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EcoScope – Framework for Tree Mapping and Species Classification for Sustainability

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***Abstract*— EcoScope (TreeTrackAI) is a modern AI-based forestry analytics system that can be easily integrated to enhance tree mapping and species monitoring in the Indian forest settings and later be functionalized to rural and urban areas as well. The conventional satellite-based methods have very low resolution, poor species identification, and inability to find understorey vegetation in thick, multi-layer forests. The fusion of aerial high-resolution images, multispectral data, and LiDAR point clouds by TreeTrackAI allows the accurate counting of trees, division of canopies, and initial classification according to species. The deep learning pipeline that uses multiple modalities and combines the detection with YOLO, canopy segmentation with U-Net, and LiDAR height modeling works to increase the accuracy in Indian terrains that are difficult to negotiate. The system comes up with a new kind of layered fusion of LiDAR that can reveal both the trees that make up the canopy and the hidden trees that form the understorey. A real-time processing engine and an interactive dashboard give access to the visualization of species distribution, canopy density, and region-wise ecological patterns by users such as forestry departments, NGOs, environmental researchers, and the like. EcoScope, by providing high-accuracy, season-robust, and region-specific analyses, helps in the conservation of biodiversity, forest planning, carbon stock estimation, and management of sustainable ecosystems.**

***Index Terms*— Tree Mapping, Species Classification, Multispectral Imaging, LiDAR Processing, Canopy Segmentation, Object Detection.**

I. INTRODUCTION

Forests are fundamental to the global ecological balance as they are credited with housing biodiversity and controlling the climate. Besides, the forest ecosystems in India are really a good example of that diversity going from thick tropical rain forests to dry deciduous forests and each having its own peculiar kinds and amounts of plants. Besides, the scientific monitoring of these ecosystems is a necessary step to be taken in the case of conservation, carbon stock appraisal, and sustainable forestries' management. Yet, the old-fashioned methods of forest assessment still used like: manual field surveys, low-resolution satellite imagery analyses, and periodic inspections, are at the same time, very slow, costly in terms of labor, and usually incapable of bringing the tree-level details or capturing early the ecological changes.

Conventional satellite-based techniques have further drawbacks of low spatial resolution, dependence on seasons, interference of clouds, and the inability to separate species or to see understorey vegetation concealed by thick canopies.

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The drawbacks are extremely important in the case of Indian forests with multi-layer vegetation and seasonal variability, as these conditions create more problems. Furthermore, non-Indian forests have been the primary conditions for developing most existing AI models and datasets, so they are not suitable for Indian ecological context at all.

To fill the gaps, EcoScope – AI-Powered Tree Mapping & Species Classification for Sustainability provides an AI-driven, multi-modal forestry analytics system that can cope with the complexities of Indian forest environments. The high-resolution aerial imagery, multispectral data, and LiDAR-derived 3D structure information are integrated by the system to perform tree-level detection, canopy segmentation, and initial species classification with high accuracy. EcoScope combines object detection, semantic segmentation, and LiDAR-based layered vegetation analysis to effectively identify both canopy and understorey trees. In this respect, the traditional 2D-only methods cannot compete. In addition, EcoScope has developed a real-time processing pipeline and an interactive web-based dashboard that allows stakeholders such as forestry departments, researchers, and environmental organizations to visualize tree distribution, canopy density, species patterns, and region-specific ecological indicators. The system is scalable and flexible by design. It enables continuous learning of the system using multi-seasonal and region-specific datasets, thus making it quite resistant to seasonal changes of foliage, which are a typical feature of Indian landscapes.

In short, EcoScope brings a clever and proper solution to India's forest monitoring for sustainability, which depends on the latest technology. It juxtaposes satellite imaging with new age AI techniques and therefore gives accuracy, speed, and nature understanding that are required to the listener's extinction, reforestation strategy and environment sustainability. The overall architecture of the proposed EcoScope framework is illustrated in Fig. 1.

