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Fallen Tree Detection and Free Urban Space RELEAF

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Abstract - The vegetation of urban streets and neighbourhoods is often impacted after storms with fallen trees while nearby vacant areas currently have no known use for replantings. In this paper, we describe a web based AI system which allows users (i.e., citizens) to automatically identify fallen trees from their camera images, geolocate the areas and provide a realistic set of nearby planting sites or locations where there is space enough for a new tree. The device developed in this study uses an object detector model (YOLOv8) to quickly confirm that a tree has recently fallen, using photos taken at street level. We utilise a simple semantic segmentation and rule engine to find suitable planting strips and parcels using satellite or map images. The project is implemented using a cloud supported application with a React frontend, firebase authentication and firestore to allow synchronous real time data exchange between users and authorities. Our implementation provides a dashboard where red markers represent hazardous areas and green markers represent potential planting spaces, allowing staff to manage incidents from report to clearance and replacement tree planting. Our evaluation of the platform using curated image sets and pilot testing with users indicates that the system significantly reduces the amount of verification required by individuals, as well as provides, at the same time, practical site specific assistance for greening urban areas.

Keywords: Fallen tree detection, Urban vacant land, YOLOv8, Semantic segmentation, Smart urban forestry, ReLeaf planning.

1. INTRODUCTION

Fallen trees on city roads disrupt mobility, damage infrastructure, and create safety risks, especially during monsoon storms and high-wind events. Most cities report these incidents through helplines, social media, or complaint portals. Unfortunately, the information is often incomplete, unverified, or delayed. Meanwhile, decisions about where to plant new trees usually come from manual surveys and expert opinions, with little use of real-time hazard data or community input. This separation between emergency response and long-term greening results in slow cleanup, scattered records, and lost opportunities to replace trees where they have fallen.The proposed system tackles these issues by combining AI-based image analysis, real-time mapping, and urban space assessment into a single platform called "Fallen Tree Detection & Free Urban Space ReLeaf." Citizens can upload geotagged photos of suspected fallen trees. A YOLOv8 model checks if a tree has indeed fallen and pinpoints its location in the image. Confirmed incidents are stored in a cloud database and marked on an interactive city map that is accessible to users and authorities.

Rapid urban growth and more frequent extreme weather events are making fallen trees a growing safety and mobility issue in cities. Blocked roads delay emergency services and daily commutes. Removing mature trees speeds up the loss of urban canopies and their benefits. Many Indian cities also have numerous vacant or underused spaces, like roadside buffers, leftover plots, and informal open areas. These spaces could support new trees, but they are often not mapped or prioritized correctly. In most cases, reporting hazards and deciding where to plant trees happen through separate channels, such as phone calls, generic complaint websites, and independent GIS studies. This results in slow responses and missed opportunities for planned replanting. This approach transforms each tree fall into the beginning of a complete detect, clear, and releaf cycle instead of just an isolated complaint. Around each confirmed hazard, the system analyzes satellite or map images and uses simple geospatial rules to identify nearby open spaces that are suitable for planting replacement trees.

2. LITERATURE REVIEW

1. Polewski et al. (2015) – LiDAR-based Fallen Tree Detection: Polewski et al. propose a geometry-based framework to detect fallen trees using airborne LiDAR point clouds. The method segments linear structures from 3D data and merges compatible segments to reconstruct fallen tree stems on the forest floor. Unlike deep learning approaches, it relies on inherent geometric properties rather than large labeled datasets. The study demonstrates robust performance for forest damage assessment and provides a foundational non-learning-based approach for fallen tree detection.

2. Jiang et al. (2019) – Dead Wood Detection via Semantic Segmentation:This work introduces a deep-learning approach using fully convolutional networks with DenseNet backbones to detect standing and fallen dead wood from very high-resolution aerial imagery. Pixel-level semantic segmentation enables precise mapping of irregular dead-wood structures under complex canopy conditions. The model effectively combines spectral and spatial features to reduce confusion with soil and shadows. The study highlights the strength of segmentation models for detailed ecological monitoring tasks.

