Optimal Path Detection Through Forest Region Using Image Analytics

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***Abstract*— Expanding the current road networks as part of development schemes often stands in the way of forest conservation and ecological sustainability. This research tries to find a solution using Optimal Path Detection through Forest Regions using Image Analytics, which uses advanced machine learning algorithms and satellite imagery. The proposed solution employs deep learning frameworks such as PyTorch as part of YOLOv11 for tree enumeration and optimal path prediction while integrating geospatial data via APIs like Google Maps for planning in real-time. For high-resolution forest analysis, image processing tools like OpenCV are utilized improving the accuracy of the results.**

Path detection algorithms such as A* algorithm are used to detect optimal routes through forest which ensures minimal disturbance to the ecology and reduces fragmentation of forest regions maintaining their integrity. This methodology offers a scalable solution for environmentally conscious urban planning and supports decision-making in sustainable infrastructure development.

***Index Terms*— Path Detection, Image Analytics, Classification/Segmentation of Satellite Images, Tree Enumeration, Convolutional Neural Networks (CNN), YOLOv11.**

I. INTRODUCTION

Optimal Path Detection through Forest Regions is an innovative approach leveraging image analytics and machine learning to address the challenge of balancing infrastructure development with ecological conservation. Using advanced deep learning models, the system analyses satellite imagery to detect tree density and distribution, enabling precise planning of road networks with minimal environmental impact. Frameworks like YOLOv11, powered by PyTorch, have revolutionized object detection by enhancing the accuracy of tree enumeration and segmentation tasks, while tools like OpenCV contribute to high-resolution forest analysis.

Geospatial data integration through APIs, such as Google Maps, ensures real-time, data-driven decision-making, while pathfinding algorithms like A* algorithm optimize route selection to minimize forest fragmentation. This project offers a transformative solution for sustainable infrastructure planning, providing tools that enable ecologically conscious urban development.

While current advancements showcase remarkable capabilities, the field continues to evolve, promising greater efficiency, scalability, and accessibility. As techniques mature, this project aims to bridge the gap between infrastructure needs and environmental stewardship, contributing to sustainable development and ecological preservation.
This project, "Optimal Path Detection through Forest Regions using Image Analytics" aims to address these critical environmental concerns. Traditional road construc tion methods often disregard ecological impacts, leading to excessive tree cutting and long-term environmental damage. By utilizing advanced technologies like machine learning and image analytics, this project seeks to propose a sustainable solution that minimizes the ecological footprint of infrastructure projects. With the ability to automatically analyze satellite imagery and geospatial data, this project will help identify paths that avoid dense forest areas and preserve trees, contributing to the reduction of deforestation. It supports the broader global goals of environmental sustainability by advocating for a smarter approach to infrastructure development. Additionally, it aligns with initiatives like reforestation, climate change mitigation, and biodiversity conservation, all of which are essential to maintaining ecological balance.

II. LITERATURE REVIEW

This literature survey presents an overview of key research and methodologies relevant to the development of a tool for optimal path detection using image analytics. It explores advancements in machine learning, image processing, and geospatial data integration, emphasizing their applicability to tree enumeration and path optimization.

1. Sizhuo Li, Martin Brandt, and Rasmus Fensholta present their work utilizing advanced computer science methods to establish national databases featuring the location, crown area, and height of large or overstory trees, both within and outside forest regions.[1] The authors propose a deep learning-based framework that identifies the location, crown area, and height of individual overstory trees from aerial images at a country scale. Their study emphasizes the importance of trees as indispensable resources that can be categorically classified using these characteristics to promote sustainable tree resource management.

2. F.Z. Bassine, A. Errami, and M. Khaldoun present their work on extracting information such as tree counting and segmentation from captured images.[2] Their project focuses on gathering data from video sequences, addressing challenges like motion blur and dynamic backgrounds. The proposed methods achieve an accuracy of approximately 90% and demonstrate potential for real-time object recognition and counting across varying shapes and sizes.

3. Chia-Yen Chiang, Chloe Barnes, Plamen Angelov and Richard Yiang.[3] This project goes further and detects dead trees in the forest from where a forest fire could likely spread. Thus, by addressing the causal factor, the impact of a forest fire can be reduced and mitigated. The project makes use of a RCNN model, which can be trained using a rich and diverse dataset. The accuracy of the model is improved by adjusting the pretrained weights.

4. Victor Lempitsky and Andrew Zisserman elaborate on techniques for counting objects in images. They propose a new supervised learning framework designed to count objects in various contexts, such as cells in microscopic images or people in surveillance footage.[5] The method introduces a loss function tailored for this type of learning, which can be computed efficiently using a maximum subarray algorithm. Once trained, the system delivers accurate object counts.

5. Devidas Dukale, Sumit Agale, Swaroop Kalunge, and Pushpak Nikam present an innovative image analytics approach that leverages satellite and aerial imagery for automating tree counting. The main goal is to create a reliable system that detects and classifies trees based on crown size and environmental factors. Cutting-edge computer vision techniques are combined with machine learning models to process the images. Extensive validation, including comparisons to ground-truth data from field surveys, ensures high precision and dependability. The outcome is remarkable, as this solution dramatically speeds up tree enumeration, removing the need for time-consuming manual work.

