ABSTRACT FOR GREEN-AI

Introduction

Odisha, an ecologically rich state in eastern India, is recognized for its commitment to combating deforestation and climate change through large-scale afforestation efforts. Each year, the state plants approximately **5 crore saplings**, emphasizing its dedication to restoring forest cover. However, the survival and healthy growth of these saplings remain significant challenges. Issues such as pest infestations, water scarcity, grazing by animals, and delayed interventions have led to suboptimal outcomes, with sapling survival rates reported as low as **65% in 2017**.

Traditional monitoring methods, like manual surveys, are time-consuming, labor-intensive, and often fail to provide the timely, precise data required for effective decision-making. A modern, scalable solution is essential to address these limitations and ensure the success of Odisha's afforestation programs.

This project proposes a **drone-based monitoring framework**, a transformative approach integrating **Unmanned Aerial Vehicles (UAVs)** equipped with high-resolution cameras, sensors, and advanced technologies such as **machine learning** and **GIS mapping**. Drones can capture detailed aerial imagery of plantation areas, enabling the identification of sapling health issues, detection of dead or missing plants, and early warnings of threats like water stress or pest attacks. This system aligns with Odisha's goals while drawing on global best practices and technological advancements:

- In **Panama**, drone technology was successfully integrated into community-led forest monitoring programs, empowering indigenous communities to detect deforestation and degradation efficiently.
- In **Australia**, UAVs with advanced sensors like **LiDAR** and **hyperspectral imaging** have been deployed to monitor reforestation efforts, demonstrating high accuracy in assessing canopy health, soil quality, and biodiversity.

Significance of the Concept

The proposed framework addresses critical gaps in Odisha's current monitoring systems, offering a scalable, efficient, and data-driven solution. Unlike traditional manual surveys that are resource-intensive and prone to delays, drones provide:

1. **Real-Time Monitoring:** UAVs enable quick data collection and analysis, allowing forest officials to identify and address issues proactively.
2. **Comprehensive Coverage:** Even in remote and hilly terrains like **Western Odisha**, drones can monitor vast areas, ensuring no plantation site is overlooked.
3. **Cost Efficiency:** By reducing dependency on manual labor, drone-based monitoring optimizes resources and minimizes operational costs.

Problem the Idea Aims to Address

Odisha's afforestation programs face several interconnected challenges:

- **Low Sapling Survival Rates:** Factors such as pest infestations, drought stress, and animal grazing remain undetected until it's too late.
- **Limited Access to Remote Areas:** Geographical constraints hinder effective monitoring in remote or hilly regions.
- **Inefficient Resource Allocation:** Delays in identifying problem areas lead to inefficient use of resources and missed opportunities for timely interventions.

The integration of **drones and machine learning** addresses these problems by enabling precise, data-driven decision-making and rapid response to threats.

Global Insights and Applicability

- Experiences from other regions underscore the potential impact of drone technology on Odisha's afforestation goals. In Panama, the use of drones in conjunction with GIS and community training empowered local stakeholders, enhancing forest management outcomes. Similarly, drone-based monitoring in Australia revealed its ability to assess reforestation success, detect early disease symptoms, and map biodiversity across vast landscapes. These applications demonstrate the versatility and effectiveness of drone technology in overcoming challenges similar to those faced by Odisha.

Aspect	Details
Global Deforestation	Over **10 million hectares** of forest lost annually from 2015 to 2020, highlighting the urgent need for reforestation.
Impact of Forests on Climate	Forests act as carbon sinks, absorbing approximately **7.6 billion tonnes of CO_2 per year**.
Success of UAVs in Monitoring	UAVs in Australia used **LiDAR** and **hyperspectral imaging** to assess canopy health, biodiversity, and soil quality.
Community-Led Monitoring	In Panama, drones empowered **indigenous communities** to monitor deforestation and manage resources effectively.
Key UAV Features	UAVs can produce high-resolution imagery with **point cloud densities exceeding 1,000 points/m²**, surpassing traditional methods.
Efficiency of UAVs	UAVs can plant **160,000 seeds/day** and monitor inaccessible areas, significantly reducing labor and time costs.
Challenges in Odisha	Odisha faces **low survival rates (65%)**, **drought stress**, **pest infestations**, and **monitoring inefficiencies**.
Advanced Technologies	**Structure from Motion (SfM)** and machine learning enable accurate detection of sapling health issues.

