



RescueNet: Joint Building Segmentation and Damage Assessment from Satellite Imagery

Rohit Gupta and Mubarak Shah Center for Research in Computer Vision University of Central Florida





- Aiding Humanitarian Aid and Disaster Response (HADR) operations
- Existing baseline approaches use 2 stage detect and compare/classify approach
 - Not end-to-end trainable
 - Achieve poor results





- Joseph Xu et al. *Building Damage Detection in Satellite Imagery Using Convolutional Neural Networks*. AI + HADR Workshop 2019
 - First Stage: Faster RCNN for building detection
 - Second Stage: Multi-Input Image Classifier (Pre/Post-Disaster Image)
- Ritwik Gupta et al. Creating xBD: A Dataset for Assessing Building Damage from Satellite Imagery. WACV 2020.
- Ritwik Gupta et al. xBD: A Dataset for Assessing Building Damage from Satellite Imagery. Arxiv
 - First Stage: U-Net based building localization
 - Second Stage: Custom ResNet-50 Image Classifier.





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Our Method

- Unified end-to-end model
 - Building Segmentation
 - Change Detection
- Novel Localization Aware loss function





(a) RescueNet ASPP Dropout BatchNorm Upscaling 1x1 Conv ReLU 3x3 Conv, Dilation = 12 Pre-Disaster Image Pre-Disaster Binary 3x3 Conv, Dilation = 24 Building Dilated Multi-Scale Cross-Segmentation Head ResNet50 Features Entropy + Detection Dice Loss Post-Disaster Image Post-Disaster Selective 3x3 Conv, Dilation = 36Damage Cross-Classification Entropy Selective Change Feature · Cross-Differences Classification Entropy Change Detection Head ----(c) Encoder-Decoder Segmentation Head (b) Simple Segmentation Head









Localization Aware Loss

- Only applies classification loss gradients to foreground locations
- Localization loss applies to all locations

$$L(y_i, \hat{y_i}) = \begin{cases} -log(\hat{y_{il}}) + \sum_{k \in C} -log(\hat{y_{ik}}) & \text{if } y_{il} = 1\\ -log(1 - \hat{y_{il}}) & \text{if } y_{il} = 0 \end{cases}$$



UCF Experiments

- xBD dataset
- Pre- and Post- Disaster Images
- ~9,000 image pairs
- Multiple disaster types: Earthquake, Hurricane, Volcanoes etc
- Multiple Locations across the world





Qualitative Results







Quantitative results

- xView Metric
- Combines Building Localization and Damage Classification F1-Scores

$$Score = 0.3 * F1_{loc} + 0.7 * \frac{n}{\frac{1}{F1_{cls1}} + \dots + \frac{1}{F1_{clsn}}}$$

Model	Localization Score	Damage Score	Overall Score
Ours	0.84	0.74	0.77
Baseline [1]	0.79	0.03	0.26





Class wise F1 Scores

Damage class	Baseline (Our Split)	RescueNet (Ours)
undamaged	0.7211	0.8832
minor	0.0235	0.5628
major	0.0105	0.7711
destroyed	0.4262	0.8079
Harmonic Mean	0.0282	0.7348





Generalization Results

• Disasters are split in 2 groups: Tier 1 & Tier 3 (Following *Gupta et al.*)

GENERALIZATION ACROSS REGIONS AND DISASTER TYPES

		Score		
Train Set	Test Set	Localization	Damage	Overall
Tier1 Train	Tier1 Valid.	0.79	0.60	0.66
Tier1 Train	Tier3	0.77	0.37	0.50



UCF Ablation Study

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Loss Function	Score			
Cross-Entropy Loss	0.69			
Localization Aware Loss	0.75			
Localization Aware Loss + Dice Loss	0.77			
Segmentation Head Architecture				
Simple (Convolution+Upscaling)	0.74			
Encoder-Decoder	0.77			
Change Detection Head				
Without change detection head	0.76			
With change detection head	0.77			

Thank you !