3. Open-source Urban Vacant Land Mapping (German Districts Study:The authors present an open-source workflow for identifying urban vacant land using remote sensing and GIS data. Vacant spaces are categorized into transport strips, natural

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constraints, leftover parcels, and brownfields, enabling structured urban analysis. The approach avoids costly proprietary data and is scalable across large regions. This work demonstrates how automated vacant-land inventories can support urban planning and green infrastructure development.

4. Mao et al. – Large-Scale Urban Vacant Land DetectionMao et al. treat urban vacant-land identification as a semantic segmentation problem using high-resolution satellite imagery. A deep neural network classifies each pixel as vacant or non-vacant, producing parcel-level maps across multiple cities. The model generalizes well across diverse urban contexts and outperforms traditional object-based methods. The study proves that scalable deep learning can support city-wide land-use planning and greening strategies.

5. Moon et al. – Practical Deep-Learning Fallen Tree Recognition: Moon et al. design a cost-effective deep-learning pipeline for fallen-tree recognition using RGB images captured by drones and roadside cameras. The system emphasizes real-time performance on affordable hardware rather than laboratory-grade accuracy. Detection results are visualized through a simple interface suitable for municipal operators. This work demonstrates the feasibility of deploying AI-based fallen tree detection in real operational environments.

6. Heinaro et al. – LiDAR Data Quality Analysis for Fallen Tree Detection: This study systematically analyzes how LiDAR point density, noise, terrain slope, and algorithm choice affect fallen-tree detection accuracy. The authors show that data quality and environmental conditions strongly influence detection reliability. No single method performs best under all scenarios, highlighting trade-offs between resolution and cost. The paper provides practical guidance for selecting sensing and processing strategies in real deployments.

7. Hu et al. – Spatio-Temporal Vacant Land and Informal Green Spaces: Hu et al. extend vacant-land detection by incorporating temporal satellite imagery to track how parcels evolve over time. The framework distinguishes long-term vacant land from temporary construction gaps and informal green spaces. This temporal perspective helps identify stable sites suitable for long-term greening initiatives. The study emphasizes the importance of time-aware analysis in sustainable urban planning.

8. Li et al. – Vision-Based Planting Site Selection for Unmanned Forestry: Li et al. present a vision-guided planting system for unmanned forestry machines using RGB-D cameras and YOLO-based obstacle detection. Detected obstacles are fused with depth data to identify safe and feasible planting locations. The system is validated in real field conditions and reduces manual decision-making. This work demonstrates how perception outputs can be transformed into actionable planting decisions.

3. PROPOSED METHODOLOGY

The Fallen Tree Detection and Free Urban Space ReLeaf system follows a multi-stage workflow. It starts with citizen reports and map data and ends with decisions about clearing hazards and potential planting locations. First, the application collects inputs from two main sources: street-level images with location details submitted via the web interface and overhead map or satellite tiles that display the surrounding urban area. Uploaded images undergo preprocessing, including resizing, normalization, and basic quality checks. They are then stored with their GPS coordinates in the cloud database. At the same time, map tiles are arranged into a consistent grid for later analysis of available spaces.

The backend performs image-based detection on each report to determine whether a fallen tree is present and to locate it. If the detection is confirmed, the incident is marked as a hazard and shown as a red marker on the city map. Meanwhile, a free-space analysis module reviews nearby parcels and areas on the map, applying rule-based checks, such as setbacks from roads and buildings, minimum width, and existing vegetation. All results are displayed on an integrated dashboard where authorities can monitor incident status, assign field teams, and select suitable ReLeaf locations. Citizens receive clear feedback on the progress of their reports.

