Enhancing Object Geolocations in Imagery to Improve Disaster Damage Mapping and Assessment

Jooho Kim[1], Sayok Bose[2], Sarah Brasseaux[2] , and Junho Kim[3]

[1] Institute for a Disaster Resilient Texas at Texas A&M University
[2] Computer Science at Texas A&M University
[3] Computer Science at Rice University

Introduction

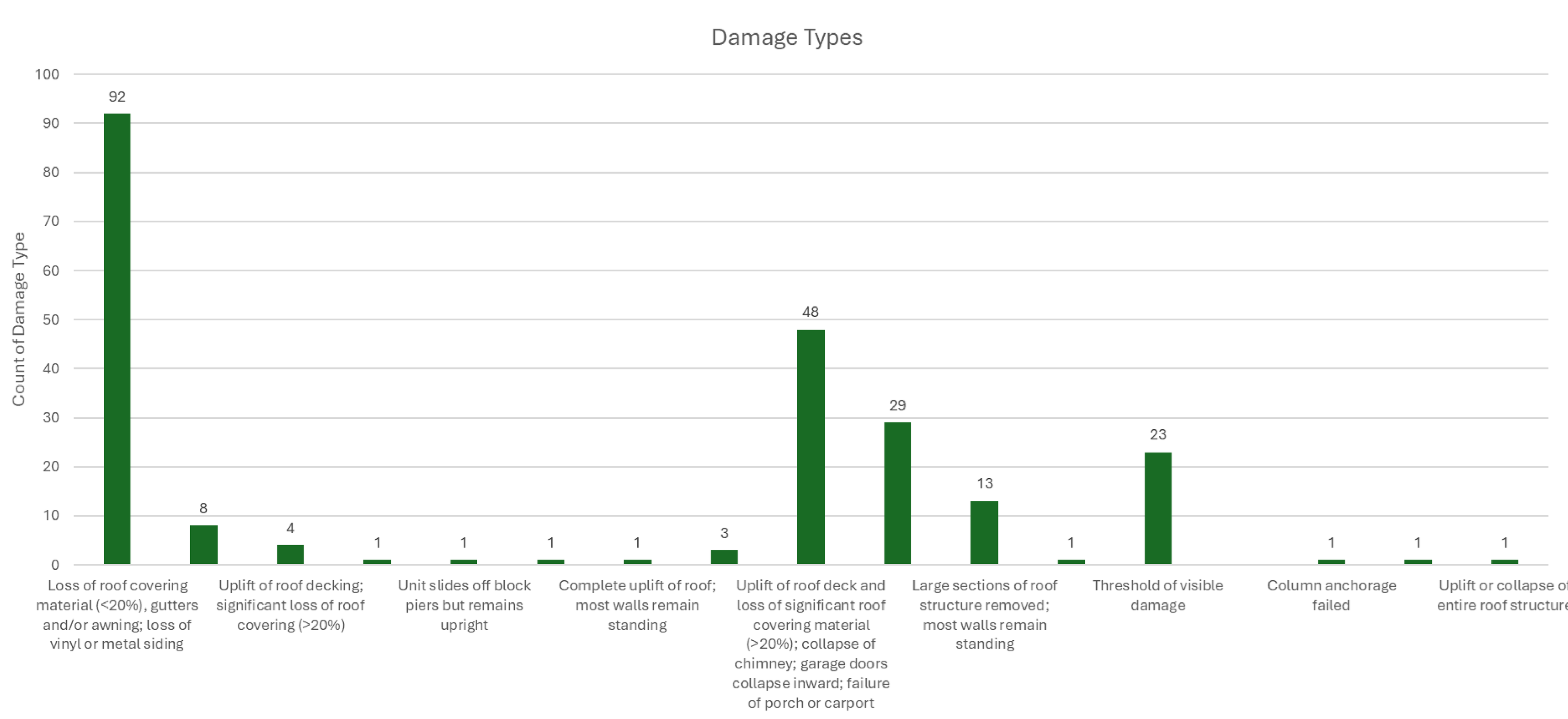
Community-driven and field survey imagery plays a crucial role in assessing disaster impacts by providing data on damage levels, locations, and extent. **This study presents a framework to improve geolocation calibration in such imagery, enhancing the accuracy of disaster impact assessments and geodatabases.** By leveraging similarity models for image retrieval and applying the haversine formula to refine search radii based on coordinates, our approach addresses geocoding limitations and enables more precise damage mapping across diverse disaster events.

