

## Automated Rapid Post-Disaster Assessment Using Uncrewed Aerial Vehicles

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### INTRODUCTION

Climate change is intensifying natural disasters, such as hurricanes and earthquakes, leading to devastating human and economic losses, which in turn create a growing demand for rapid and accurate post-disaster assessment. Traditional ground-based inspections are time-consuming, resource-heavy, and often delayed due to inaccessible areas.

Recent research highlights the advantages of Uncrewed Aerial Vehicle (UAV) imagery, which provides high-resolution, multi-perspective views that enable more accurate building damage detection [1,2]. Despite these advancements, many methods still rely on pre- and post-disaster data [3], which are not always available. To address this gap, this study proposes a framework for rapid and automated post-disaster assessment of residential houses using only single post-disaster UAV images, with the goal of enabling fast prioritization in emergency response.

### MATERIALS AND METHODS

This study is conducted in two main stages. In the first stage, YOLOv8 segmentation model combined with DeepSort object tracking model are used to automatically detect and identify individual residential houses from UAV-recorded video footage. Reverse geocoding is then applied to map these buildings and extract their precise addresses, which could be crucial for rapid post-disaster response teams.

In the second stage, a feature-based classification approach is implemented to enhance the accuracy of damage detection. Each house image undergoes detailed processing to extract four key features: texture-based features including dissimilarity and homogeneity, as well as edge-based features including entropy and angle distribution. These features are then used to construct four indices, which are then evaluated through a Naïve Bayesian Classifier to estimate the probability of damage for each building.

### RESULTS AND DISCUSSION

The proposed method was tested on a real post-disaster case: the April 2020 hurricane in Chattanooga,

Tennessee, USA. Six residential houses were selected for evaluation, as shown in Fig. 1, and labelled with the letters D (damaged) and U (undamaged). The corresponding damage analysis results are summarized in Table 1. Findings show that when all extracted features are utilized, the method correctly distinguishes between damaged and undamaged houses. In contrast, relying solely on texture features (dissimilarity and homogeneity) or solely on edge features (angle distribution and entropy) leads to misclassification in some cases. This highlights the critical role of combining both texture and edge features to achieve reliable damage detection.



**Fig 1** An image showing post-hurricane damages in Chattanooga, Tennessee, US in April 2020.

### CONCLUSIONS

This study proposes a novel framework for automated rapid post-disaster of damaged buildings, leveraging artificial intelligence and image processing techniques using UAV imagery. The proposed method automatically detects unique house images and extract their addresses, followed by integrating texture-based image features with the edge-based ones to improve the damaged building detection, critical for rapid post-disaster assessments.

### REFERENCES

- [1] Zhang R et al. *Nat Haz Risk* **11**: 1912–1938, 2020.
- [2] Jozi D et al. *Int J Disast Risk Red* **111**: 104707, 2024.
- [3] Deng L and Wang Y *Sci Rep* **12**: 15862, 2022.

**Table 1:** Damage assessment results for selected houses in Fig. 1.

True Category	Damaged				Undamaged	
Building Label	D1	D2	D3	D4	U1	U2
Probability of being damaged using texture features only (%)	100	99.9	99.7	82.8	55.5	51.6
Probability of being damaged using edge features only (%)	83.9	62.2	63.9	14.4	4.2	20.0
Probability of being damaged using all features combined (%)	100	100	99.9	59.8	9.0	32.9