Flow and Architecture

The proposed solution represents an advanced system for monitoring afforestation programs by combining drone imagery, machine learning, and geospatial analytics into an efficient and scalable framework. Designed to address critical challenges in sapling survival and growth monitoring, this system provides actionable insights and timely interventions to improve the overall success of plantation efforts.

Drone imagery captures high-resolution data of plantation areas, processed into geo-referenced orthomosaics for spatial analysis. These orthomosaics serve as the foundation for extracting metrics such as sapling health, survival, and growth trends. The workflow is organized into sequential steps that include data preprocessing, image segmentation, feature extraction, and output visualization, ensuring comprehensive analysis and reporting.

Problem Statement

- **Goal**: Develop a solution to monitor afforestation efforts using drone imagery, identifying casualties (non-surviving saplings) and analysing growth.
- **Input**: Raw drone imagery of afforestation patches
- **Output**: Reports/visuals highlighting sapling survival and growth, along with casualties

Tools and Technologies

Category	Tools/Technologies	Purpose
Programming	Python, OpenCV, NumPy, Pandas, GeoPandas	Image processing, data handling, and analysis.
Frameworks	Django (HTML, CSS, JavaScript, 3.js)	Web-based data visualization and analysis.
Cloud Services	GCP (Vertex AI, Cloud Vision API, Compute Engine)	Deployment, storage, and advanced processing.
Drone Imagery Tools	Pix4D	Preprocessing drone imagery and orthomosaic generation.
Visualization	Matplotlib, Looker Studio	Data visualization, dashboards, and charts.

Understanding the Operations

1. **OP1 (March-May, Year 1)**:

   Dig pits (45› 45› 45 cm) and expose them to sunlight to eliminate microbes. Visible in drone imagery.

2. **OP2 (June 15–July 30, Year 1)**:

   Plant 18-month-old saplings (4–6 ft) during the monsoon when soil moisture is optimal. Saplings are detectable from aerial views.

3. **OP3 (Oct–Nov, Year 1–3)**:

   Annual weeding within a 1-meter radius around saplings for three years to support growth. Cleared areas are visible in drone imagery.

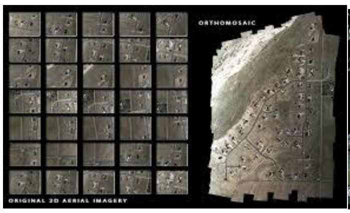
Solution Approach

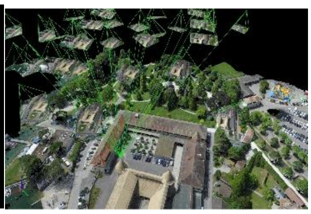
A. Understanding the Data

1. **Drone Elevation:**
   - Set between **70–80 meters** to maintain consistent scale.
2. **Pixel Resolution:**
   - High resolution of **2.46–2.81 cm per pixel**, ideal for detecting individual saplings.
3. **Overlap for Coverage:**
   - Ensure **65% sidelap** and **75% endlap** for complete image coverage.

B. Data Preprocessing

1. **Organize the Raw Data:**
   - **Metadata:** Includes time, geo-coordinates (latitude/longitude), and camera settings.
   - **Steps to Organize:**
     - Sort images into folders based on survey stages:
       - Folder 1: Before_OP1
       - Folder 2: After_OP1
       - Folder 3: After_OP2
       - Folder 4: After_OP3
     - Check for duplicates/corrupted files and rename images for easier identification (e.g., OP1_IMG_001.jpg).
2. **Generate Orthomosaics:**
   - **What is it?**
     - A large, stitched-together map from drone images with accurate geo-referencing.
   - **Why use it?**
     - Provides a bird's-eye view, making analysis simpler and more accurate.
   - **Steps to Create:**
     - Use tools like **Pix4D** to stitch drone images with overlaps (65% sidelap, 75% endlap).
     - Ensure the orthomosaic retains real-world geo-coordinates.