For this case study, we analyzed data from the 2023 tornado in Norman, Oklahoma, using the **NOAA database**[1] to evaluate our framework. We compared the NOAA dataset with Google Street View images to align coordinates for each image. **Our framework utilized open-source models, including CLIP[2] and DreamSim[3], to compute similarity metrics.** These models were applied to both original images with background context and cropped images focusing on buildings. Attention maps further highlighted the models' focal points, enriching the analysis.

By addressing data uncertainty to improve geolocation accuracy, our framework offers a novel approach to improve disaster related geodatabase This can help communities generate detailed and reliable damage maps, enabling more precise interventions and optimizing resource allocation for disaster response and recovery through advanced AI tools.

Data Description

Data sources: Data Sources: NOAA Damage Assessment Toolkit (2023 Norman, OK tornado) and Google Street View (GSV).



Sample images from the NOAA dataset

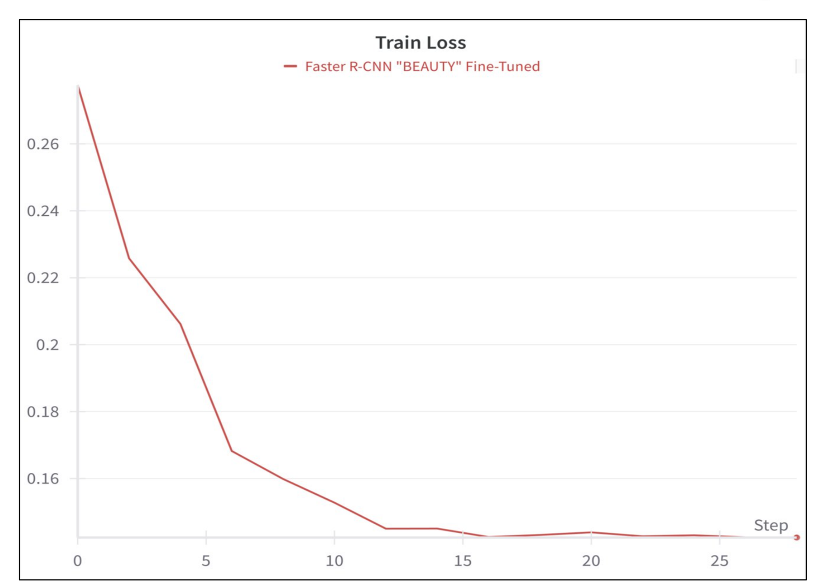
35.1937, -97.3987 | 35.1733, -97.4333 | 35.1936, -97.3988

