

Big Visual Data Analytics for Damage Classification in Civil Engineering

Chul Min Yeum¹, Shirley J. Dyke^{2,1}, Julio Ramirez¹, and Bedrich Benes³

¹Lyles School of Civil Engineering, Purdue University, United States

²School of Mechanical Engineering, Purdue University, United States

³School of Computer Graphics Technology, Purdue University, United States



Aftershock of Nepal Earthquake



**218 dead
3500+ injured**

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

Post-Disaster Damage Evaluation by Incorporating Big Visual Data

Big collection of images



Processing & Analysis



Image collection platform



Robotic platform

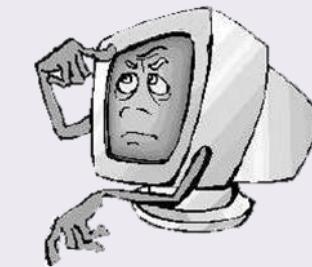
Smart device



Social media

Crowd sourcing

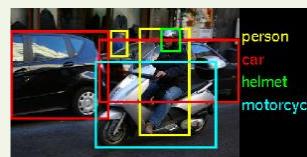
Autonomous decision making



Damage?
Unsafe?

Undamage?
Safe?

Computer vision



Object detection



Image 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.

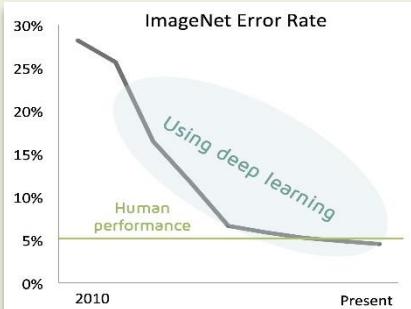
Approach

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)

Deep learning for
computer vision

HOME | ABOUT RECONNAISSANCE | UNCLASSIFIED

Beginning in 2000, EERI created a series of virtual earthquake clearinghouses after major earthquakes where information coming from the affected area could be quickly shared with members and others. These virtual clearinghouses were developed to facilitate the sharing of information between the field and the reporting members of EERI reconnaissance teams. The virtual clearinghouses primarily capture ephemeral data about each event, and are not updated with recovery and rebuilding information. Check out EERI's Learning Tools Earthquake Reconnaissance for more information on how to use these clearinghouses effectively. There is also a link at the bottom of this page to the California Earthquake Clearinghouse, a multi-agency cooperative effort to prepare the scientific and engineering communities for the next major California earthquake.

Clearinghouse website

- [Mei 8 – Mexico, Escalante Earthquake Clearinghouse, April 16, 2014](#)
- [Mei 8 – Northern Taiwan Earthquake Clearinghouse, April 11, 2015](#)
- [Mei 4 – Southern Taiwan Earthquake Clearinghouse, February 5, 2016](#)
- [Mei 3 – Japan, Chile Earthquake Clearinghouse, September 16, 2015](#)
- [Mei 2 – Chile Earthquake Clearinghouse, April 22, 2014](#)
- [Mei 0 – Chile Earthquake Clearinghouse, August 24, 2014](#)
- [Mei 2 – Japan, Chile Earthquake and Tsunami Clearinghouse, April 1, 2014](#)
- [Mei 2 – Chile Earthquake Clearinghouse](#)
- [Mei 7.2 – Eastern Turkey, Clearinghouse Website](#)
- [Mei 7.2 – Virginia, USA Clearinghouse Website](#)
- [Mei 8.0 – Chile, Japan, Clearinghouse Website](#)

Earthquake data clearing (EERI)

2016 MEINONG, TAIWAN EARTHQUAKE

Event Date: 02-06-2016
Location: Taiwan
Report Date: 03-14-2016
Event Category: Earthquake
Sequence of Events: No
EQ Magnitude: 6.3
Report Number: GEER-046
Event Latitude: 22.93
Event Longitude: 120.54
Team: Joseph Sun, Tara Hutchinson, Kevin Chaten, Ramiyah Menq
Collaborators: NOUS, NORE, Sintech
Sponsors: NOUS, NORE, Sintech
Summary: The mainshock registered a magnitude of 6.3 (Mw 6.4) with a focal depth of 6.7 km (10.4 km). The Weather Bureau (CWB) and 23 km by USGS. The focal mechanism to the main event was characterized as strike-slip with an oblique thrust component.