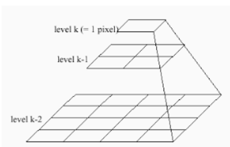


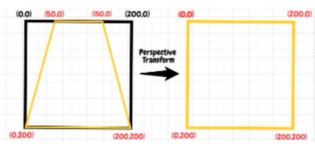
C. Image Preprocessing

1. **IMAGE RESIZING:-**

   i. RESIZING: Adjust the image dimensions using cv2.resize().
   ii. IMAGE PYRAMID: Modify image resolution (scale up or down) using cv2.pyrDown() and cv2.pyrUp().
   iii. PERSPECTIVE RESIZING: Correct or adjust image perspective using OpenCV and NumPy functions:

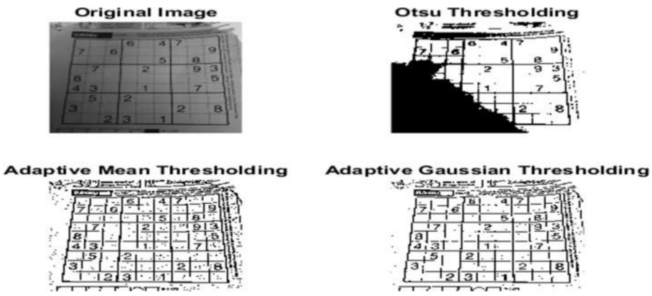
   - cv2.getPerspectiveTransform()
   - cv2.warpPerspective()



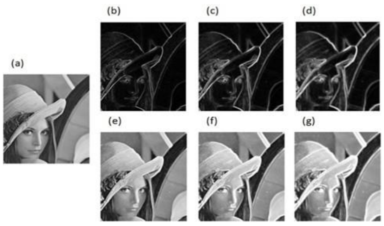


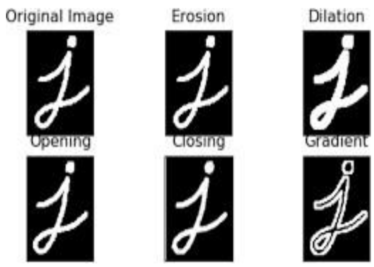
1. **Converting Images to Grayscale:**
   - Reduces data complexity and focuses on brightness and patterns.
   - Benefits: Faster processing, better edge detection, and reduced storage.
   - Use OpenCV functions like `cv2.cvtColor()` for conversion.
2. **Image Thresholding:**

- **Multi-Otsu Thresholding:**
  - Separates the image into multiple intensity classes, e.g., soil, saplings, and dead patches.
- **Adaptive Thresholding:**
  - **Description:** Divides the image into smaller regions and applies a threshold to each region based on local pixel intensity.
  - **Steps:**
    1. Calculate a local threshold for each small region of the image.
    2. Combine these thresholds to generate the segmented output.
  - **Use Case:** Ideal for uneven lighting conditions or complex images with varying pixel intensities.
    - Example: Segregating saplings from soil and shadowed regions.



3. **Image Filtering:**
   - Removes irrelevant artifacts (e.g., shadows, water patches). • Techniques include:
     - Smoothing (e.g., `cv2.GaussianBlur()`),
     - Noise reduction (e.g., `cv2.fastNlMeansDenoising()`), ∘ Contrast enhancement (e.g., `cv2.equalizeHist()`).





Category	Function	Use
Smoothing	cv2.blur, cv2.GaussianBlur	Noise reduction
Sharpening	cv2.filter2D, cv2.addWeighted	Enhancing details
Contrast Adjustment	cv2.equalizeHist, cv2.convertScaleAbs	Enhancing contrast
Edge Detection	cv2.Canny, cv2.Sobel, cv2.Laplacian	Highlighting edges
Noise Reduction	cv2.fastNlMeansDenoising	Removing image noise
Morphological Ops	cv2.morphologyEx, cv2.erode	Structural enhancement

D. Image Segmentation

Goal: Isolate saplings from the background for individual analysis.

1. **Thresholding:** Use Otsu's or adaptive thresholding for basic segmentation.
2. **Deep Learning Models:** Apply **U-Net** or **Mask R-CNN** for pixel-level segmentation.
3. **Steps:**
   - Detect sapling boundaries using `cv2.findContours()`.
   - Draw bounding boxes around saplings for further measurements.

E. Feature Extraction

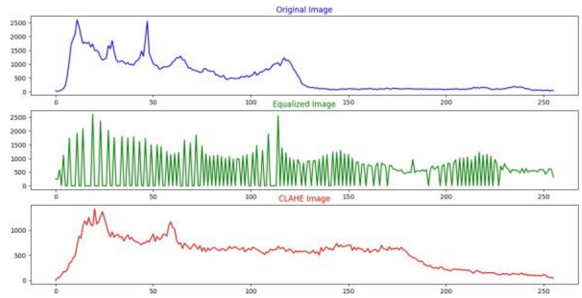
1. **Survival Detection:**
   - Classify saplings as "alive" or "casualty" using features like:
     - **Color:** Average RGB/HSV values.
     - **Texture:** Haralick features or Local Binary Patterns (LBP).
     - **Size:** Bounding box dimensions.
   - **Model:** Use Convolutional Neural Networks (CNNs) like ResNet, EfficientNet, or MobileNet for binary classification.
2. **Growth Measurement:**
   - Predict sapling height, canopy size, or biomass using deep learning regression models.