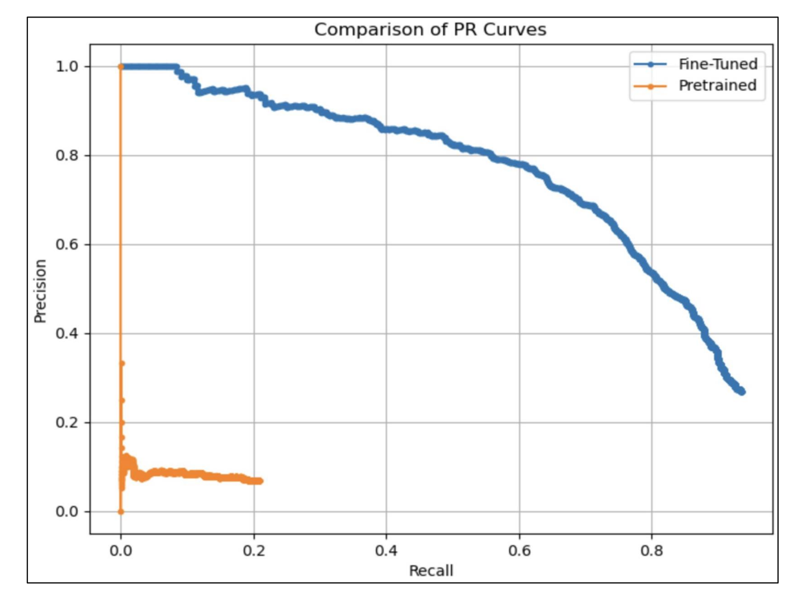
Sample images from the GSV dataset

35.32178, -97.2123 | 35.24687, -97.32171 | 35.212072, -97.392560

Building Detection and Image Cropping

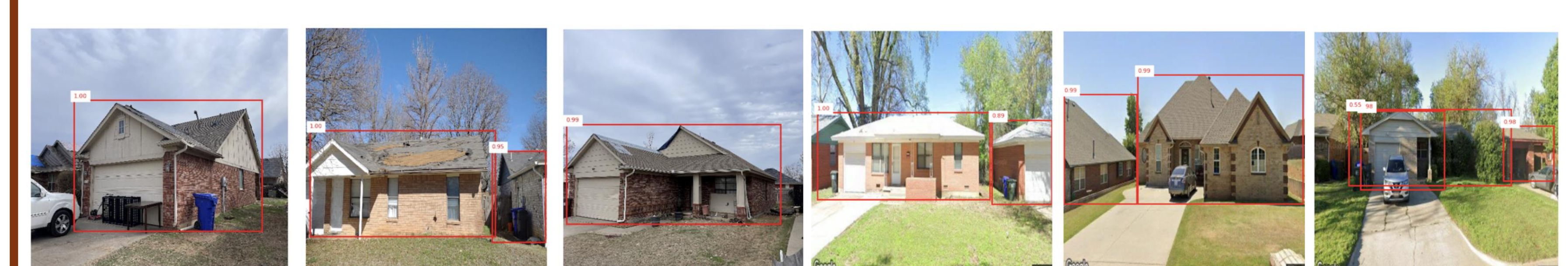
- **Fine-tuned Faster R-CNN with Building Dataset[4]**





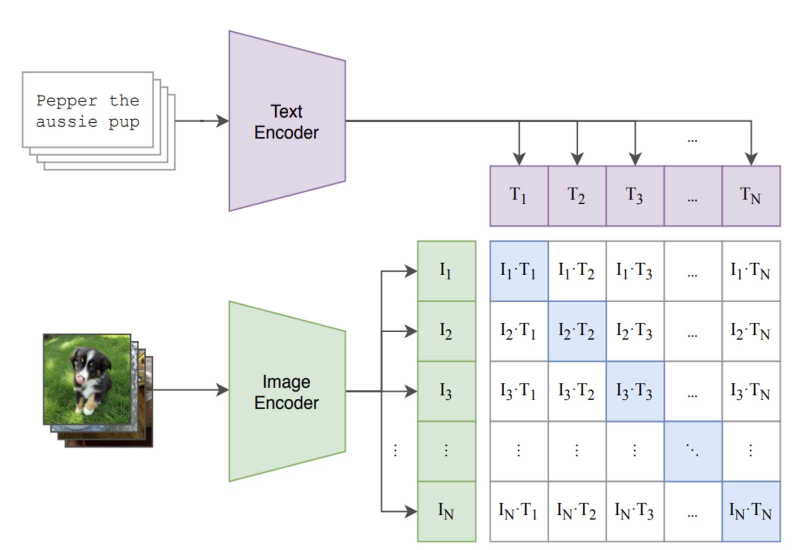
- **Bounding Boxes for Buildings in Unseen Datasets (NOAA, GSV)**