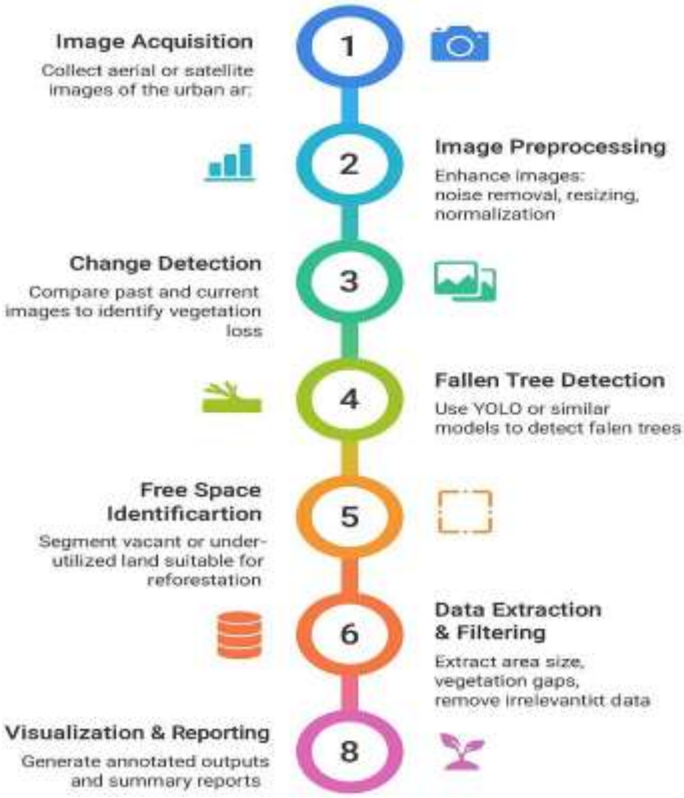

Fig: Overall workflow and model architecture

A. Data Validation Procedure

The system checks every fallen tree report and free space suggestion for completeness and consistency before any detection or mapping occurs.

Objective: To ensure that the uploaded image, location, and basic incident details are clearly defined and logically acceptable. This prevents missing, corrupted, or contradictory records from entering the processing pipeline.

Validation Process:

The system detects and rejects null or missing fields so incomplete reports are not stored as valid incidents.

It verifies data types and formats, for example, the image file type and size, numeric latitude and longitude, and correctly formatted timestamps.

The system performs logical consistency checks. This includes confirming that coordinates fall within the supported city boundary and that the capture time is not in the future.

Mathematical Representation:

Let x denote the input record for a single report (image + metadata + location). Define the validation function

$V(x)=(\{1 \text{ if } x \text{ is complete and consistent}\},\{0 \text{ otherwise}\})$

Only records for which $V(x)=1V(x)=1$ are forwarded to the fallen-tree detection and ReLeaf analysis stages;
if $V(x)=0V(x)=0$, the system prompts the user to correct or resubmit the report.

B. YoloV8 Object Detection Algorithm

YOLOv8 detects fallen trees from street-level images or video frames in a single attempt. The model splits the image into regions and predicts bounding boxes along with class scores for each area. It classifies objects as either "fallen tree" or "standing/background." Detections that exceed a confidence threshold are recorded as confirmed incidents.

Mathematical Representation:

$Y=\{(x_i, y_i, w_i, h_i, p_i^{obj}, p_i^{(c)})\}^N i=1$

Where:

- i = Index of a particular prediction, from 11 to NN, where NN is the total number of predicted boxes.
- x_i= X-coordinate of the centre of the i-th bounding box in the image.
- y_i = Y-coordinate of the centre of the i-th bounding box.
- w_i = Width of the i-th bounding box.
- h_i = Height of the i-th bounding box.
- $P_i^{(obj)}$ = Objectness score for box ii; the model's confidence that *some* object is present inside that box.
- $P_i^{(c)}$ = Class-probability for class c for box ii; given that an object is present, how likely it is to belong to class cc.

C. Convolutional Neural Network Algorithm

Within YOLOv8, a deep CNN backbone performs feature extraction on the input image. Convolution, non-linear activation, and pooling layers learn low-level patterns such as edges and textures, and higher-level structures such as long horizontal trunks and branch clusters.

