Big Visual Data Analytics for Damage Classification in Civil Engineering

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Aftershock of Nepal Earthquake

http://theconversation.com/nepal-earthquake-such-huge-aftershocks-are-rare-41833

Post-Disaster Damage Evaluation by Incorporating Big Visual Data

Big collection of images

Image collection platform

Robotic platform

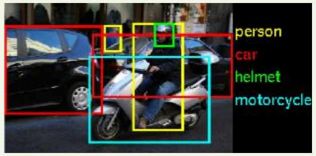
Smart device

Social media

Crowd sourcing

Processing & Analysis

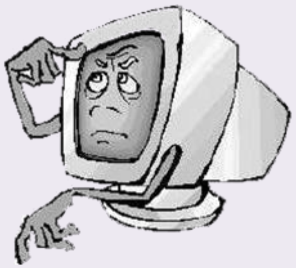
Computer vision



Object detection

Image classification

Autonomous decision making



Damage? Undamage?

Unsafe? Safe?

Damage classification

Buckling

Spalling

Collapse

Overview of the Research

Objective

Develop a **post-disaster evaluation method** through autonomous **big** visual data analysis that will support decision-making regarding safety of civil structures.

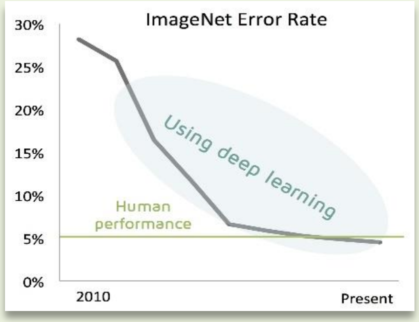
Approach

Implement and develop computer vision methods capable of detection, classification, and evaluation of big visual data using recent **deep convolutional neural network** algorithms.

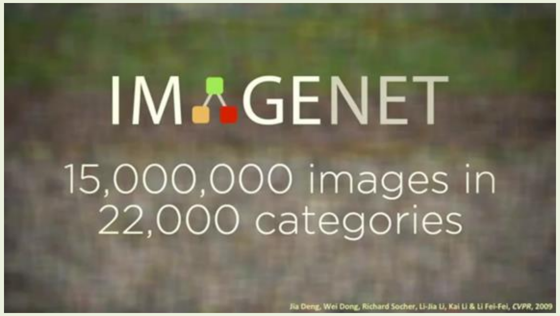
Outcome

Demonstrate and validate the methods using **large-scale real-world** images collected from past events.

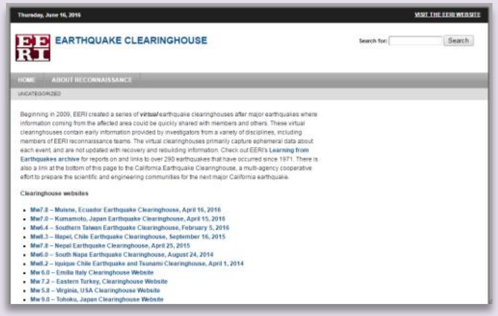
Several Great Opportunities for the Research



Convolutional neural network

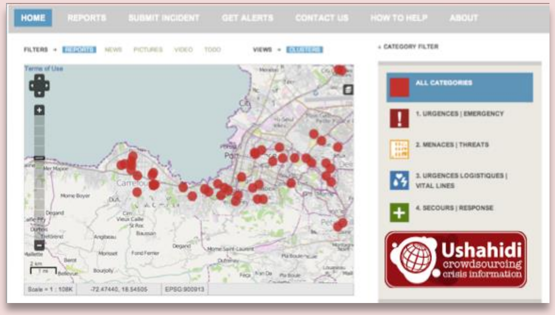


Large-scale image annotation (imageNET)



Earthquake data clearing (EERI)

Vast number of earthquake reconnaissance reports



Crisis map (Haiti earthquake in 2011)