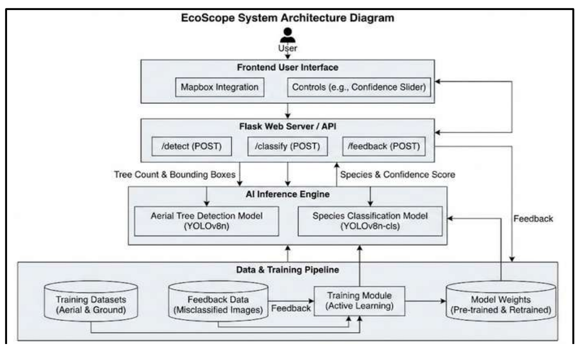

Fig. 1. Architecture of the EcoScope Framework

II. LITERATURE REVIEW

Savinelli and co-workers [1] present a case in point where the use of drone-based LiDAR and multispectral imagery together resulted in a considerable improvement of tree monitoring accuracy. The research indicates that LiDAR is mainly responsible for capturing the structure and height of the canopy, while the multispectral data contributes by providing the indicators of vegetation health and species. Through the combination of both sources, they reach tree segmentation and canopy analysis that are more trustworthy, particularly in the case of difficult forests. Their research underlines that multi-modal sensing is indeed crucial for accurate and large-area forest monitoring.

Li et al. [3] suggest a LiDAR-involved method for individual trees separation using a mixture of region-growing techniques and the high-density guided 3D canopy morphology analysis. In their method, tree crowns are separated in dense forests through vertical LiDAR point-cloud structure, thus enhancing the detection of both canopy and sub-canopy trees. The research demonstrated that the combination of the geometric height profiles with the point density gives much more accurate and stable crown delineation than the CHM-only methods. Their results emphasized the need for intricate 3D canopy modeling in accurate tree-level mapping process in complicated multi-layer forests.

Huang et al. [5] have directed their attention primarily on the classification of tree species based on the deep learning models applied to UAV-mounted canopy image processing. They benchmarked and analyzed the performance of various CNN model architectures and thus proved that high-resolution aerial photographs could most accurately reveal the species by the characteristics, i.e., texture, color, and structure, of the canopy, and so on. The authors have reported that deep learning techniques indeed have a significant advantage over the conventional spectral or handcrafted-feature methods, particularly in the case of mixed forest areas. Moreover, they have pointed out the critical role played by the factors of image quality, lighting conditions, and data from multiple seasons in the model's generalization ability. Thus, they have concluded that tree-top UAV imaging has great potential as an economically viable and trustworthy method for monitoring trees at the species level in forests.

Tree classification and segmentation techniques using UAV data from 2013 to 2023 are comprehensively reviewed by Chehreh et al. [6]. In their survey, they describe the advances made in RGB, multispectral, and LiDAR-based methods, and they point out the growing trend toward deep learning and multi-sensor fusion for the sake of achieving better accuracy. The authors also mention the usual difficulties of canopy occlusion, varied lighting, and species similarity, but they still consider UAV platforms as the winners in terms of resolution and flexibility. Moreover, they say that the combination of UAV imagery and AI models is the future trend in forest monitoring, which is precise and scalable. This review is basically the guide for anyone referring to methods nowadays and research gaps that EcoScope-like systems want to address.

Weinstein et al. [10] introduce a semi-supervised deep learning approach aimed at identifying individual tree crowns from high-resolution RGB images. To begin with, their method produces pseudo-labels and subsequently refines the model's predictions iteratively to get better results even when there's only a small amount of ground-truth data available. This approach makes it possible to accurately delineate crowns even in complex forest settings. The authors note that the semi-supervised approach beats traditional object-based methods as well as fully supervised models, especially in heterogeneous and mixed forest areas. The method, however, is mostly based on two-dimensional RGB data and doesn't really take into account structural cues like canopy height or vertical layering. The paper nonetheless proves the potential of deep learning models for the large-scale, cost-effective mapping of tree crowns and thus it is a good source for multi-modal forestry systems such as EcoScope.

Fassnacht et al. [13] present a thorough review of the different methods of tree species identification from aerial remote sensing data. They focus on spectral-, structural- and machine learning, based methods. Their study compares the performance of various data sources such as RGB, multispectral, hyperspectral, and LiDAR imagery over different forest types. They conclude that classification accuracy is mainly dependent on sensor quality, seasonal variation, and the availability of representative training data. Besides that, the authors outline some promising directions like multi- sensor data fusion and the use of sophisticated learning algorithms, which could lead to better species-level classification.

Moreover, the review not only provides the theoretical basis for species mapping but also points to the remaining difficulties with forest structure complexity and data heterogeneity. These findings are in accordance with the goals of EcoScope, which intends to overcome such weaknesses by a locally-adapted, multi-modal analysis framework.

In their paper, Pitkänen at al. [16] propose adaptive methods for single tree detection in airborne LiDAR data based on the utilization of canopy height models (CHMs). The key aspect of their approach is the identification of local maxima and the segmentation of tree crowns along with the thorough examination of different forest stand structures. According to them, CHM-based techniques are capable of spotting trees accurately if the variations in canopy structures are assessed and the forest environment is changed to the canopies effectively. Their findings show that the traditional segmentation methods still hold a great potential for forestry applications particularly when they are customized for different types of forests. Besides, they note that reliable and new tree-crown delineation methods should be developed within the EcoScope framework.