Vast number of earthquake
reconnaissance reports

HOME | REPORTS | SUBMIT INCIDENT | GET ALERTS | CONTACT US | HOW TO HELP | ABOUT

FILTERS: SEARCH | NEWS | PICTURES | VIDEO | TODO | VIEWS: EARTHQUAKE

Ushahidi crowdsourcing crisis information

Crisis map (Haiti earthquake in 2011)



Drone mapper (Nepal
earthquake in 2015)

Advanced data collection
platform

Deep Convolutional Neural Network



Object segmentation



Drone navigation

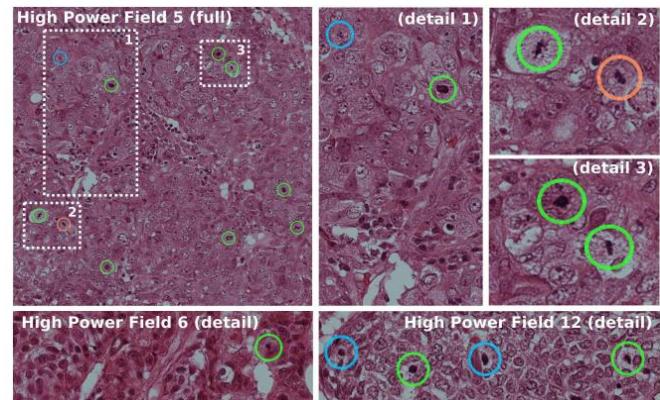
A B C D E F G
H I j K L M N O
P Q R S T

A B C D E F G H I J
K L M N O P Q R S T

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), Hurricane 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

