

# Intelligent Tree Enumeration and Forest Analysis System for Environmental Monitoring

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**Abstract**—Forest monitoring plays a critical role in sustainable environmental management, biodiversity conservation, and climate change mitigation. Traditional methods for tree enumeration, species classification, and green cover estimation are labour intensive, prone to human error, and inefficient for large-scale applications. This research presents an automated image-based forest monitoring system that integrates deep learning and remote sensing techniques to enhance accuracy and efficiency. The proposed framework serves as a robust tool for forest management authorities, policymakers, and researchers seeking data-driven solutions for environmental monitoring and conservation planning.

**Index Terms**—GRVI, Machine Learning, NDVI, Random Forest, YOLOv8

## I. INTRODUCTION

Forests are essential ecosystems that contribute to climate regulation, carbon sequestration, and biodiversity preservation. Accurate tree enumeration, species classification, and vegetation analysis are fundamental tasks for forest conservation, sustainable resource management, and deforestation monitoring. Conventional forest survey techniques, which rely on manual fieldwork and satellite-based assessments, are time-consuming, resource-intensive, and often lack precision in dense forest regions. Recent advancements in computer vision, machine learning, and remote sensing offer promising alternatives to automate these processes with higher accuracy and efficiency.

In this study, we propose a forest monitoring system that integrates deep learning-based object detection, vegetation index analysis, and spatial optimization algorithms. The system consists of five core modules:

1. **Tree Counting and Detection:** Utilizes YOLOv8, an object detection model, to accurately detect and count trees in aerial images.
2. **Species Classification:** Implements Random Forest classifiers trained on tree-specific features such as leaf shape, colour, and canopy structure to identify different species.
3. **Green Cover Estimation:** Employs GRVI (Green Red Vegetation Index) [3] calculations to measure forest density and track vegetation health over time.
4. **Optimal Pathfinding Algorithm:** Uses Dijkstra's algorithm [8] which determines the most optimal routes in forest to minimize the impact on tree populations.
5. **Historical Data Analysis Module:** It leverages time-series analysis to track deforestation rates and ecosystem changes over time.

## II. BASIC TERMINOLOGY

### A. Problem Statement

The project aims to address the challenge of accurately enumerating trees in forest areas by developing an image analytics system to automate tree enumeration. The feasibility study highlights the technical potential of using satellite imagery, machine learning, and geospatial analysis to automate these tasks. Traditional methods are time-consuming and prone to errors, making it crucial to develop an automated solution.

### B. Motivation

Intelligent Tree Enumeration and Forest Analysis System for Environmental Monitoring is important for effective management of forest and conservation efforts. An automated and all-inclusive system ensures efficiency in data collection, reducing human error and increasing accuracy. Better diversion of forest land

can be achieved through precise mapping and analysis, preventing unnecessary deforestation and supporting sustainable development. Additionally, such data provides valuable insights for developmental projects, ensuring that urban expansion and infrastructure growth occur with minimal environmental impact. Ultimately, these efforts contribute to forest conservation, preserving biodiversity and maintaining ecological balance for future generations.

### III. BACKGROUND STUDY

1. Title: UAV-Based Intelligent Detection of Individual Trees in Moso Bamboo Forests with Complex Canopy Structure

Author: Lujin Lv et al.

Findings:

- Utilizes UAV-based remote sensing to detect individual trees in bamboo forests with dense structures.
- Employs machine learning algorithms to improve detection accuracy.

Security Mechanisms:

- High-resolution aerial imagery analysis.
- AI-based object detection models.

Limitations:

- Difficulty in differentiating closely packed tree crowns.
- Computational resource demands for processing large datasets. [1]

2. Title: NDVI-Based Change Detection in Sundarban Mangrove Forest Using Remote Sensing Data

Author: Sumona Akter Shimu et al.

Findings:

- Uses NDVI to detect the vegetation changes in mangrove forests.
- Evaluates environmental impacts and deforestation trends.

Security Mechanism:

- Satellite-based NDVI analysis for vegetation health monitoring.