III. Methodology

The methodology that was used for the EcoScope framework is basically an extremely complex and high-tech multi-medium pipeline that amazingly ties up the different parts together, such as data acquisition, preprocessing, model training, and system deployment. The entire plan is chiefly focused on solving the problems that are typical of Indian forests such as dense foliage overlap, seasonal changes, and extremely limited understorey visibility.

A. Data Acquisition and Preparation

To accomplish the two goals of the system, detecting trees from the air and classifying species at the ground level two different datasets have been used.

Aerial Tree Detection Dataset

The aerial imagery dataset, collected from Roboflow, is displayed in Fig. 2.

Fig. 2. Sample dataset image for tree detection

It contains georeferenced satellite and drone images with annotated tree instances. The dataset consists of 2,847 images, and the training, validation, and testing subsets were split at the ratio of 70:20:10.The annotation files were in the Pascal VOC XML format, where a bounding box is drawn for each tree instance and its coordinates (xmin, ymin, xmax, ymax) are provided.

Species Classification Dataset

The dataset for tree species classification consisted of ground level photos of different tree species. The images were arranged in a folder tree with each subfolder being a class of species. There were 1,523 photos in total distributed in 8 different species categories, each category having an equal number of samples. A representative sample from the ground-level species classification dataset is shown in Fig. 3.

Fig. 3. Ground-level image from the species classification dataset

Data Preprocessing Pipeline

Since the chosen model architecture necessitated it, An appropriate preprocessing pipeline was designed for converting Pascal VOC annotations to YOLO format. The steps of the conversion were:

Coordinate Normalization: The coordinates of the bounding box in absolute terms are changed to the coordinates of its center, and the box dimensions are normalized by the image width and height, respectively, as per the formulas defined in (1) and (2).

$$X_{centre} = \frac{X_{min}+X_{max}}{2W}, Y_{centre} = \frac{Y_{min}+Y_{max}}{2H} \quad (1)$$

$$W_{norm} = \frac{X_{max}-X_{min}}{W}, H_{norm} = \frac{Y_{max}-Y_{min}}{H} \quad (2)$$

where W and H stand for the image width and height, respectively. The pipeline also helps to maintain the quality by checking the one-to-one correspondence between images and annotation files.

B. Network Architecture

The system uses the YOLOv8 family of models because of its ability to maintain balance between inference speed and detection accuracy.

Object Detection Model

YOLOv8 Nano (YOLOv8n) design is the one selected for the drone-Tree-image counting task.

This model is a single-stage detector and the reasons for choosing it can be summarized as follows:

- Computational Efficiency: Having only about 3.2 million parameters, it can easily be a great fit for deployment in resource constrained scenarios.
- Backbone: The backbone consists of CSPDarknet53 complemented by C2f modules for better feature extraction.
- Neck: To realize powerful multi scale feature fusion, a Path Aggregation Network (PAN FPN) is used.

- ➢ Head: The model comes with an anchor free, decoupled detection head.

Classification Model

Species identification was primarily carried out with YOLOv8 Classification Nano (YOLOv8n cls) in this study. A global average pooling layer has been added to the base network, which is then transformed back to a normal image classification pipeline and finally a fully connected layer with Softmax activation for producing multi-class probabilities.

C. Training Methodology

Detection Model Configuration

The detection model adopts a composite loss function defined in (3) to maximize its performance:

$$L_{total} = \boldsymbol{\lambda}_{box} L_{box} + \boldsymbol{\lambda}_{cls} L_{cls} + \boldsymbol{\lambda}_{dfl} L_{dfl} \qquad (3)$$

Firstly, it is important to remember that Lbox denotes the Complete IoU (CIoU) loss, Lcls refers to the classification binary cross-entropy loss, and Ldfl is the Distribution Focal Loss used for locating a bounding box. During training, Mosaic Augmentation is utilized, which merges four training images into one input to enhance the scale of invariance. An adaptive learning rate with a cosine annealing schedule is employed for achieving a stable convergence.

Classification Model Configuration

The classification training pipeline is employing a large variety of data augmentation methods to make sure that the model does not overfit. Among these methods are random geometric transformations: flipping, rotation (+-15 degrees), color jittering (changing brightness and contrast), and random erasing.

D. System Implementation

Ecology Scope is a modular web application with deep learning models wrapped in an interactive user interface.