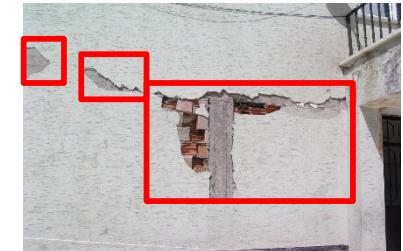


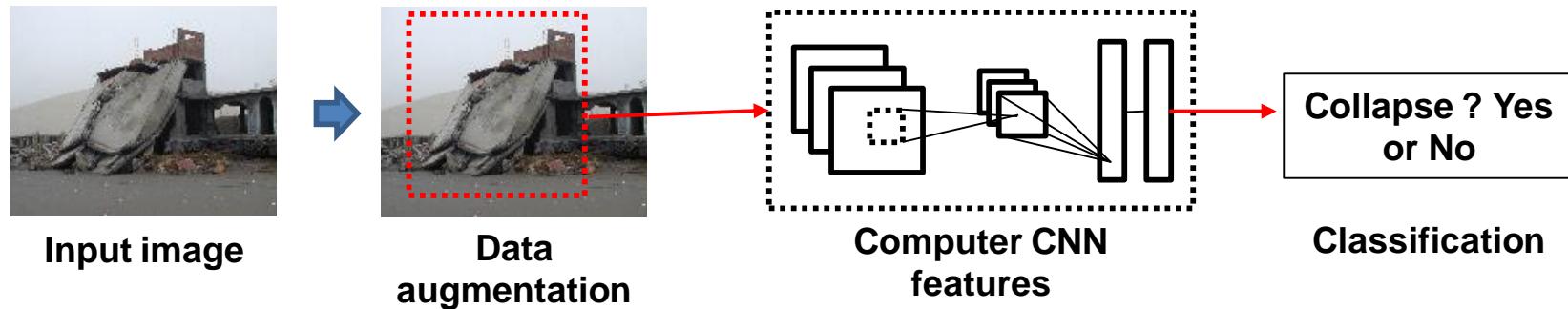
Image including

- 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

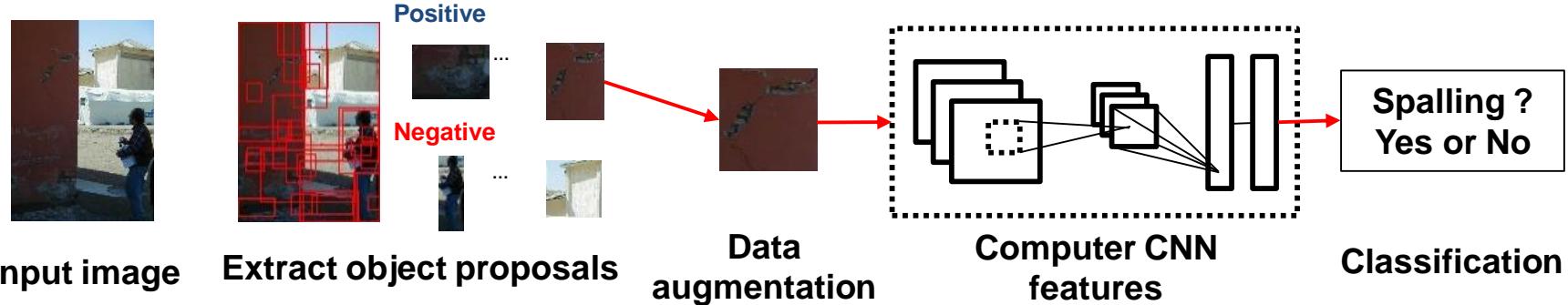
Deep Convolutional Neural Network



Collapse Classification



Spalling detection



Annotation of Collapse and Spalling



Image annotation among ~67,000



Collapse image annotation: 1,918 images



Spalling area annotation: 1,086 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)