III. SYSTEM DESIGN

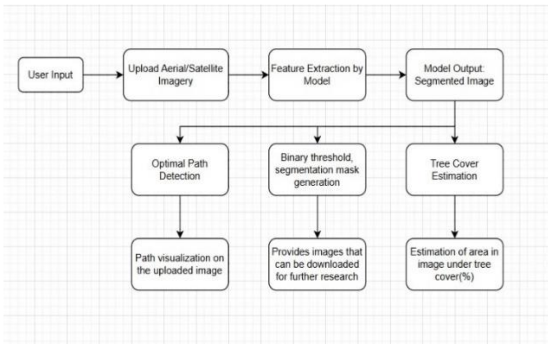

Figure-1: System Architecture

System architecture refers to the conceptual model that defines the structure, behavior, and more of a system. It provides a high-level blueprint that outlines how different components or modules of a system interact with each other and how the system operates as a whole. In the context of software engineering, system architecture describes the organization of software components, their relationships, and the ways they collaborate to achieve system functionality.

IV. METHODOLOGY

1. Data Preparation

High-resolution satellite imagery or aerial photographs covering forested areas targeted for tree enumeration were obtained. The dataset, sourced from platforms such as Kaggle and Roboflow, includes annotated satellite images of trees. To obtain more high-resolution pictures, additional images were obtained from NEON RGB dataset which provides the user with images across different locations. Annotation tools were used to label the images, highlighting specific features for the model to recognize. Using Meta's Segment Anything Model (SAM2), annotation was faster and more precise. The model allows the user to decide between keeping simple or complex boundaries which also letting the use to customize the label if needed. The dataset was prepared using tools from Roboflow.

2. Data Preprocessing

The images were loaded into the system and visualized to ensure data consistency and integrity. Image processing techniques were employed to generate density maps. The preprocessing workflow included reading images from the specified directory, resizing them to a uniform dimension of 640 × 640 and converting them into a PyTorch-compatible format. Pixel values were normalized to floating-point numbers within the range [0, 1] to meet the requirements of image processing tasks. These steps ensure uniformity in input data dimensions, a critical factor for training machine learning models.

3. Tree and Tree Region Visualization

Using the annotated images, tree regions were visualized using the generated model after training. The tree regions were identified by bounding boxes and visualized using segmentation masks. Segmentation masks generated are overlayed upon the image uploaded by the user. These regions are colored with a specific color to help achieve further functionalities like Tree Cover Estimation, creating segmentation masks and ultimately generating the optimal path.

4. Tree Cover Estimation

Contrary to the observed methods of calculating tree cover by using just image analytics, we used the obtained segmentation masks to identify trees and tree-regions. These masks help to accurately identify where the regions are and visualizes them. The effective green space (which consist of just the trees, leaving out other vegetation like bushes, grass, shrubs), is thus more accurate. Traditional methods focused on using image analytics tools to nullify the red and blue channels in an image to filter out the green regions and then calculating the green pixels. This was not always accurate, as an image with just one tree in the Savannah, reported about 70% tree cover/green space. Thus actually knowing the tree-regions helps to make the result more precise.

$$Tree\ Cover\ \% = \frac{Count\ of\ Tree\ Pixels * 100}{Total\ number\ of\ pixels}$$

5. Optimal Path Detection

a. Image Segmentation

The input image uploaded by the user is passed through the instance segmentation YOLOv11 model to identify the tree regions and visualizing them using tree masks. The tree regions when colored with a specific color would act as a constraint through which the path should not pass. If the path is not possible by avoiding the trees, the algorithm ensures that path traversed minimum tree regions.

b. Pathfinding Using A*'s Algorithm

The A* algorithm was implemented to compute the optimal path within the segmented image. The binary mask obtained from Roboflow segmentation was treated as a graph, where each node represented a pixel and edges captured the connectivity between neighboring pixels. Weights were dynamically assigned based on pixel class (tree or non-tree), Euclidean distance, and proximity to tree boundaries or image edges.

$$\text{cost}[v]=\min(\text{cost}[v],\ \text{cost}[u]+\text{weight}(u,v))$$

A priority queue (min-heap) was used to iteratively select the pixel with the lowest estimated total cost—combining actual cost from the start and the heuristic to the goal (favouring diagonal movement from top-left to bottom-right). The algorithm continuously updated the path cost of neighbouring pixels, avoiding tree-covered areas when possible and minimizing traversal through dense forest regions.

This implementation intelligently balanced path length and tree avoidance, producing realistic and efficient paths suitable for autonomous navigation or forest trail analysis.

V. ALGORITHM AND FLOWCHART

A. ALGORITHM

1. *Start*

2. *Input Satellite Imagery*

- High-resolution satellite images of the forest region are acquired as the primary data source.
- These images are used to identify key terrain features, vegetation density, and potential obstacles.