Limitations:

- Susceptibility to atmospheric disturbances affecting NDVI readings.
- Limited spatial resolution in remote sensing data. [2]

3. Title: Applicability of Green-Red Vegetation Index for Remote Sensing of Vegetation Phenology

Authors: Takeshi Motohka, Kenlo Nishida Nasahara, Hiroyuki Oguma, Satoshi Tsuchida

Limitations:

- Requires validation across diverse ecological zones.
- Affected by sensor calibration errors.

Findings:

- Proposes GRVI as an alternative to NDVI for vegetation monitoring.
- Shows improved sensitivity to seasonal changes in foliage.

Security Mechanisms:

- GRVI-based remote sensing approach. [3]

4. Title: Increasing the Accuracy and Automation of Fractional Vegetation Cover Estimation from Digital Photographs.

Authors: André Coy, Dale Rankine, Michael Taylor, David C. Nielsen, Jane Cohen

Limitations:

- Requires high-quality images for accurate estimations.
- Sensitivity to lighting and shadowing effects.

Security Mechanisms:

- Machine learning integration for image classification.

Findings:

- Enhances fractional vegetation cover estimation using digital photography and automated algorithms.
- Improves precision in ecosystem monitoring. [4]

5. Title: Identification of Tree Species in Forest Communities at Different Altitudes Based on Multi-Source Aerial Remote Sensing Data

Authors: Haoran Lin, Xiaoyang Liu, Zemin Han, Hongxia Cui, Yuanyong Dian

Limitations:

- Requires extensive training datasets for AI models.
- High computational cost for processing multi-source data.

Findings:

- Produces results utilizing the aerial remote sensing through multiple sources for classification of tree species across varying altitudes.

6. Title: Identification of Tree Species in Forest Communities at Different Altitudes Based on Multi-Source Aerial Remote Sensing Data

Authors: Lin, H., Liu, X., Han, Z., Cui, H., Dian, Y.

Limitations:

- Similar constraints as the previous study.

Findings:

- Reiterates the methodology and findings of the previous study by the same authors.[6]

7. Title: Improving the Precision of Tree Counting by Combining Tree Detection with Crown Delineation and Classification on Homogeneity Guided Smoothed High Resolution (50 cm) Multispectral Airborne Digital Data

Authors: Katoh, M., Gougeon, F.A.

Limitations:

- Computational intensity of high-resolution image processing.
- Requires specialized software for implementation.

Findings:

- Enhances tree counting accuracy through a hybrid approach integrating tree detection and crown delineation.
- Uses high-resolution multispectral imagery for refined analysis. [7]

8. Title: Determining an Optimal Path for Forest Road Construction Using Dijkstra's Algorithm

Authors: Parsakhoo, A., & Jajouzadeh, M.

Limitations:

- Requires accurate topographic data for effective route planning.
- Sensitive to elevation and terrain variations.

Findings:

- Uses Dijkstra's algorithm to optimize forest road planning.
- Minimizes environmental disruption while ensuring accessibility.[8]

#### IV. EXISTING SYSTEM ANALYSIS

The traditional methods of tree enumeration and forest monitoring are largely manual, involving on-ground surveys and satellite-based assessments. These conventional techniques consume more time. They are labour intensive as well as prone to human error, making them inefficient for large-scale forest analysis. Current solutions primarily rely on NDVI (Normalized Difference Vegetation Index) [2] tools, drone surveys, satellite imaging, and individual machine learning models for species classification. However, they often lack integration, automation, and real-time analysis capabilities.

Challenges in Existing Systems:

1. Manual Surveys – Require extensive human effort, making large-scale forest monitoring impractical.
2. Limited Accuracy – Traditional methods struggle with dense forest canopies and mixed vegetation, leading to incorrect tree counts.
3. Slow Data Processing – Time-consuming techniques delay decision-making in forest conservation efforts.
4. Species Identification Issues – Many existing systems lack automated species classification, relying instead on labour intensive field studies.
5. Inadequate Historical Analysis – Current systems fail to integrate past data for tracking long-term deforestation and biodiversity changes.
6. Lack of Optimal Pathfinding – Route mapping in forested areas is often based on cost efficiency rather than ecological preservation.