Example: Collapsing Building Classification using Web Images

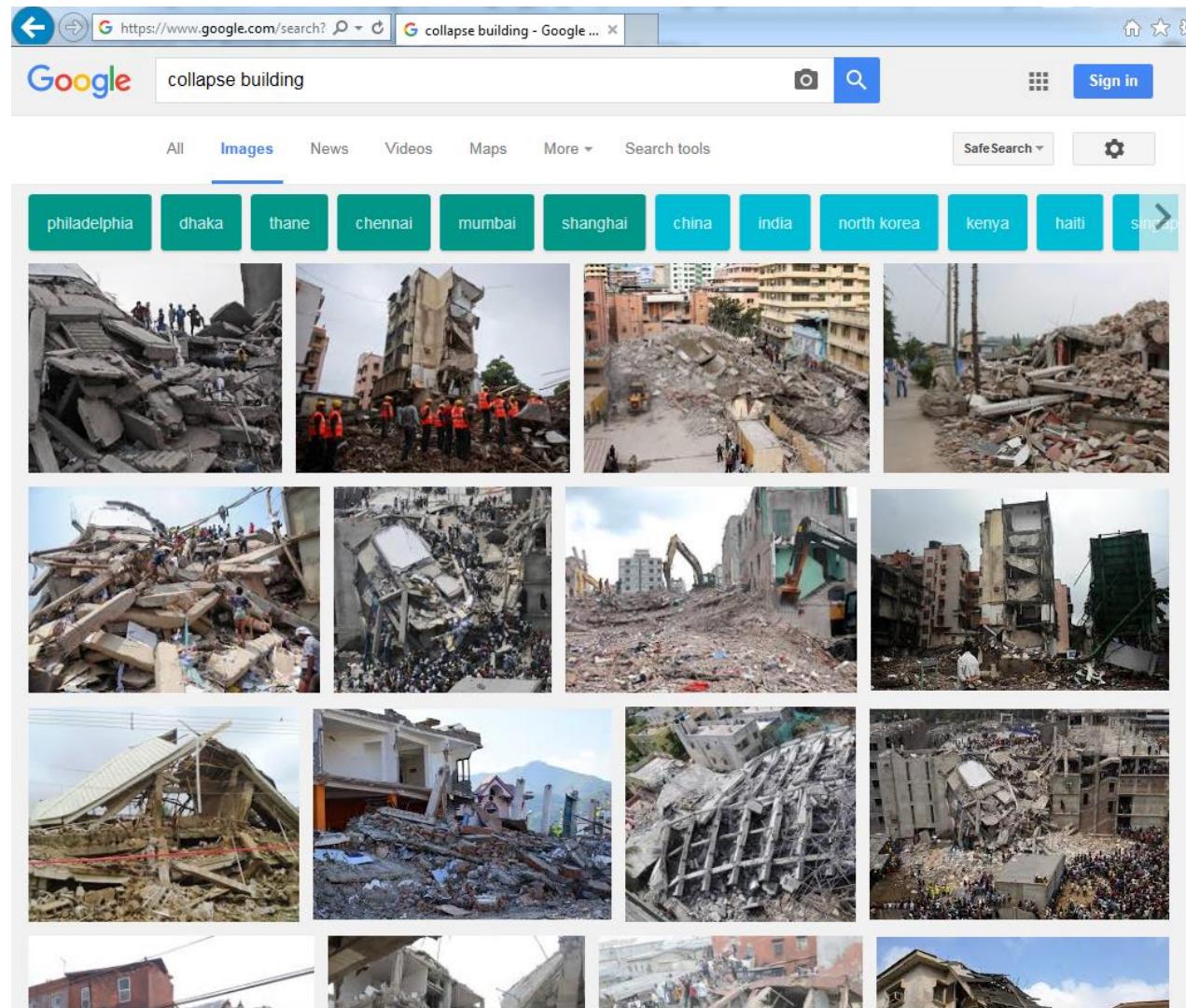
Keywords

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

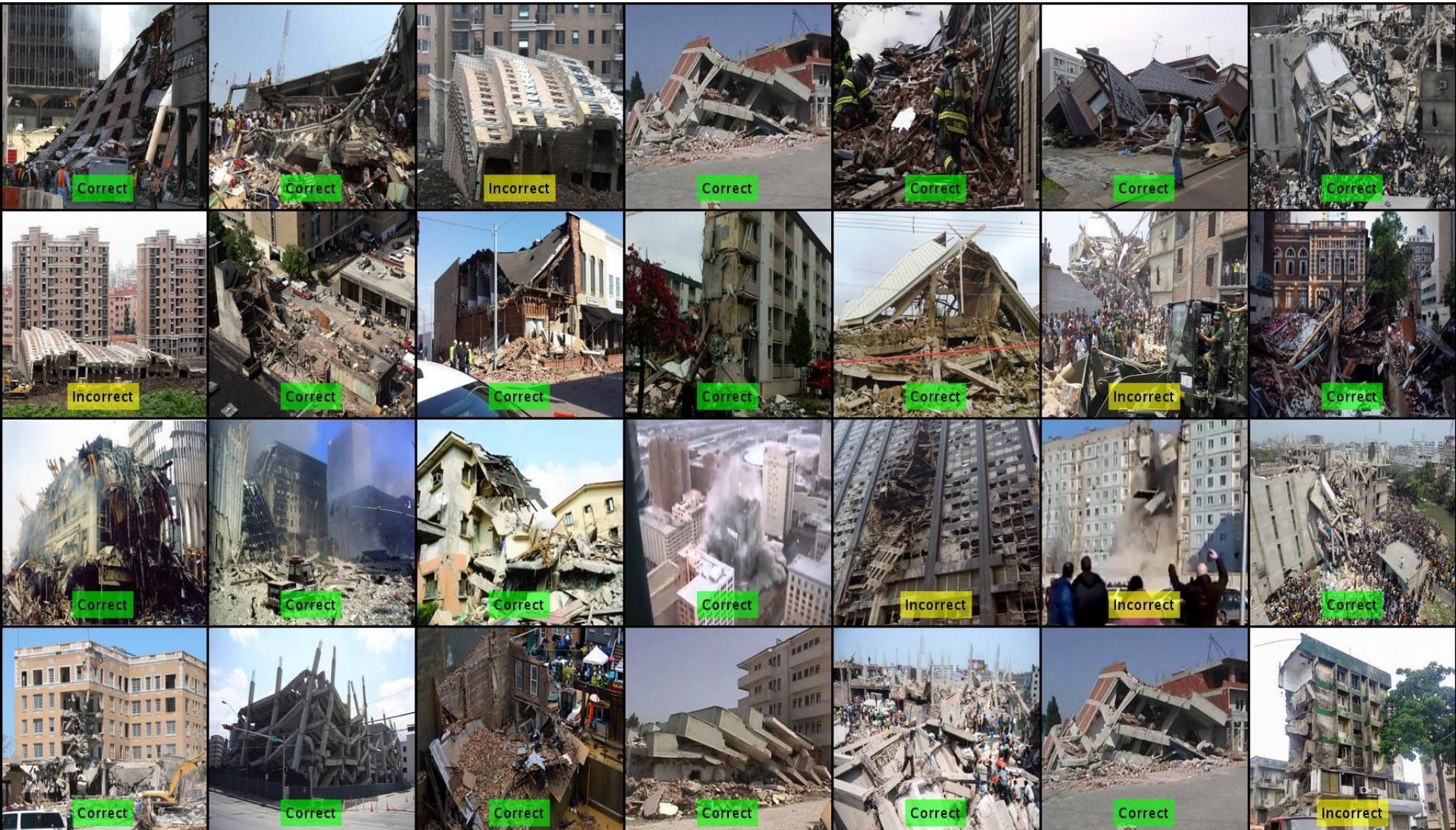
(64 downloadable limits)