F. Machine Learning Models

1. **For Visual Feature Extraction:**
   - CNNs like ResNet or EfficientNet.
2. **For Object Detection:**
   - YOLO or Faster R-CNN to locate and count saplings.
3. **For Change Detection:**
   - Compare images over time to identify patterns or changes.

G. Output Visualization

1. **Heatmaps or Overlays:** Highlight casualties and healthy saplings on drone images.
2. **Dashboards:** Track plantation health and growth metrics over time with user-friendly visualizations.



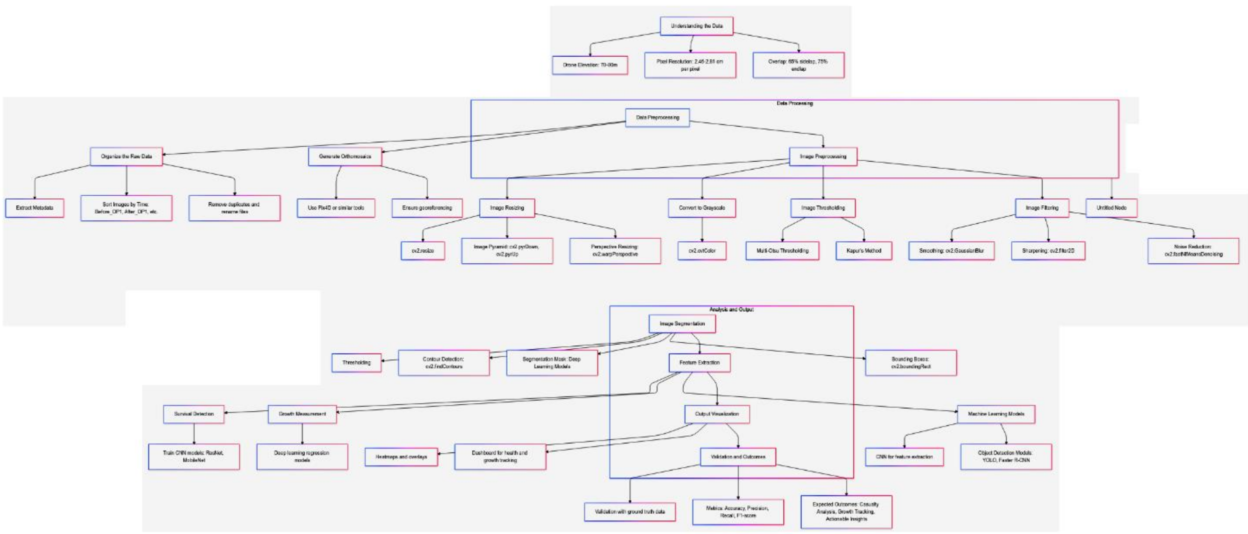
- **Original Image (Blue Curve)**: Represents the initial intensity distribution, with visible peaks indicating concentrated intensity levels. This serves as a baseline for comparison.
- **Equalized Image (Green Curve)**: After applying histogram equalization, the intensities are redistributed, resulting in a more uniform histogram. This enhances the global contrast, making finer details more prominent.
- **CLAHE Image (Red Curve)**: Demonstrates the effect of Contrast Limited Adaptive Histogram Equalization (CLAHE), where intensities are adjusted locally. The histogram shows balanced enhancement, avoiding over-amplification and preserving details in both bright

H. Validation

1. **Compare with Ground Truth Data:** Provided by the forest department.
2. **Evaluation Metrics:** Accuracy, precision, recall, and F1-score.

Expected Outcomes

1. **Casualty Analysis:** Identify and quantify non-surviving saplings.
2. **Growth Tracking:** Visualize and quantify growth patterns of saplings.
3. **Actionable Insights:** Provide detailed reports to assist the forest department in decision-making.



Impact and Benefits

The proposed solution integrates drone technology, machine learning, and geospatial analytics to address the challenges in monitoring large-scale afforestation programs. Its implementation ensures enhanced efficiency, accuracy, and scalability, while also creating significant value for stakeholders across environmental, operational, and socio-economic dimensions.