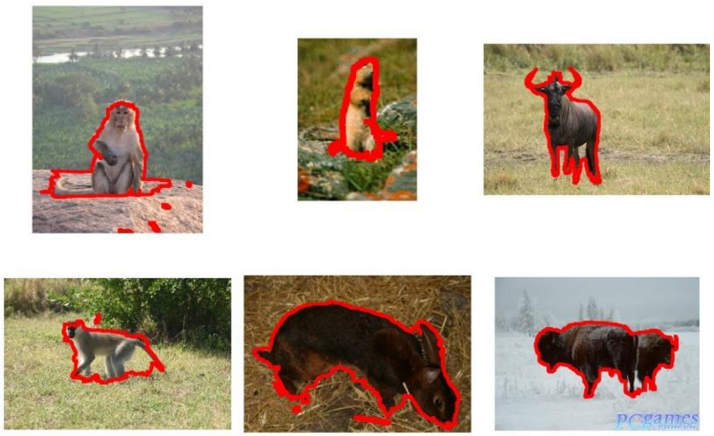
Drone mapper (Nepal earthquake in 2015)

Deep learning for computer vision

Available existing data

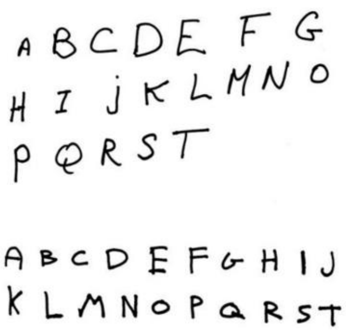
Advanced data collection platform

Deep Convolutional Neural Network



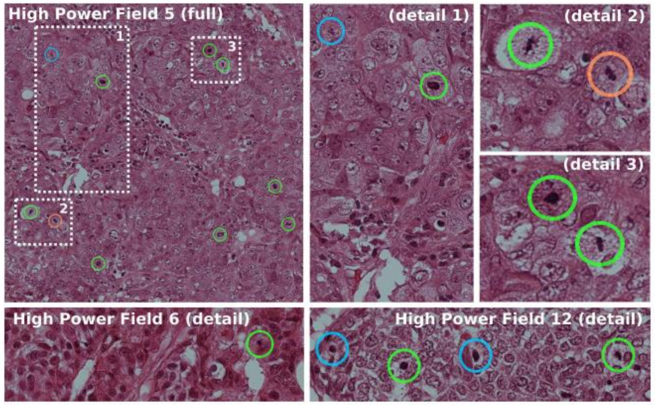
Object segmentation

Drone navigation



character recognition

Self-driving



Mitosis detection

Our Post-disaster Image Database

Number of images: **66,974** (documented) + more than 20,000 (still documenting)

Event (disaster): Turkey earthquake (1999), Peru earthquake (2007), Haiti earthquake (2010), Nepal earthquake (2015), Taiwan earthquake (2016), Hurrican at Florida, USA (2004), Tornado at Greensburg, USA (2007), L'Aquila earthquake in Italy (2009), Chile earthquake (2010) etc.

Source: CrEED at Purdue University (USA), EUCentre (Italy), Instituto de Ingenieria UNAM (Mexico), NIST (USA), FEMA (USA), individual contributors.

Copyright: Public (82.0 %) and Unknown (18.0%).

Sample Data in Our Database

Haiti earthquake in 2010 (3,439 images)

L'Aquila (Italy) earthquake in 2009 (414 images)

Florida hurricanes in 2004 (1,178 images)

Nepal earthquake in 2015 (10,490 images)

Taiwan earthquake in 2016 (First-person view video data)

Implementation of Damage Classification : Collapse and Spalling Detection

Collapse

Instance of a structure falling down or in.

Spalling

Break off in fragments

Ground Truth Annotation of Collapse and Spalling

Collapse

Image showing that the buildings or building components

- lost their original shapes
- produce a large amount of debris
- are not serviceable or accessible

Spalling

Image including

- exposed masonry areas in a wall due to cracking followed by flaking
- exposed rebar in a columns
- small section lose due to large cracking in a concrete wall

Deep Convolutional Neural Network

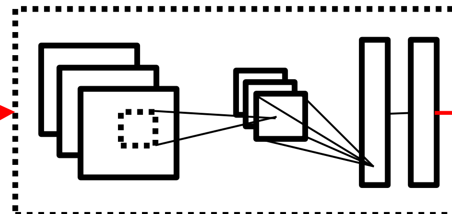
Big images data → **Training parameters** → Ground truth (labels)

