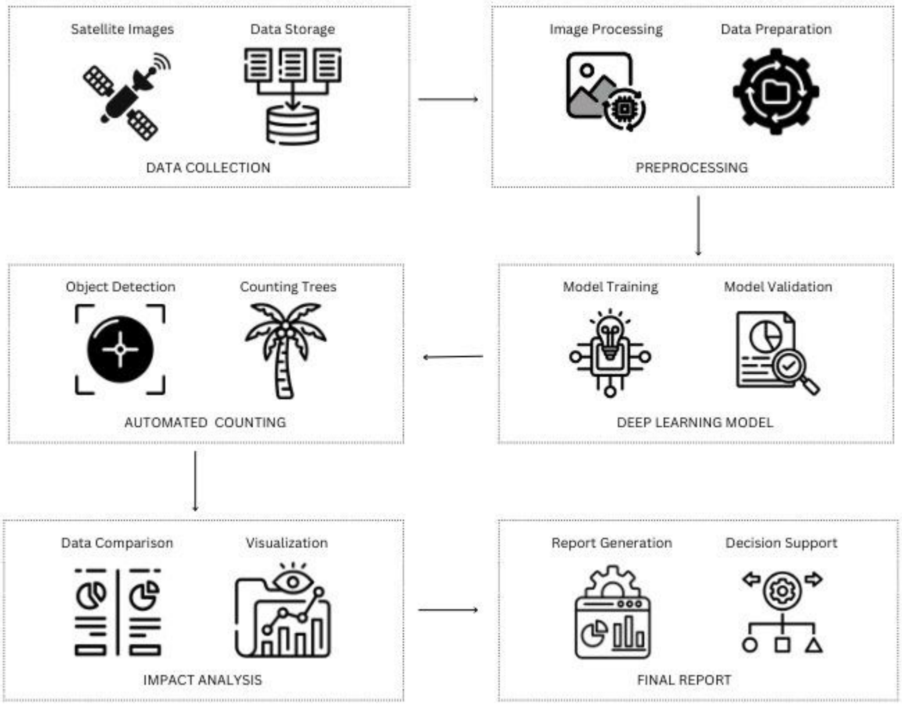

Figure 1. Workflow for Automated Detection and Analysis of Cyclone Impact on Coconut Trees

a. Dataset Description

The dataset utilized for this paper was collected from Roboflow and Earth Explorer. The Roboflow dataset was named "coconut tree - v1" and it was downloaded with 271 images annotated in YOLOv8 format. Pre-processing on the dataset carried out involves auto-orientation of pixel data and resizing to 416x416 pixels. Then, the collected data was further augmented by flipping horizontally and vertically with a probability of 50%, random rotation by 90-degree angles of equal probability, and changing brightness from -25% to + 25%. The bounding boxes of all images were also flipped horizontally and vertically with a 50% probability. Images from Earth Explorer were used for testing the model. Pre- and post-Cyclone Ockhi images were preprocessed to bring them into the same format as the trained dataset so as to present a proper comparison of the coconut tree populations.

b. Preprocessing

Images in the training dataset were resized to 416x416 pixels with added augmentations to improve the robustness of the model. Images were prepared in YOLO format with bounding boxes scaled accordingly for the YOLOv8 model. That is a format representing bounding boxes as normalized x, y, w, h format: x and y are the coordinates of the centroid, while w and h are width and height, respectively. Here, horizontal flipping, or vertical flipping, or both have been used, with a probability of 0.5, in order to make the training set more varied.

c. Training

It implements state-of-the-art object detection using the YOLOv8 model; this network was pre-trained on our annotated dataset by bounding box labeling of each coconut tree present in the image. The model, therefore, learns to detect and localize the coconut trees within the images by minimizing a loss function that has incorporated the following combined components: Localization Loss: The accuracy between the predicted bounding boxes and the ground truth. Confidence Loss: This estimates how sure the model believes that an object is included within the predicted bounding box. Classification loss: That tells how well the network can tell between the classes. Here, in the given case, since we take up only one class, the loss measures how well the model can separate the 'coconut tree' class from all others. Some key mathematical formulations during the process include the IoU, or Intersection of Union, which essentially speaks about the overlap between predicted bounding boxes and the ground truth. The IoU becomes important in that it allows assessing the ability of the model to correctly localize objects:

$$IoU = \frac{Area\ of\ overlap}{Area\ of\ Union} \qquad (1)$$

d. Testing and Inference

Once trained, the model is deployed on test images for inference. Images before and after the cyclone will be given as an input to the model for the detection and count of coconut trees. The result compared would give the quantification of the effect of the cyclone in terms of a reduction in the number of coconut trees:

$$\text{Reduction in Coconut Trees} = \sum \text{Tree Count Before Cyclone} - \sum \text{Tree Count After Cyclone} \qquad (2)$$