While solutions like Google Earth, Sentinel Hub, and TensorFlow-based species classifiers exist, they operate in isolation, offering either tree detection or species classification but not both. Similarly, satellite land monitoring tools provide large-scale coverage but lack real-time, species-specific data.

#### V. PROPOSED MODEL

The proposed work for the Intelligent Tree Enumeration and Forest Analysis System focuses on automating forest monitoring using advanced image analytics, machine learning, and geospatial analysis. The system is designed to replace traditional, labour-intensive methods with an AI-driven approach that enhances accuracy and efficiency.

Key Aspects of the Proposed Work:

Data Acquisition & Preprocessing

- The system will utilize high-resolution satellite images and aerial photos for forest analysis.
- Image preprocessing techniques such as noise reduction, segmentation, and vegetation index calculations (GRVI) [3],[4] will enhance image quality for accurate analysis.

1. Tree Detection & Enumeration

- The YOLOv8[1],[7] deep learning model will be used for detecting and counting trees in forested areas.
- Advanced object detection techniques will help differentiate individual trees [1], even in dense canopies.[16]

2. Tree Species Classification

- The system will implement Random Forest classification [6] to categorize tree species based on leaf shape, canopy structure, and colour.
  - This will aid in biodiversity analysis and forest health assessment.[17]
3. Green Cover Estimation
- The system will employ the Green-Red Vegetation Index (GRVI) [3] to measure vegetation density.
  - This approach eliminates the need for infrared sensors, making it cost-effective and accessible.[18]
4. Optimal Path Generation
- The system will use Dijkstra’s Algorithm [8] to compute the most efficient and eco-friendly paths through the forest.
  - This will assist in sustainable navigation for conservationists, forest planners, and researchers.[19]
5. Historical Data Analysis & Trend Monitoring

- The system will integrate time-series analysis to track deforestation rates and ecosystem changes.
  - By analyzing historical data, the system will provide predictive insights for better decision-making.[20]
6. User-Friendly Data Visualization & Reports
- The results will be presented in an interactive dashboard with annotated maps, species distribution graphs, and green cover analytics.
  - This will make the system easy to use for forest management authorities, policymakers, and researchers.

Innovations & Advantages

- Real-time & Automated Analysis: Reduces manual work and delivers instant results.