60 million parameters

Collapse Classification

Input image

Data augmentation



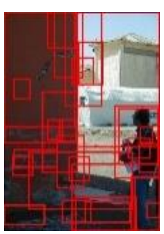
Computer CNN features

Collapse ? Yes or No

Classification

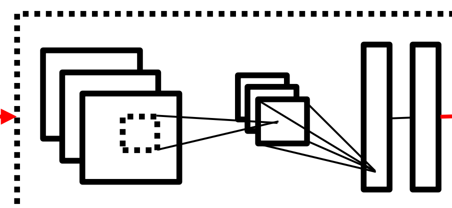
Spalling detection

Input image



Extract object proposals

Data augmentation



Computer CNN features

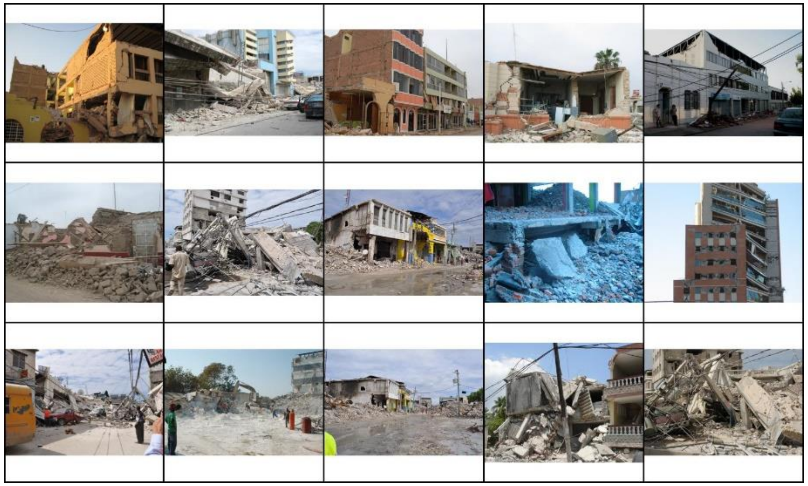
Spalling ? Yes or No

Classification

Annotation of Collapse and Spalling

Image annotation among ~67,000

Spalling area annotation: 1,086 images



Collapse image annotation: 1,918 images

Non-collapse images: 3,427 images

Configuration of Training and Testing

CNN architecture	**: Alexnet for binary classification**
CNN framework (library)	**: MatCovnet (CNN for Matlab)**
# of images with/without collapsing damage	**: 1,850/ 3,420 images**
# of images with spalling damage	**: 1086 images (21,932/1,617,713 windows)**
Batch division for spalling detection	**: 0.3/0.7 (positive/negative)**
Ratio of training, validation and testing	**: 0.5, 0.25, and 0.25**
# of images in a batch size	**: 512**
Training time (spalling detection)	**: 6 hours/epoch (20 epoch) using 1 gpu**
Training time (collapsing detection)	**: 0.1 hour/epoch (300 epoch) using 1 gpu**

Evaluation Metrics

		Predicted Value	
		Positive (P')	Negative (N')
Actual Value	Positive (P)	True Positive (TP)	False Negative (FN)
	Negative (N)	False Positive (FP)	True Negative (TN)

- True positive (TP) = correctly identified (e.g. Collapse correctly identified as collapse)
- False positive (FP) = incorrectly identified (e.g. Non-collapse incorrectly identified as collapse)
- True negative (TN) = correctly rejected (e.g. Non-collapse incorrectly identified as non-collapse)
- False negative (FN) = incorrectly rejected (e.g. Collapse correctly identified as non-collapse)

Positive predictive value (= precision)

$$PPV = TP/(TP + FP)$$

True positive rate (= recall)

$$TPR = TP/P = TP/(TP + FN)$$

Accuracy

$$ACC = (TP + TN)/(TP + FP + FN + TN)$$

Result: Collapse Classification

Result: Collapse Classification (Continue)

392 (TP)	70 (FN)
56 (FP)	799 (TN)