**Correct detection: 249
images among 315 image**

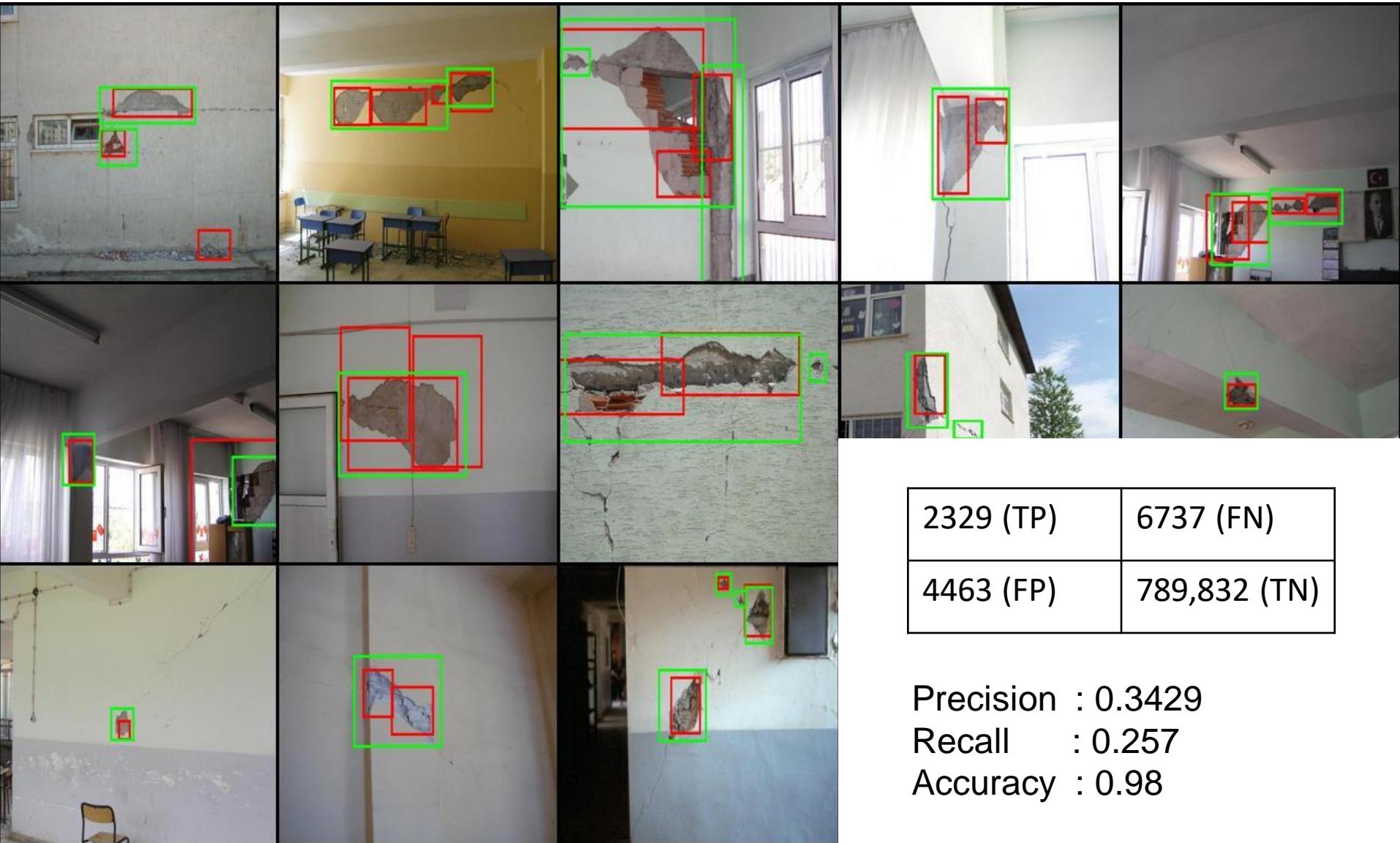
Recall: 79%



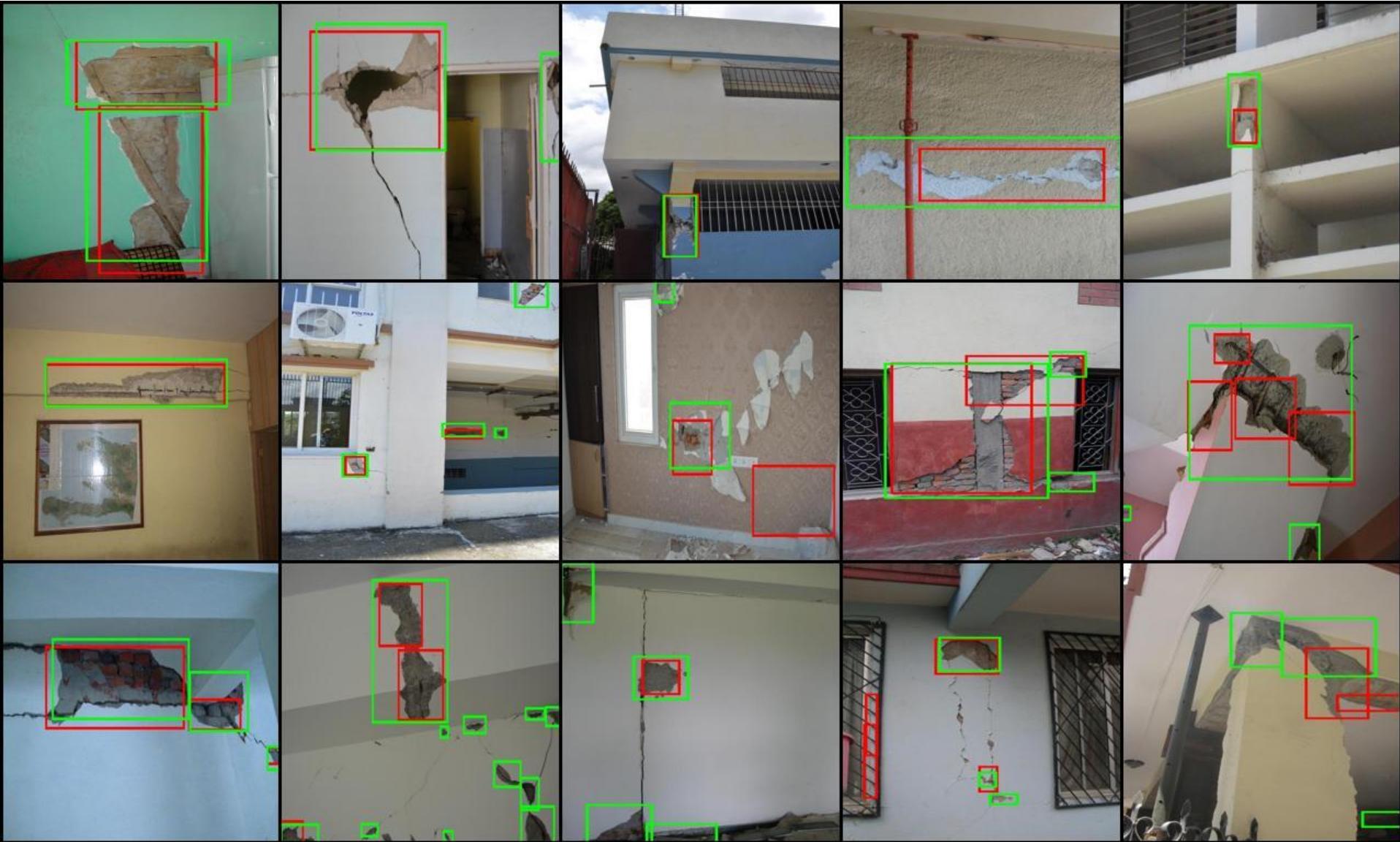
Example: Collapsing Building Classification using Web Images



Result: Spalling Detection on the Images having Spalling



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**



DATATHUB



FEMA



INSTITUTO
DE INGENIERÍA
UNAM

CEISMIC
Canterbury Earthquake Digital Archive

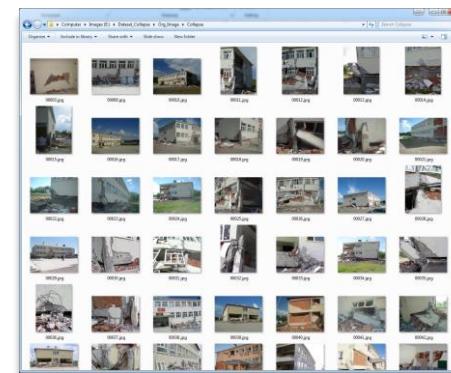


EUCENTRE™

European Centre for Training and Research in Earthquake Engineering



FIND CONTRIBUTORS: 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