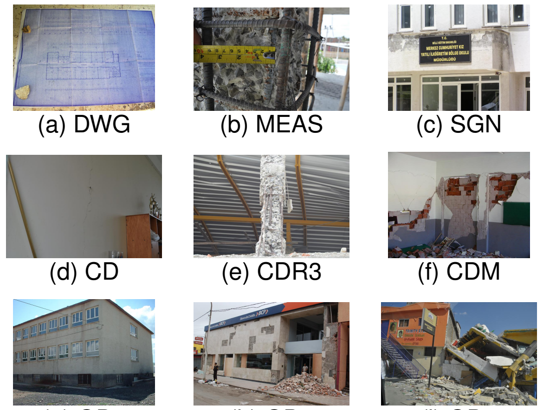
# Automated Image Classification for Post-Earthquake Reconnaissance Images

Juan Park, Chul Min Yeum — University of Waterloo, ON, Canada
Jongseong Choi, Xiaoyu Liu — Purdue University, IN, USA
Email: {j246park, cmyeum}@uwaterloo.ca, {choi343, liu1787}@purdue.edu ,

## Abstract

In the aftermath of earthquake events, many reconnaissance teams are dispatched to collect as much data as possible, moving quickly to capture the damages and failures on our built environments before they are recovered. Unfortunately, only a tiny portion of these images are shared, curated, and utilized. There is a pressing need for a viable visual data organizing or categorizing tool with a minimal manual effort. In this study, we aim to build a system to automate classifying and analyzing a large volume of post-disaster visual data. Our system called Automated Reconnaissance Image Organizer (ARIO) is a web-based tool to automatically categorizing reconnaissance images using a deep convolutional neural network and generate a summary report combined with useful metadata. Automated classifiers trained using our ground-truth visual database classify images into various categories that are useful to readily analyze and document reconnaissance images from post-disaster buildings in the field.



(a) DWG (b) MEAS (c) SGN
(d) CD (e) CDR3 (f) CDM
(g) OD0 (h) OD1 (i) OD2

*Fig. 1:* Sample images in the key designed classes

## 1 Introduction

After an earthquake, vast amounts of images are collected by teams of structural engineers to better understand failure mechanisms from the event. Among various collected visual information, damaged building and components are a crucial content because visual damage provides valuable evidence of undesirable consequence on structures. Suitable classification and documentation of such images enable efficient and systematic analysis as well as discoverability and overall reuse in the future. However, two major realistic challenges have hindered this process: First, there is no clear definition of the terms or category to describe the visual damage and large ambiguity in words to represent its level of severity, causing inconsistent classification. Second, visual data classification still greatly relies on human engineers. Manual sorting and analysis of a large volume of images are prohibitively tedious and expensive. Recently, Yeum [1] and Yeum et al. [2] developed a large postevent reconnaissance image database for use in training classifiers for each category. An extensive collection of approximately 300,000 color images has been acquired by practitioners and researchers after past natural disasters. The database includes images from hurricane, tornado, and seismic events (e.g., from disaster responders, Purdue University's datacenterhub.org, and Earthquake Engineering Research Institute image collection). However, to discuss this demonstration, we focus on earthquake images. To address the challenges, we propose an automated method to classify visual damage on earthquake images using a computer vision method, called ARIO. We design a new domain-oriented visual damage category for earthquake images. Then, multi-label deep convolutional neural network (CNN) is trained to extract the new category of classes from the images.

## 2 Methodology

Field engineers were consulted to develop appropriate categories and an associated hierarchical structure that support the needs of the application. The classes selected must be useful for the specific application, although classification can only proceed if images in the classes can be visually distinguished. A hierarchy can also be determined to enable efficiency and accuracy in the classification. The key categories of the class hierarchy are: Drawing (DWG), GPS, irrelevant (IRR), non-building components (NON), sign (SGN), watch (WAT), measurement (MEAS), building and building components (BBC), image Location (LOC), building exterior (LOCEX), building interior (LOCIN), building descriptor (DEP), building component (BCP), building overview (BOV), component damage (CPDMG), component type (CPTYPE), overview damage (OVDMG), overview type (OVANG), minor/no damage (CD), moderate concrete damage (CDR2), severe concrete damage (CDR3), masonry damage (CDM), column (CPCOL), beam (CPBEAM), wall (CPWALL), canonical view (OVCAN), front view (OVFRT), minor overall damage (OD1), moderate overall damage (OD2), severe overall damage (OD3). Images of 9 sample classes out of 22 are shown in Fig. 1.

For classification of the images following these categories, we employed a multi-label CNN classifier to identify all relevant classes per images. The major difference between multi-label and multi-class is that for multi-class, the classes are mutually exclusive while for multi-label, each class is independant of the other classes. In the developed hierarchy of categories, the classes have a mix of mutually exclusive, and independant classes. For example, CPTYPE and CPDMG are not mutually exclusive and thus, images can be categorized as child classes from both class. Thus, the classifier should be trained to produce multiple relevant classes per image.

The Xception [3] architecture was used to train the multi-label classifer. The model was trained for 50 epochs using stocastic gradient descent with a learning rate of $10^{-4}$ and sigmoid as the last layer's activation function. The model was trained on Keras, a deep learning package in Python using a GTX1080Ti graphics card.

## 3 Experimental Result

Prior to training, hierarchical inconsistencies in the dataset (e.g. an image labelled with CPTYPE should also have CPDMG and LOC labels) were removed, and 8,780 images were used for training. Since it is of interest to pursue a higher recall to precision ratio, a weighted loss function was used to balance out the loss contributed from sparse true labels with abundant false labels. Training results yielded favorable results, with a sample weighted recall and precision average of 90% and 79%, which takes into consideration the class dataset size imbalances.

The proposed method is brought together in ARIO to allow users to upload images of disaster-effected buildings and generate a single report for each building with categories extracted from all images using the trained classifier. The extracted information is then organized along with the metadata in a ready to use format.

## 4 Conclusion

In this study, we developed a novel approach for rapidly and autonomously classifying and organizing post-earthquake reconnaissance building images. Automation was achieved by exploiting and adapting recent developments in multi-label convolutional neural networks to analyze this type of complex and unstructured real-world images. We demonstrated the approach through the organization of images from damaged buildings during past earthquake reconnaissance missions. Using a large volume of real-world images from past missions, we successfully trained and deployed the classifiers into ARIO with a weighted recall and precision of 90% and 79%.

## References

[1] C. M. Yeum, "Computer vision-based structural assessment exploiting large volumes of images," p. 1036, 2016.

[2] C. M. Yeum, S. J. Dyke, J. Ramirez, T. Hacker, S. Pujol, and C. Sim, "Annotation of image data from disaster reconnaissance," in *Proc., 16th World Conf. on Earthquake Engineering*, 2017.

[3] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 1251–1258.