Precision : 0.848
Recall : 0.875
Accuracy : 0.936

Example: Collapsing Building Classification using Web Images

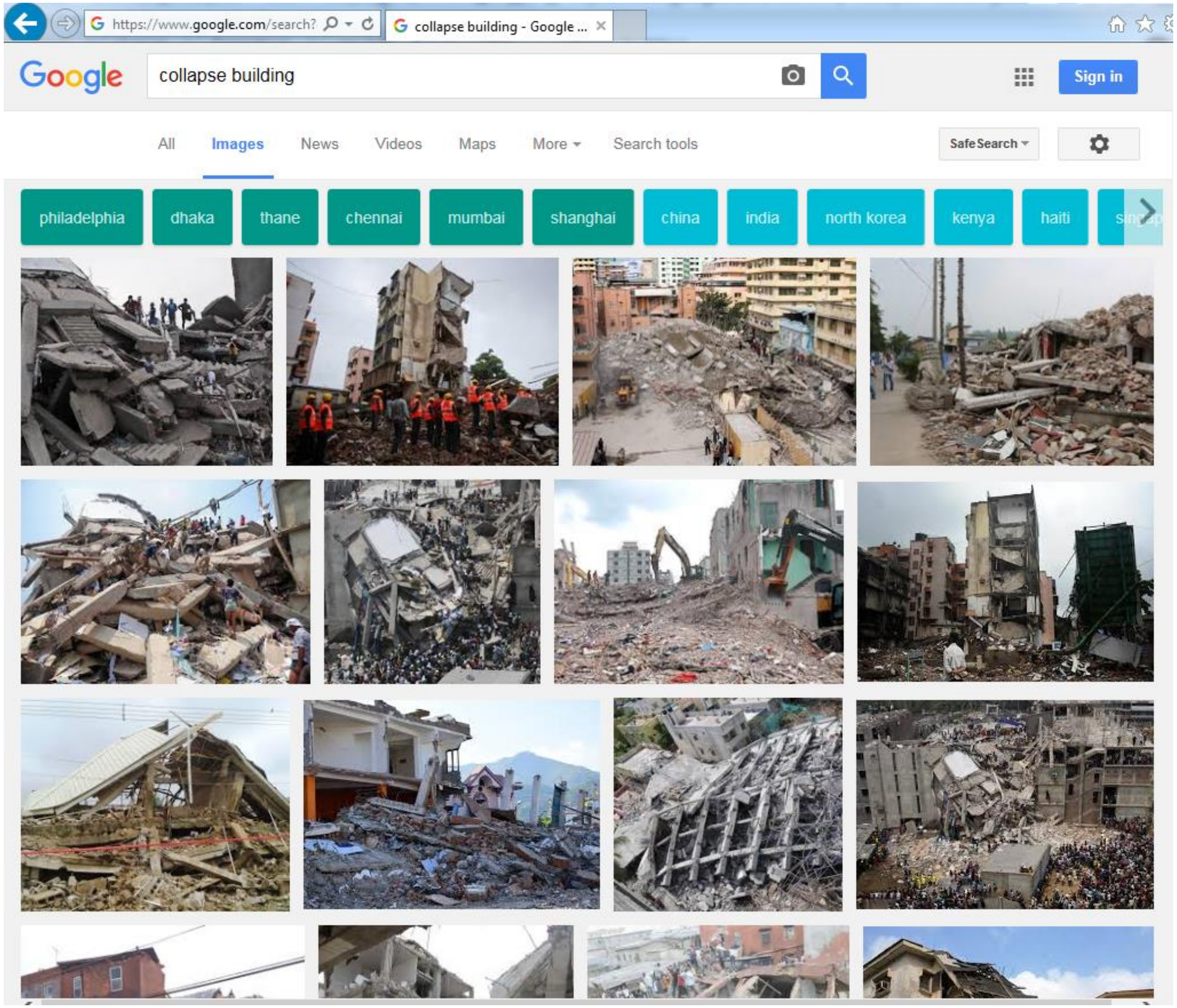
Keywords

Collapse building
Collapse buildings
Collapsing building
Collapsing buildings
Collapsed building
Collapsed buildings