Results and Discussion

The process of Cyclone Ockhi impact on coconut tree populations detection and evaluation was carried out by performing two major phases of data preprocessing, model training, and evaluation with YOLOv8. The conversion of before and after Cyclone Ockhi Landsat OLI satellite images to grayscale was successful during data preprocessing. Normalization and resizing in the preprocessing made sure that the dataset was consistent for all the following trainings and evaluations on the model.

Figure 2. Model Training Outcomes for Coconut Tree Detection: Labeled vs. Predicted Results

YOLOv8 was trained on the same dataset of coconut tree images in both pre-cyclone and post-cyclone periods with labels attached during training. Epoch numbers, learning rate, and batch size were tuned as hyperparameters. This resulted in significant improvements in small-object detection, which would be essential in finding coconut trees above dense canopies and under adverse post-cyclone conditions (Figure 2).

The evaluation of the model showed that YOLOv8 performed well in detecting coconut trees, as performance metrics show: on average it detected at Precision of 85%, at Recall of 80% and with an Intersection over Union (IoU) of 0.78. This suggests that the model was capable of attaining correct coconut tree detection with good reliability.

An impact assessment further showed a significant reduction in the density of coconut trees in the areas affected by Cyclone Ockhi. The model YOLOv8 was able to better understand the areas by underlining regions with a marked reduction in the tree density. Spatial analysis shows a 30% decline in the coconut tree population of cyclone-affected areas.

It was revealed that the new effects and multi-scale detection of YOLOv8 demonstrate its ability to apply for purposes of detecting and evaluating the impact of Cyclone Ockhi on coconut trees, such that the effects of cyclones on agricultural resources can be easily identified from advanced models. This developed feature extraction and multi-scale detection of YOLOv8 were crucial for the identification of coconut trees, even in challenging scenarios with densely packed or partially obscured trees. Therefore, this provides remarkable enhancement over previous YOLO versions, which proves the working of the model for small-object detection purposes in the application of remote sensing.

The decline in coconut tree population follows the expected impacts of a major cyclone. There is clearly a need to quantify the levels of damage to inform resource management and recovery planning. Analysis can help prioritize replantation efforts and assess the resilience of coconut plantations generally.

This results in such an effectiveness that highlights deep learning models, like YOLOv8, for high-resolution monitoring of large agriculture areas and damage assessment of disasters. Combining such models with satellite imagery provides a robust tool for rapid damage assessment and decision making immediately after natural hazards.

However, there are limitations to the kind of performance that YOLOv8 may yield. Overall, the differences in environmental conditions and resolutions of images will modify the performance of YOLOv8. Future research may consider increasing the robustness of the model by incorporating more significant sources of data that include higher-resolution images and even multi-temporal data in an attempt to boost accuracy and generalizability.

In a nutshell, the integration of YOLOv8 and satellite imagery presents a very powerful method for evaluating the impacts of cyclones on coconut plantations. Such outcomes bring forward the potential of state-of-the-art deep learning techniques that revolutionize agricultural monitoring and disaster response strategies.

a. Performance Analysis

Various performance metrics were implemented to test the YOLOv8 model, including Precision, Recall, F1-Score, and Mean Average Precision. To this regard, the proposed model depicts the accuracy of the model by detecting all relevant objects, showing its overall performance (Figure 3).