NOAA **GSV**

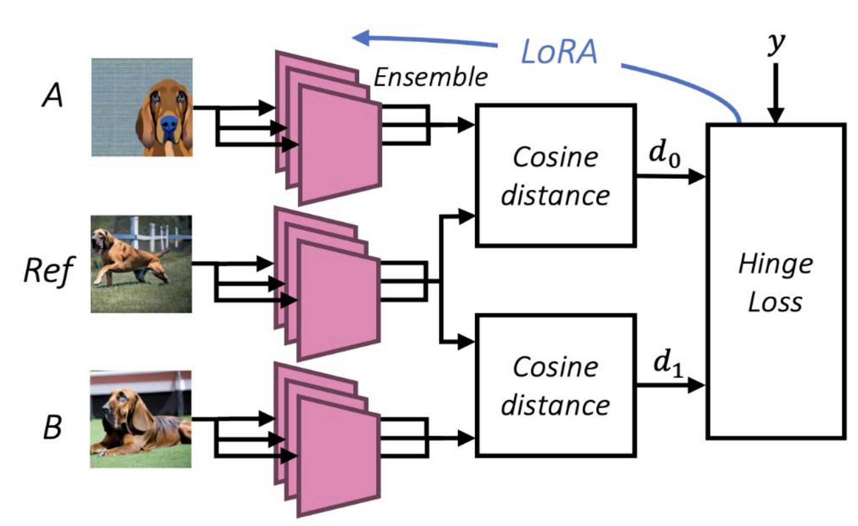


Model as Image Similarity Metric

CLIP



DreamSim



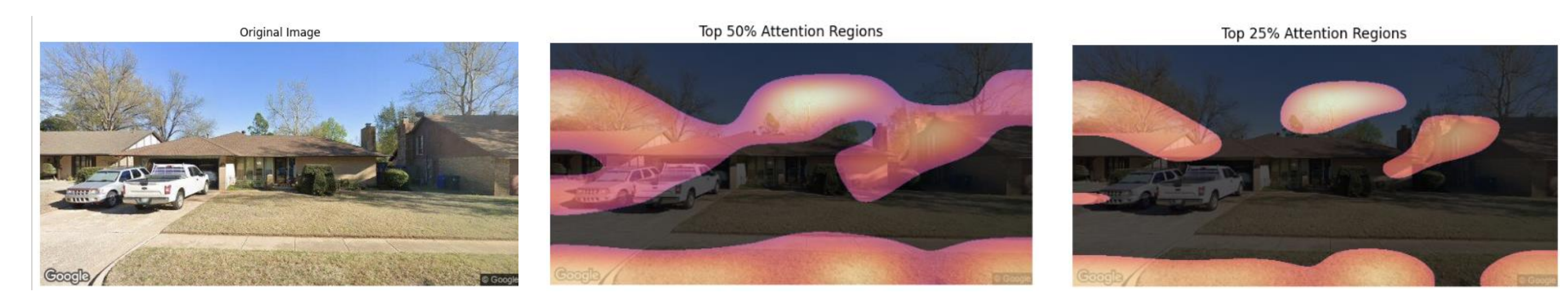
Results

- **CLIP-based Similarity Scores for Original Images**

- **CLIP-based Similarity Scores for Cropped Building Images**

- **DreamSim-based Similarity Scores for Cropped Building Images**

- **Attention Maps for CLIP**



Limitations and Future Work

Ground Truth Dataset: We lack a ground truth dataset to validate image correspondences between NOAA (query) and GSV (target) datasets but plan to create one for the selected 81 NOAA images.

Deep Model Analysis: While CLIP and DreamSim provide similarity rankings and attention maps, further analysis is needed to identify patterns, improve interpretability, and address biases.

Generalizability: Our framework is limited by geographic scope, damage levels, and background artifacts. Future studies should extend its application to diverse regions and more severely damaged structures.

References

[1] National Oceanic and Atmospheric Administration. NOAA Damage Assessment Toolkit. https://apps.dat.noaa.gov/stormdamage/damageviewer/

[2] Radford, Alec, et al. "Learning transferable visual models from natural language supervision." International conference on machine learning. PMLR, 2021.

[3] Fu, Stephanie, et al. "Dreamsim: Learning new dimensions of human visual similarity using synthetic data." arXiv preprint arXiv:2306.09344 (2023).

[4] Zhao, Kun, et al. "Bounding boxes are all we need: street view image classification via context encoding of detected buildings." IEEE Transactions on Geoscience and Remote Sensing 60 (2021): 1-17.