Outcomes of the Proposed Solution

1. **Improved Survival Rates:**

- Early detection of struggling or dead saplings enables timely interventions, such as replanting or resource allocation. This proactive approach significantly increases sapling survival rates and ensures the overall success of afforestation programs
- For instance, the solution addresses historical challenges like the 2017 report where only 65% of saplings survived due to delays in detecting pests, drought, or grazing issues.

2. **Actionable Insights:**
   - High-resolution drone imagery combined with machine learning models generates precise data on sapling health, vegetation growth, and areas requiring intervention. This empowers stakeholders to make data-driven decisions and optimize resource distribution.
3. **Environmental Gains:**
   - By ensuring higher survival rates and better plantation management, the solution directly contributes to increased forest cover, improved biodiversity, and enhanced carbon sequestration—critical in mitigating climate change.

Advantages of the Solution

1. **Automation and Efficiency:**
   - The system automates labor-intensive and error-prone manual surveys, reducing costs and human error while improving the speed and reliability of reporting cycles.
   - Real-time insights ensure swift action, preventing small problems from escalating into larger, costlier issues.
2. **Comprehensive Monitoring:**
   - Drone-based aerial surveys provide a holistic view of plantation sites, covering even remote or inaccessible areas. Combined with geospatial analytics, this ensures no sapling is overlooked.
3. **Cost-Effectiveness:**
   - Although initial investments in drone technology and machine learning tools are required, the long-term savings from reduced labor costs and increased program efficiency outweigh these expenses.

Scalability of the Framework

1. **Adaptability Across Regions and Terrains:**
   - The modular design of the framework allows it to scale seamlessly across plantations of varying sizes and terrains. This makes it suitable for Odisha’s rugged landscapes and beyond.
   - Its adaptability ensures the solution can be deployed in similar afforestation programs globally, addressing large-scale environmental challenges.
2. **Future-Proof Design:**
   - The solution can be enhanced further with emerging technologies such as IoT sensors for real-time soil and weather monitoring, making it resilient to evolving environmental challenges.

Value Addition for Users and Stakeholders

1. **For Forest Departments and Policymakers:**
   - Transparent, data-driven reporting builds credibility for afforestation programs and supports better policy-making and resource allocation.
   - Accurate monitoring outcomes strengthen funding proposals for environmental initiatives.
2. **For Local Communities:**
   - The project creates jobs in drone operation, data analysis, and sapling maintenance, fostering rural economic growth.
   - Enhanced forest cover leads to long-term ecosystem benefits like better water retention, improved soil health, and climate regulation, positively impacting livelihoods.
3. **Global Benchmark:**
   - By adopting cutting-edge technologies, Odisha can set an example for innovative and sustainable afforestation practices, inspiring other regions to follow suit.

Conclusion

The proposed drone-based monitoring framework introduces a transformative approach to afforestation management by integrating advanced technologies such as machine learning, geospatial analytics, and drone imagery. By addressing key challenges like inconsistent monitoring, delayed problem detection, and scalability issues, the solution ensures enhanced efficiency, accuracy, and reliability in tracking sapling survival and vegetation health.

This project delivers significant outcomes, including improved sapling survival rates, actionable insights for decision-making, and contributions to environmental sustainability. The framework’s scalability allows it to be deployed across diverse terrains and regions, making it a versatile tool for managing large-scale afforestation programs. Its cost-effectiveness and automation further optimize resource utilization while reducing dependency on manual labor and minimizing human error.

Beyond its operational advantages, the project holds immense value for stakeholders. Forest departments benefit from precise data and transparent reporting, enabling better policy-making and funding support. Local communities gain from new job opportunities and the long-term ecological benefits of enhanced forest cover, such as improved water retention, soil conservation, and climate regulation. Additionally, the project sets a global benchmark for leveraging technology in environmental conservation.

As Odisha continues its ambitious efforts to expand forest cover, this innovative framework aligns with the state’s mission to mitigate climate change and preserve biodiversity. By embracing this technology, Odisha can enhance the impact of its afforestation programs and inspire other regions to adopt similar sustainable practices.

In conclusion, this project is not merely a technological upgrade but a critical step toward building a greener, more sustainable future. Its integration of modern tools with sustainable practices ensures long-term success, setting the stage for transformative progress in environmental management and conservation.

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