REAL-TIME DRONE-BASED AI SYSTEM FOR FALLEN TREE DETECTION

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1.Introduction

- Natural disasters often cause fallen trees that obstruct roads and delay emergency response efforts.
- Traditional methods such as manual inspections and satellite analysis are slow and inefficient
- This project proposes an AI-powered system that combines satellite imagery with UAV-based aerial data to enhance the speed and accuracy of fallen tree detection.

2. Research Objective

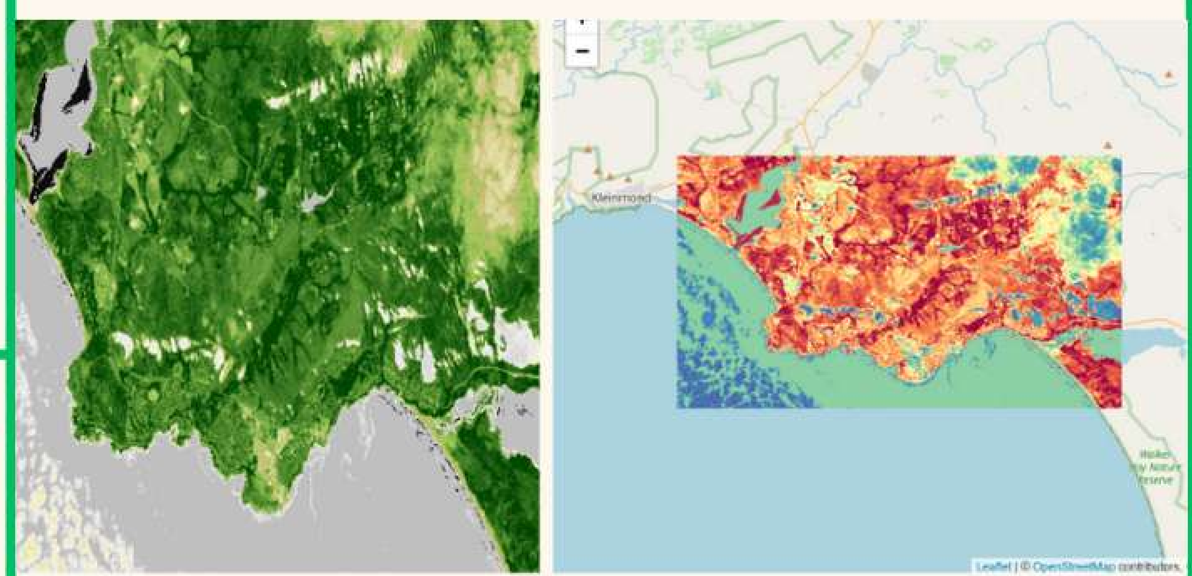
- This project aims to develop a real-time AI-powered drone system that autonomously detects and geotags fallen trees on roadways using computer vision and edge computing.
- By integrating Google Maps for road prioritization and GIS tools for hazard mapping, the system enhances emergency response efficiency and supports faster post-disaster road clearance.

3.Literature Review

- Recent studies have highlighted AI's potential in disaster management, with models like Faster R-CNN and U-Net showing strong detection performance for remote sensing (Liu et al., 2021) and fallen tree detection (Wegner et al., 2019).
- However, these studies often lack real-time deployment and integration with edge computing. Zou et al. (2020) and Huang et al. (2022) also explore object detection and UAVs for disaster surveillance but do not focus on real-time decision-making.
- This project addresses these gaps by combining UAV data, satellite imagery, and AI models (YOLOv8, Faster R-CNN, U-Net) on edge devices, along with GIS tools for real-time road clearance prioritization.

4. Dataset

- The dataset used in this analysis is derived from Sentinel-2 L2A products, provided by the Copernicus Satellite Program.
- Sentinel-2 captures multi-spectral imagery at a spatial resolution of 10m, 20m, and 60m.
- The primary bands used for fallen tree detection include Blue (490 nm), Green (560 nm), Red (665 nm), Near-Infrared (842 nm), and SWIR (1610 nm).
- These products are atmospherically corrected and ideal for vegetation monitoring.



5.Methodology

- The goal is to create a drone-based AI system that can detect fallen trees and prioritize road paths for faster disaster response.

- Data will be gathered from Sentinel-2 satellites and UAV sensors (RGB camera and LiDAR) to assess areas before and after disasters.
- The data will be cleaned up and converted into maps using GIS software, with image segmentation used to spot roads and obstacles.
- The drone will follow main roads using Google Maps API and Dijkstra's Algorithm to ensure it stays on the optimal path.
- For fallen tree detection, AI models like YOLOv8 and Faster R-CNN will be used, with LiDAR data filtering out false positives.
- If a tree is detected, the drone will log the exact GPS coordinates and send real-time alerts to rescue teams through 4G/5G or satellite.
- Data will be uploaded to the cloud (AWS or Google Cloud) for easy access and hazard map generation for emergency responders.
- The system will be optimized for real-time processing with edge computing using Raspberry Pi and battery management to maximize flight time.