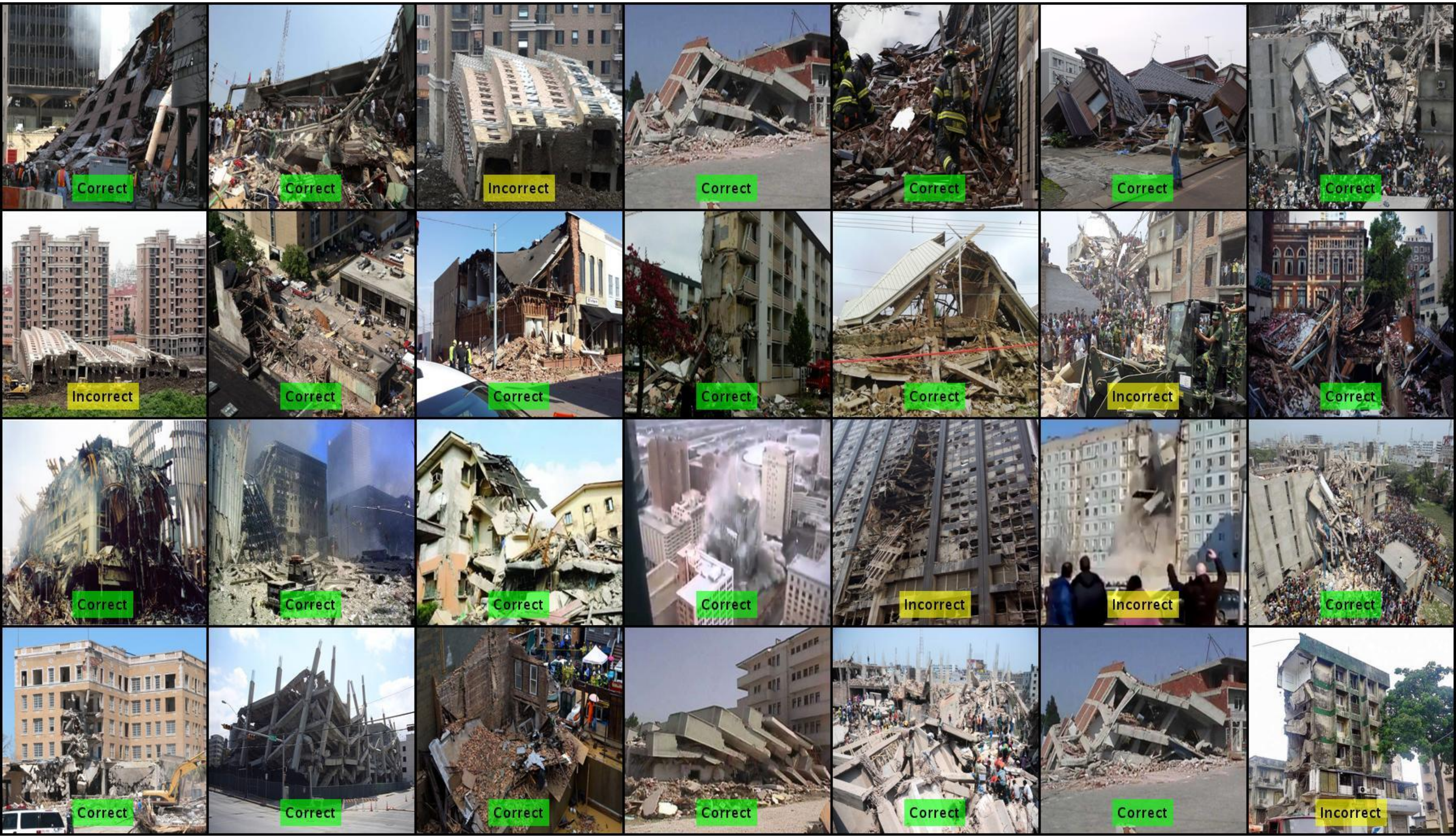
(64 downloadable limits)