3. *Image Preprocessing*
   - The input images undergo preprocessing to prepare them for analysis:
   - Conversion to grayscale for simplified processing.
   - Noise reduction using filters like Gaussian filters.
   - Application of image thresholding techniques to segment the image into distinct regions, such as vegetation, open terrain, and water bodies.

4. *Feature Extraction from Geospatial Data*
   - Image processing techniques, such as edge detection and object recognition, are used to detect features like trees, tree-crowns, and their separation from the background.
   - The instance segmentation results from YOLOv11 model returns the pixel values thus formulating accurate tree crowns.

5. *Constraint Definition and Objective Formulation*

The algorithm incorporates constraints such as:

- Minimizing the number of trees cut.
- Reducing the overall path length.
- The objective is to balance environmental preservation with the feasibility of road construction.
- Additional constrains enable the path to not stick to the edges of the image and favor a more diagonal like path.

6. *Pathfinding Using Computational Models*

Graph-Based Approach:

- The forest is modelled as a weighted graph, where nodes represent regions and edges represent potential paths.
- Weights are assigned based on geospatial features like tree density, slope, and terrain complexity.
- Pathfinding algorithms such as Dijkstra's or A* are employed to determine the shortest or least impactful path.

Deep Learning Approach:

- Convolutional Neural Networks (CNNs) are used for terrain feature detection and classification.

7. *Output Generation*
   - The final path is overlaid on the satellite image, highlighting the optimal route for road construction.

8. *End*

B. FLOWCHART

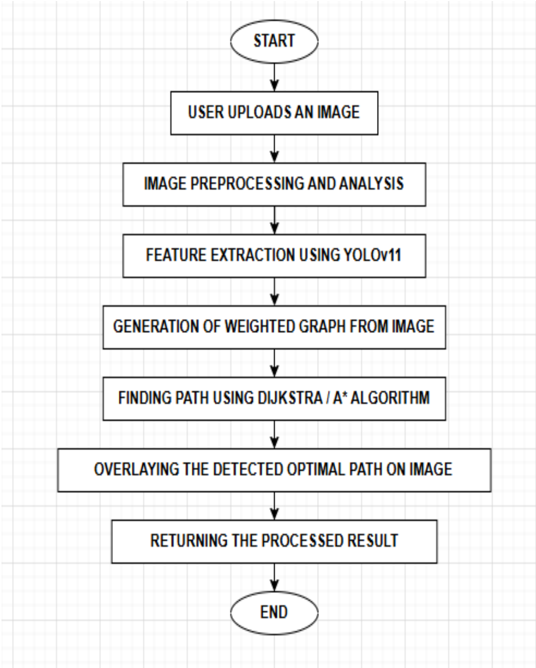

Figure-2: Flowchart of the System

VI. RESULTS

An aerial image from a satellite or a drone can be provided to the system and it returns the optimal path overlayed on the image itself.

The system successfully achieved its objectives by accurately segmenting tree regions from uploaded images using Roboflow inference, estimating the green cover percentage, and computing the optimal path from the top-left to the bottom-right corner of the image while minimizing traversal through tree-covered areas.

Importantly, the A*-based pathfinding algorithm was enhanced with additional factors such as Euclidean distances, tree mask density, and proximity to terrain boundaries to improve the accuracy and adaptability of the path planning process. This integration ensures robust and context-aware pathfinding, particularly in complex forested environments with varying vegetation density.

Output:

Figure-3: Optimal Path generated after passing an aerial image

VII. CONCLUSION AND FUTURE SCOPE

Conclusion:

In conclusion, the project "Optimal Path Detection through Forest Regions using Image Analytics" presents a significant advancement in the intersection of technology and environmental sustainability. By leveraging satellite imagery, machine learning algorithms, and geospatial data integration, the system provides a robust solution for identifying optimal paths that minimize ecological disruption. The benefits of this project extend beyond efficient infrastructure planning; it supports wildlife management, disaster response, and recreational development while promoting environ mental conservation. However, the effectiveness of the system is contingent upon the quality of data and computational resources. Future enhancements may focus on im proving data acquisition methods, refining algorithms for diverse environments, and expanding the system's applicability. Overall, this project holds promise for foster ing a balance between development and ecological preservation, contributing to more responsible land-use practices.

Future Scope:

The future scope of the project "Optimal Path Detection through Forest Regions using Image Analytics" includes:

- Integration of Real-Time Data: Enhancing the system by incorporating real-time data from drones, sensors, and IoT devices to improve accuracy and adaptability in dynamic forest environments.
- Advanced Machine Learning Techniques: Exploring the use of advanced algorithms, such as reinforcement learning, to optimize path detection further and enhance model performance across diverse terrains.
- User Customization Features: Developing customizable tools that allow users to tailor parameters according to specific project requirements, increasing the system's applicability for various stakeholders.
- Expansion to Diverse Ecosystems: Adapting the system to function effectively in different ecosystems and geographic regions, promoting broader applications in sustainable land management practices.

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