6.Technologies

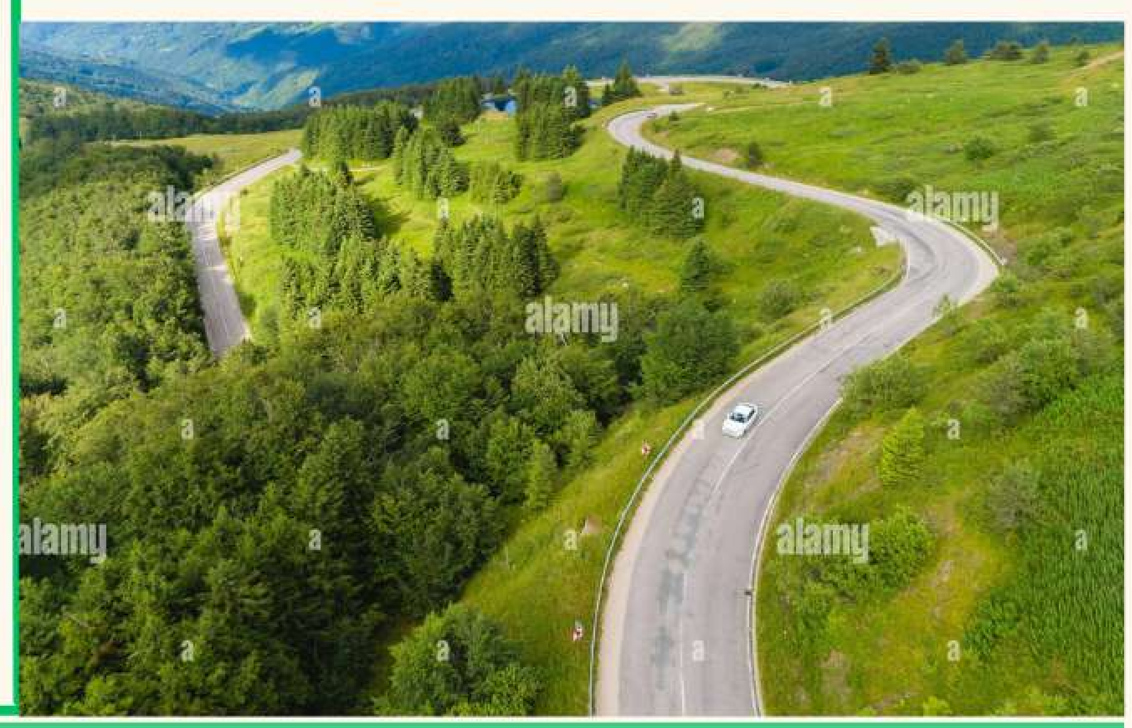
7.Early Indications and Next Steps

Early Indications:

- Studies show that combining drone and satellite images could really speed up fallen tree detection after disasters.
- Models like YOLOv8 and Faster R-CNN have strong potential for this kind of task.
- Devices like the Jetson Nano seem like a good fit for doing fast, on-the-spot processing in the field.

Next steps include:

- Start training the AI models using Sentinel-2 and drone data.
- Add LiDAR support to help reduce false alarms.
- Test drone routes using Google Maps and Dijkstra's Algorithm.
- Get the system running on an edge device and plan for field testing.



References

1. Huang, W., Song, G., Li, D. and Chen, H. (2022) 'UAV-based forest disaster detection: A review', Forest Ecology and Management, 507, p.119987. Available at: 10.1016/j.foreco.2021.119987.
2. Liu, Y., Zheng, S., Cheng, G. and Wang, J. (2021) 'Deep learning for remote sensing object detection: A review', ISPRS Journal of Photogrammetry and Remote Sensing, 179, pp.63-85. Available at: 10.1016/j.isprsjprs.2021.07.013.
3. Wegner, J.D., Turker, S. and Schindler, K. (2019) 'Automated mapping of fallen trees after a storm using deep learning and airborne imagery', Remote Sensing of Environment, 231, p. 111253. Available at: 10.1016/j.rse.2019.111253.
4. Zou, Z., Shi, Z., Guo, Y. and Ye, J. (2020) 'Object detection in 20 years: A survey', Proceedings of the IEEE, 109(1), pp.247-289. Available at: 10.1109/JPROC.2020.3002199.