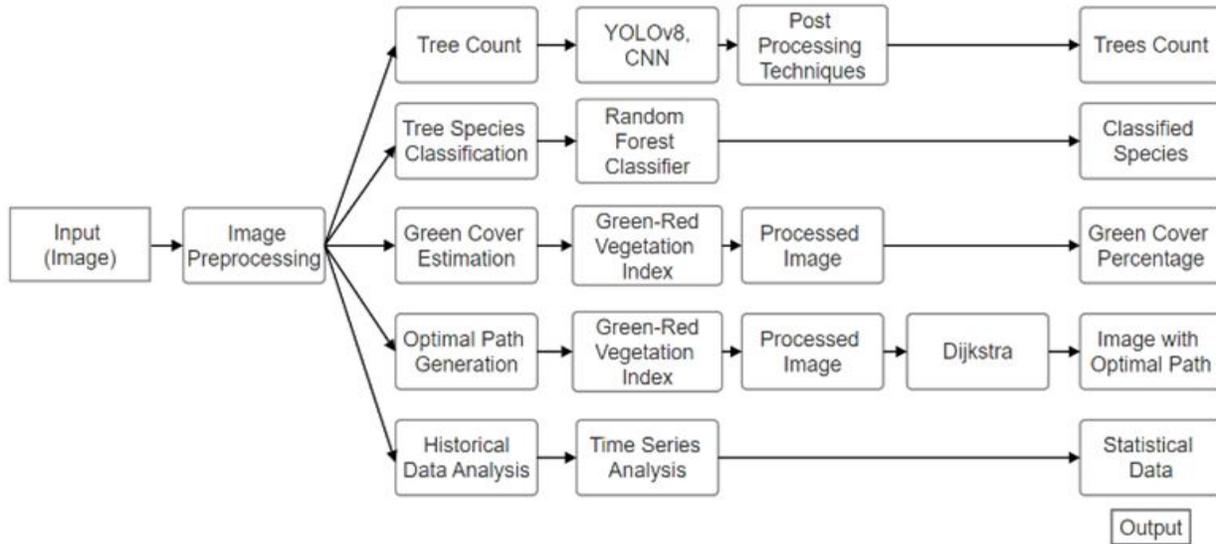


Fig. System Architecture

- Cost-Effective Monitoring: Eliminates expensive infrared-based vegetation analysis.
- Comprehensive Solution: Combines tree counting, species classification, green cover estimation, and navigation into a single system.
- Eco-Friendly Approach: Ensures minimal disturbance to forests while planning pathways.
- Scalability & Adaptability: Can be expanded for use in urban forestry, agriculture, and conservation efforts. This proposed work aims to revolutionize forest monitoring, providing an intelligent, scalable, and data-driven solution for sustainable environmental management.

VI. METHODOLOGY

1.Green Cover Analysis

The following steps outline the implementation of Green Cover Analysis using GRVI [3] in our project:

Step 1: Image Acquisition and Preprocessing:

We used high resolution drone captured images as input. Images were pre - processed using OpenCV to extract Red (R) and Green (G) colour channels.

Step 2: GRVI Calculation:

We computed GRVI using the formula:

$$GRVI = (G-R)/(G+R+1e^{-6})$$

where:

G = Green channel’s intensity.

R = Red channel's intensity.

$1e^{-6}$  is added to avoid division by zero.

Step 3: Normalization:

We normalized the GRVI values between 0 and 1 to improve visual representation:

$$GRVI_{norm} = \frac{GRVI - \min(GRVI)}{\max(GRVI) - \min(GRVI)}$$

Step 4: Vegetation Masking and Green Cover Calculation:

We applied a threshold of 0.1 to generate a binary vegetation mask. Pixels with  $GRVI > 0.1$  were classified as vegetation. The green cover percentage was calculated as:

$$\text{Green Cover (\%)} = \left( \frac{\text{Number of Vegetation Pixels}}{\text{Total Number of Pixels}} \right) \times 100$$

The output included:

GRVI Image: A normalized GRVI heatmap to visualize vegetation intensity.

Vegetation Mask: A binary mask highlighting areas classified as vegetation.

Green Cover Percentage: A numeric value representing the proportion of green cover.

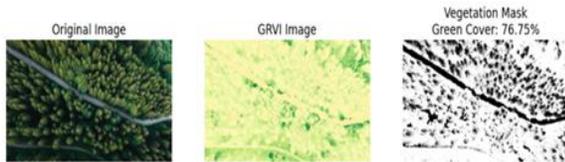


Fig. GRVI output image

## 2. Tree Count

### YOLO-Based Tree Detection

The following steps outline the implementation of YOLOv8 [1],[7] for tree detection in our project:

Step 1: Model Selection and Initialization

We used the YOLOv8 model for tree detection. The model was initialized using the pre-trained weight file (yolov8n.pt). This variant was chosen for its balance between speed and accuracy.

Step 2: Model Training

The model was trained using our dataset, which was defined in a data.yaml file. The training process involved:

Epochs: The model was trained for 100 epochs for ensuring sufficient learning.

Image Size: The input images were resized to 640×640 pixels to standardize training.

Batch Size: Batch size of 16 is used for optimal memory utilization.

Workers: 4 workers were used for efficient data loading.

Device: The training was conducted on a CPU, but it supports GPU acceleration.

Early Stopping: A patience value of 20 was set, meaning the training would stop if no improvement was seen in 20 consecutive epochs.

Data Augmentation: Augmentation techniques were enabled to improve model robustness.

Optimizer: The Adam optimizer was used for better convergence.

Learning Rate Scheduler: A cosine learning rate scheduler was applied to adjust the learning rate dynamically.

Caching: Image caching was enabled to speed up training.

The trained model was saved under runs/train/tree\_detection.

Step 3: Model Validation

After training, the model was validated using the same dataset (data.yaml). This step assessed the model's accuracy in detecting trees before deployment.