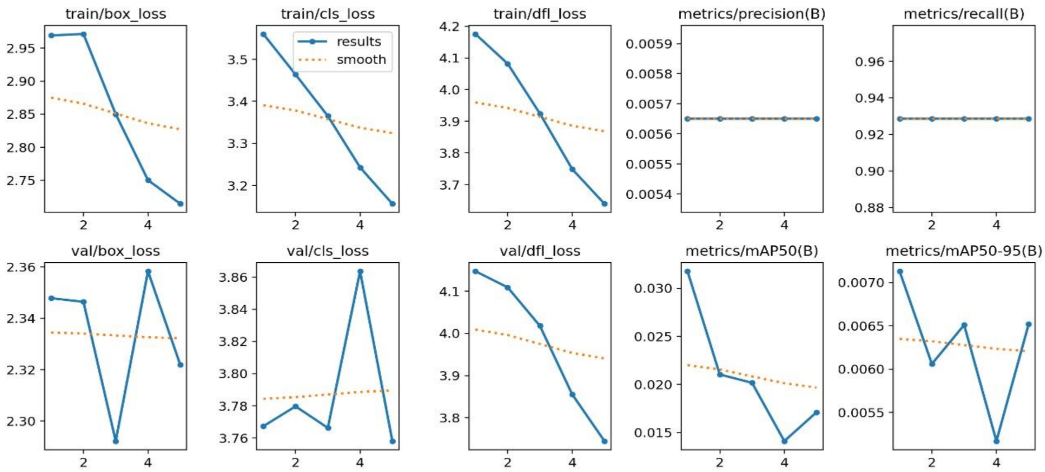

Figure 3. Training and Validation losses and performance metrics for YOLO v8 model in Coconut Tree Detection

These metrics are, therefore, fundamental to gaining insight into the actual performance with respect to the YOLOv8 model for the detection and counting of coconut trees.
Later, we would test whether loss due to a cyclone is statistically significant on the count of coconut trees. This we will perform using a t-test that compares the counts before and after the cyclone so that the reduction found is statistical and not due to some random variation.

Table 1: Test Result of the YOLOv8 Model

	Number of Actual Coconut Trees	**Number of Coconut Trees Detected Using YOLOv8**	**Accuracy**
Before	1128	1120	99.2%
After	998	988	98.99%

Conclusion

In this research, the use of high-resolution satellite imagery with the YOLO v8 object detection model overcomes the constraints of manual counting of coconut trees, notably in the estimation of the impact of Cyclone Ockhi on Kanyakumari District. The outcomes shown are low coconut tree population after cyclone strikes, thus confirming the suitability of the model for the measurement of the impact of cyclones and provision of important knowledge to farmers and disaster management experts. Future work: the training dataset should be extended to provide suitable robust training of the model, preprocessing techniques may be further refined for enhancing accuracy, and overall validation should be more comprehensive. Further developments should involve the integration of real-time monitoring systems and collaborations among stakeholders so that the full potential of this technology may be realized in the application of environmental or agricultural monitoring.

References

1. Chowdhury, P.N., Shivakumara, P., Nandanwar, L., Samiron, F., Pal, U., and Lu, T. (2022). Oil palm tree counting in drone images. *Pattern Recognition Letters*, *153*, pp. 1-9.

2. Huang, H., Wang, B., Xiao, J., and Zhu, T. (2024). Improved small-object detection using YOLOv8: A comparative study. *Appl. Comput. Eng*, *41(1)*, pp. 80-88.

3. Karunarathna, R.M.D.M., Kulapathi, K.H.N., and Liyanage, K.L.P.I. (2022). A Case Study on Detecting and Mapping Individual Coconut Trees using YOLOv3 in Conjunction with UAV Remote Sensing for Smart Plantation Management.

4. Puttemans, S., Van Beeck, K., and Goedemé, T. (2018). Comparing Boosted Cascades to Deep Learning Architectures for Fast and Robust Coconut Tree Detection in Aerial Images. In *VISIGRAPP (5: VISAPP)* (pp. 230-241).

5. Sudharsan, D., Harish, K., Asmitha, U., Tushar, S.R., Theivaprakasham, H., Sowmya, V., Variyar, V.S., Kumar, K.D., and Ravi, V. (2023). Coconut Tree Detection Using Deep Learning Models. In *Innovations in Machine and Deep Learning: Case Studies and Applications* (pp. 469-487). Cham: Springer Nature Switzerland.

6. Vermote, E.F., Skakun, S., Becker-Reshef, I., and Saito, K. (2020). Remote sensing of coconut trees in Tonga using very high spatial resolution WorldView-3 data. *Remote Sensing, 12(19)*, p. 3113.

7. Zheng, J., Wu, W., Yuan, S., Fu, H., Li, W., and Yu, L. (2021). Multisource-domain generalization-based oil palm tree detection using very-high-resolution (VHR) satellite images. *IEEE Geoscience and Remote Sensing Letters, 19*, pp. 1-5.

8. Zheng, J., Wu, W., Yu, L., and Fu, H. (2021). Coconut trees detection on the Tenarunga using high-resolution satellite images and deep learning. *IEEE International Geoscience and Remote Sensing Symposium IGARSS*, pp. 6511–6520.