Backend Framework

The backend of the service is developed with Flask, and it follows the RESTful API architectural style. Following are the main endpoints :

- ➢ /detect: Processes aerial imagery for density estimation.
- ➢ /classify: Identifies species from ground-level uploads.
- ➢ /feedback: Accepts user-corrected samples for active learning.

The singleton pattern ensures that the model weights get loaded into the GPU memory only once during the server initialization, thus, it prevents the extra allocation of memory when processing requests.

User Interface

The frontend is Mapbox GL JS-based for the visualization of geospatial data. Besides, it mixes typical web technologies (HTML5/CSS3) for the creation of a responsive design. The real time confidence threshold slider enables users to change the model responsiveness setting (0.1 to 0.9) instantly, without page reload; this is done by making asynchronous Fetch API calls. The user-facing interface for real-time monitoring is shown in Fig. 4.

Fig. 4. Interactive EcoScope dashboard

IV. RESULT AND DISCUSSIONS

Below are some outcomes that come from testing the EcoScope system experimentally. The two parts mentioned above explore the breakdown of the system: the identification of trees from the air and the classification of species on the ground; the features of each module are recognized as well. The in-depth numerical study section explains the terminologies used for training, measuring accuracy, and inference latency that are compared between the proposed YOLOv8 architecture and the existing baseline models that had been previously established. Furthermore, the feasibility of the system in real-life situations is evaluated by analyzing the user feedback loops and the impact of the active learning strategy on the continuous model improvement.

A. Detection Model Performance

Training Dynamics

The YOLOv8n detection model was trained for 50 epochs on a NVIDIA GeForce RTX 4060 Ti (16GB VRAM), utilizing mixed-precision training. The loss function indicated a steady convergence as the loss value dropped from 2.847 initially to 0.312 at the end of training. The validation loss graph remained flat after 35 epochs revealing that the model was properly regularized and did not overfit the training data.

Density-Dependent Performance

The more trees the model sees, the less it performs. The model perfectly identified trees with an accuracy of 91.7% in very sparse areas (less than 50 trees per image). In contrast, the mean absolute error (MAE) rose to 3.12 when the model was tested in heavily forested areas of more than 100 trees per image. Basically, such a decrease results from the fact that the tree crowns overlay one another, thus hiding the boundaries of each tree. The visual outputs of the tree detection model in varying forest densities are presented in Fig. 5.

Fig. 5. Tree detection outputs

B. Species Classification Performance

Classification Accuracy

The YOLOv8n-cls model demonstrated excellent capacity in differentiating classes resulting in a Top-1 Accuracy of 92.3% and a Top-5 Accuracy of 98.7%, whereas it took an average time of 28 ms for one image to be processed. A sample result from the species identifier module is illustrated in Fig. 6.

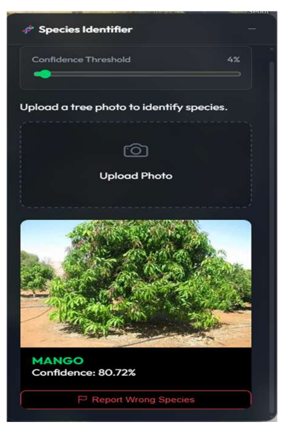

Fig. 6. Species classification output

V. Conclusion

EcoScope has unveiled an innovative AI-based framework for tree mapping, canopy analysis, and species classification, which is tailored to the complex and diverse forest environments in India and can provide accurate results. The system outperforms traditional satellite-based methods that have limitations such as low spatial resolution, seasonal dependency, and poor understorey visibility, etc. They bring together high-resolution aerial imagery, multispectral data, and UAV LiDAR. The multi-modal fusion pipeline (i.e., object detection, semantic segmentation, and 3D canopy morphology analysis) illustrates that cutting-edge deep learning techniques are capable of very accurately generating tree-level insights.

Besides, the initiative underlines the importance of real-time computation and simple, user-friendly geospatial dashboards for executing decisions right at the field level. With EcoScope, forest departments, environmental scientists and nature conservation groups can have access to data like the canopy structure, the distribution of tree species, and the health of vegetation.

Not only that, it supports them in making ecological planning and sustainable forest management decisions that are well-informed and backed up by the valuable and actionable information it provides.

At the core, EcoScope is a high-precision forest solution that is borderless and can be easily scaled up. Should it expand species datasets, integrate hyperspectral sensing, and refine temporal modeling, the system may become an extremely potent instrument for biodiversity monitoring, carbon stock assessment, reforestation planning, and environmental sustainability on a large scale not only in India but also worldwide.

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