Step 4: Tree Detection on New Images

Once trained, the model was tested on a new image. The detection process involved:

Confidence Threshold: A confidence level of 0.3 was set to filter out low-confidence detections.

Bounding Box Visualization: The detected trees were displayed with bounding boxes.

Step 5: Tree Counting

The total detected trees were counted using the bounding box outputs from the YOLO model. The count was displayed alongside the image.

Step 6: Visualization

For better interpretability:

OpenCV and Matplotlib were used to process and display the images.

Bounding Boxes were overlaid on the detected trees.

Tree Count was displayed on the image.

The final output included:

A detected tree image with bounding boxes.

The total number of trees detected.

This automated process significantly improves efficiency and accuracy in forest monitoring compared to traditional methods.



Fig. Tree Count output image

### 3. Optimal Path

#### Step 1: Image Acquisition and Preprocessing

We used pre-processed binary images (from threshold green-enhanced images) as input. Green vegetation was enhanced by nullifying red and blue channels and applying a pixel intensity threshold.

#### Step 2: Graph Construction from Image Grid

Each pixel was treated as a node in a grid-based graph. Each node was connected to its 8 neighbouring pixels, provided they were within image bounds.

#### Step 3: Weight Calculation for Edges

Edge weights were computed using a custom cost function combining:

Pixel intensity (lower intensity = more vegetation).

Euclidean distance to the target.

#### Step 4: Dijkstra's Algorithm for Pathfinding

We applied Dijkstra's algorithm using a min-heap (priority queue) to always expand the node with the lowest cumulative cost from the start node.

The algorithm tracked parent nodes to reconstruct the shortest path once the target was reached.

#### Step 5: Path Tracing and Visualization

The path was traced back from the target node to the start node using parent links.

The optimal path was visualized on both the threshold binary image and the original RGB image, overlaid as a coloured line.

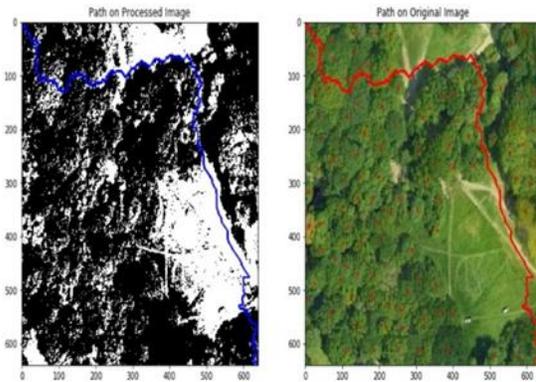


Fig. Optimal Path output image

### 4. Species Detection

#### Methodology: Tree Species Identification

To enable the identification of tree species based on visual characteristics, a machine learning-based model was developed using the Random Forest classifier. The following steps were employed:

1. Dataset Preparation: A labeled dataset was created using images of various tree species, downloaded via the iNaturalist API. The images were stored in class-specific folders and resized to a standard dimension of 128x128 pixels.

2. Feature Extraction: For each image, two types of features were extracted: color histograms from the HSV color space and texture features using Sobel edge detection. These features were combined into a single feature vector for classification.

3. Model Training: A Random Forest classifier with 100 estimators was trained on the extracted features using an 80-20 train-test split. The classifier was evaluated using metrics such as accuracy and classification report to determine its performance across multiple tree species.

4. Inference and Visualization: To classify a new tree image, the model extracted features using the same process and predicted the species label. The results were visualized using matplotlib, displaying the image along with the predicted species.



Fig. Species Detection image

## VII. CONCLUSION

The Intelligent Tree Enumeration and Forest Analysis System for Environmental Monitoring leverages machine learning and structured datasets to revolutionize forest monitoring. By automating tree counting, species classification, green cover estimation, and optimal pathfinding, it enhances accuracy and efficiency over traditional methods. The integration of historical data analysis provides critical insights into forest trends, supporting sustainable management and conservation efforts. This system empowers researchers, policymakers, and environmental agencies with data-driven solutions to combat deforestation and promote ecological balance. By bridging technology and sustainability, it ensures that forests are preserved, monitored, and managed efficiently for future generations.

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