Correct detection: 249 images among 315 image

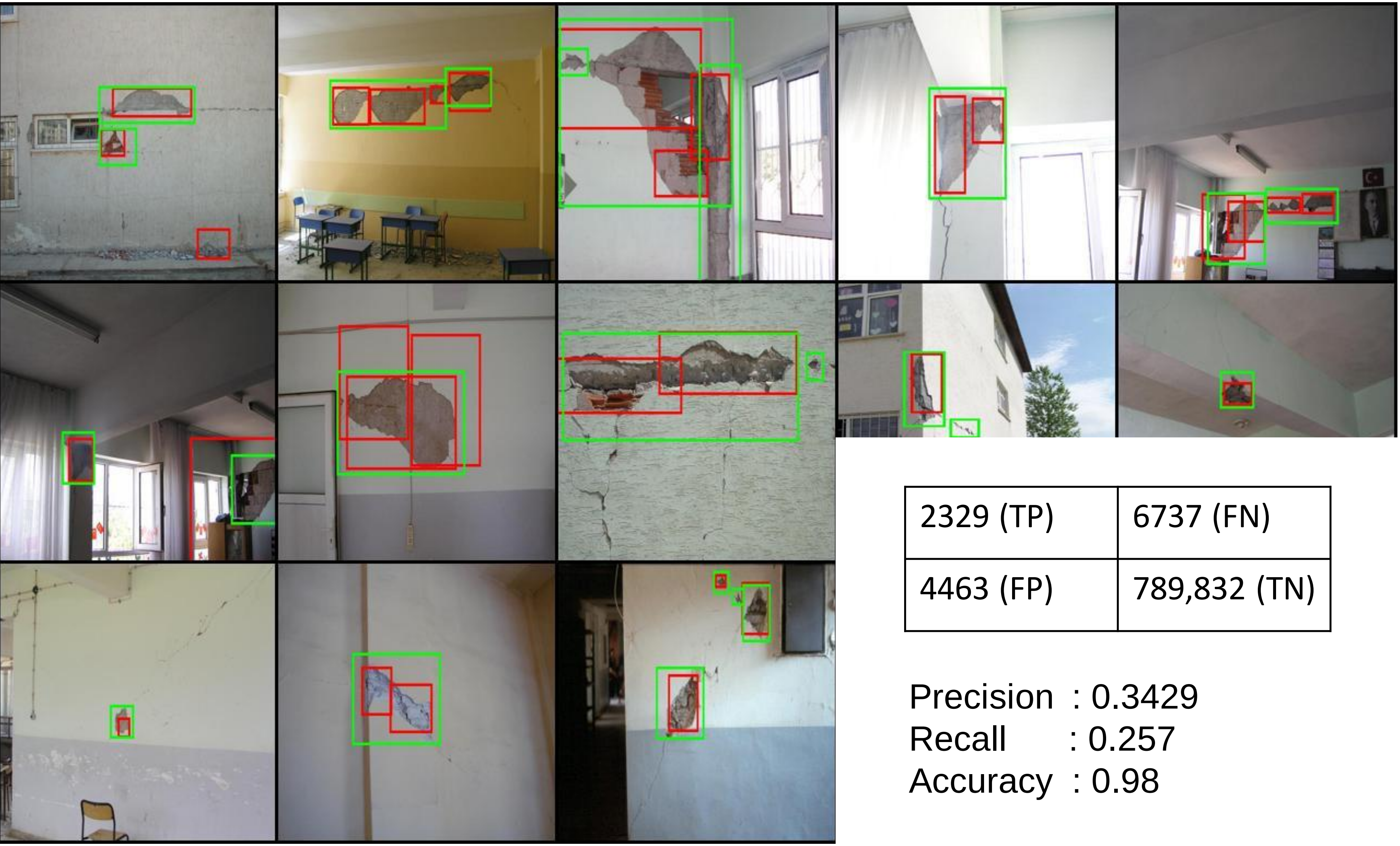
Recall: 79%



Example: Collapsing Building Classification using Web Images



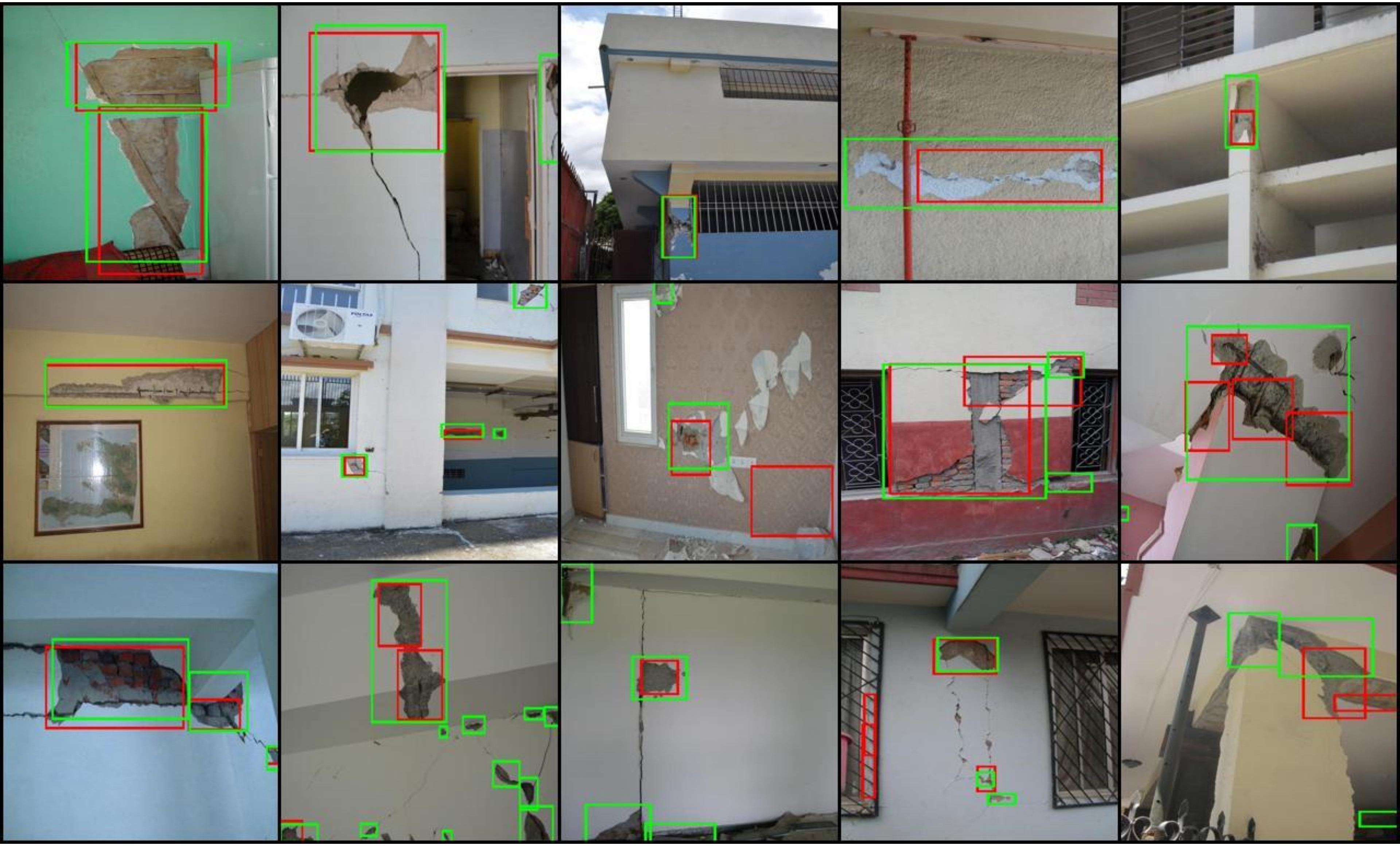
Result: Spalling Detection on the Images having Spalling



2329 (TP)	6737 (FN)
4463 (FP)	789,832 (TN)

Precision : 0.3429
Recall : 0.257
Accuracy : 0.98

Result: Spalling Detection on the Images having Spalling (Continue)



Conclusion

- Automated post-disaster image classification is developed by processing and analyzing big visual data.

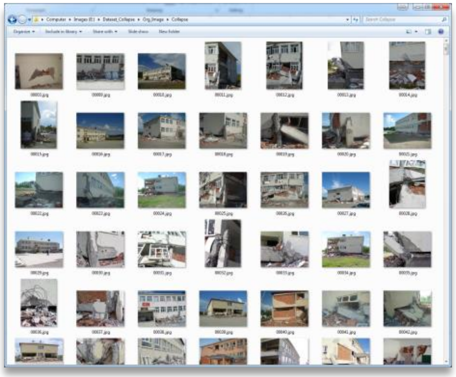
- The method is demonstrated on a specific example classification focused on collapse classification and spalling detection.

- However, the general method can be applied to other civil applications that use large-scale visual data. In the future we plan to incorporate and validate a broader array of damage evaluation methods for broader application.

Acknowledgement

- CDS&E (NSF) ???
- CREED (Center for Earthquake Engineering and Disaster Data) at Purdue
- EERI and CEISMIC
- EUCentre (Pavia, Italy),
- Instituto de Ingenieria, UNAM (Mexico)
- FEMA, USA

FIND CONTRIBUTOERS: WE ARE COLLECTING YOUR VALUABLE IMAGES



Ontology: Annotation of Earthquake Reconnaissance Images

Motivation

No image annotation structure (scheme) for disaster research and evaluation

Objective

Design domain-oriented visual data annotation structures to extract informative visual contents needed for evaluating damage (conducting domain-applications)

Contribution

Establish large-scale image annotation database

Spalling on a captive column