Mathematical Representation:

$F_k^{(l)} =\sigma(W_k^{(l)} * F^{(l-1)} + b_k^{(l)})$

Where:

- $W_l^{(l)}$= convolution kernel for channel k; at layer l)
- * = Convolution operation
- $B_k^{(l)}$ = bias team
- σ = non-linear activation

4. RESULT AND DISCUSSION

The Fallen Tree Detection and Free Urban Space ReLeaf system integrates automated hazard detection, real-time mapping, and replanting support into a single platform. Users can upload geotagged images and receive fast, accurate confirmation through a YOLO-based model, with incidents instantly reflected on a live city map. Authorities manage and monitor cases efficiently using a dashboard that supports filtering, status updates, and hazard visualization with real-time public visibility. The ReLeaf module further links cleared incidents to nearby free spaces, transforming fallen tree events into planned opportunities for urban replanting and long-term greening.

The image shows the prediction screen of the Fallen Tree Detection application, where a street scene with a collapsed tree is analyzed by the AI model. A blue bounding box labeled "Fallen Tree 0.90" highlights the detected trunk, while a results panel confirms the detection with high confidence. Navigation options and action buttons for image upload, classification, video testing, and map analysis demonstrate the system's interactive and multi-mode detection capabilities.

Fig: Prediction page of fallen tree

The "Classify Map Areas" function focuses on identifying potential planting spaces by analyzing high-resolution satellite images of urban neighborhoods. The system highlights unused plots with blue bounding boxes labeled "Bare_land" and high confidence scores, while a results panel and bar chart summarize the number of detected free spaces. Together with action buttons for image, video, and map analysis, this feature supports data-driven replanting after fallen tree clearance.

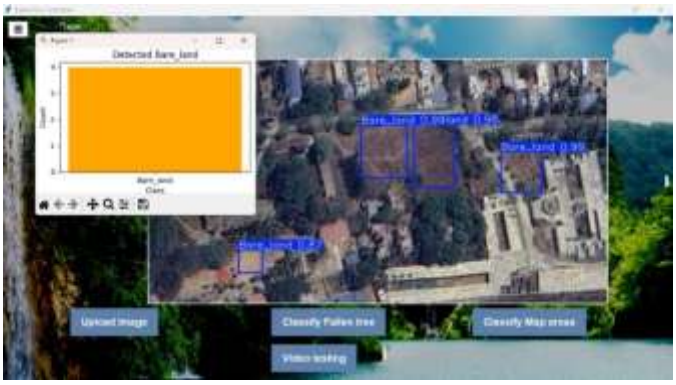

Fig: Identification of free urban space

5. CONCLUSION

The AI-powered tour and recreation planner show how AI can truly change the way people plan and enjoy their trips. Instead of just focusing on providing generic plans, the system creates a personalized travel experience by looking at crucial details such as budget, trip duration, the number of travelers, and what kinds of activities the people are interested in.It can generate day-wise plans, suggest the best time to visit places, and also recommend local events and recreational activities, making it more than just a planner. With map-based route guidance and notifications about events, it feels like a complete travel companion rather than just another app.From a technical viewpoint, the project demonstrates how tools such as Next.js, Firebase, SQL, Clerk, and the Gemini API can be combined in an endeavor to craft a secure, intelligent, and scalable application.

Testing indeed proved that not only does the system make planning easier but also keeps the users more engaged and satisfied by making relevant and practical suggestions. In other words, the project pieces together all the scattered bits of travel planning onto one platform so as to make the road to organizing one's trip smooth, stress-free, and enjoyable.

FUTUIRE WORK

Several improvements can be implemented to further strengthen and expand the system:

- Strengthen the AI models by training them on richer, more varied data so they perform better in difficult conditions.
- Enhance the decision logic by adding more contextual information (like planning and infrastructure data) to make suggestions more trustworthy.
- Extend the system to use extra data sources beyond user photos, building a continuous city-wide view of tree health and hazards.
- Introduce smarter scheduling and prioritisation so authorities get better support during large or complex events.
- Scale and harden the platform through systematic testing of performance, relia- bility, and cost for full city deployments.

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