AUTOMATION OF POST-EARTHQUAKE CIVIL INFRASTRUCTURE RECONNAISSANCE

BY
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SENIOR PROJECT REPORT

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Abstract:

Traditionally post-earthquake structural engineering reconnaissance consists of a team of experts who are deployed to the field to record and capture earthquake damage data, which is later uploaded into online repositories. Despite many advances to these data archives in recent years, the entries in online repositories often have limited metadata which make it difficult and time consuming to extract specific damage evidence that can be used for meaningful analysis. This report outlines the author's contributions to overcoming these challenges via the development of a neural network that automatically filters and classifies post-earthquake civil infrastructure damage data after a seismic event. In addition, this document summarizes the author's progress on utilizing neural network output to rapidly generate geospatial maps from reconnaissance data.

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1. Research Background and Context

An interdisciplinary team at California Polytechnic State University – San Luis Obispo was established in late 2016 to address the existing shortcomings with the current manual methods of curating and adding metadata to post-earthquake civil infrastructure damage images collected during in-field reconnaissance missions. The research team has been utilizing machine learning to address this engineering problem and consists of a structural engineering and computer science group. The author of this report is an undergraduate student member of the structural engineering group.

1.1 Research Motivation

Currently, post-earthquake civil infrastructure reconnaissance consists of two stages. The first stage involves sending experts into the field to collect as-built and damage information. This information consists of images, hand drawn plans, formal engineering plans, and qualitative damage notes. The second stage is uploading the collected data into online repositories, so professionals and researchers can later access these large data-sets to analyze damage patterns associated with a particular seismic event or structure type. Existing repositories (such as NISEE PEER library [1]; EERI Learning from Earthquakes (LFE) Reconnaissance Archive [2]; GEER Reconnaissance Reports [3]; datacenterhub.org [4]) have thousands of images and information of multiple events publicly available. However, the current state of these repositories is where the research team has found major shortcomings.

Most of the aforementioned repositories are organized to have a single database for each seismic event where local engineers and deployed reconnaissance teams can batch upload their damage images and associated information. These teams collect a massive amount of data, and often do not have the time to manually filter, classify, and individually upload it based on specific damage or civil infrastructure type. Therefore, the data batch is given a simple classification, such as the name of the individual who collected the data or the relevant earthquake engineering topic area (structural, geotechnical, lifelines, social science, etc.). This method makes it extremely difficult for a repository user to query the database for sub-sets of information to perform a meaningful analysis related to the relation between observed damage and location or material and building systems type; all of which would be useful to learn from the earthquake.

Currently repository managers, industry members, and researchers are looking into alleviating some of the prominent issues with curation of damage reconnaissance image data so that they have greater utility for understanding the earthquake performance of civil infrastructure. In the recent EERI LFE 2017 Puebla Mexico Earthquake repository, in collaboration with FEMA, provides more options for filtering data and adding interactive maps where the user can search directly for the type of damage or building type of interest [5]. From the industry perspective, a team from Skidmore, Owings, & Merrill (SOM) has begun investigating computer vison to automate the process of differentiating structural from non-structural damage and the corresponding levels of severity in post-earthquake images [6]. Researchers are also engaged in developing these types of neural networks to enable image recognition, notably a team at Purdue University are automating the detection of spalling in concrete buildings and cracks in bridges [7, 8]. The issues with earthquake reconnaissance repositories are an impediment to a greater progression in the structural engineering field, and both the practitioners and researchers are pursuing various approaches to remedy these deficiencies.

1.2 Research Objectives

The research team has both long term and short-term objectives to fulfill by creating a neural network and automated reconnaissance maps.

Short Term:

- Train the neural network on a variety of damage types and civil infrastructure types.
- Use information from the manual tagging tool to create automated earthquake reconnaissance maps using GPS coordinates.
- Publish and present research at conferences to garner interest from industry in collaboration, sponsorship, and/or mentorship to guide the direction of the research.

Long Term:

- Create a neural network that can accurately tag and classify a range of damage and associated civil infrastructure type (referred to as “damage-structure pair”). As an example, an infill wall collapse in a reinforced concrete frame building would have a damage-structure pair of “collapse-infill wall”.
- Use the output information from the neural network to automatically create reconnaissance maps using GPS coordinates and damage/structure metadata.
- Curate an earthquake reconnaissance online repository using the classified and filtered data from the neural network.

1.3 Research Tasks

There were two primary tasks: providing the large volume of image data necessary for training/validation of the neural network (NN) and creating automated reconnaissance maps from NN output. The workflow required to develop both the NN and the automated reconnaissance maps is outlined below, with specific indication as to the contribution of the author of this report.

Neural Network Development

- Human Training: Author created training documents
- Image Collection: Author collected multiple image sets (typ. 200+ images/set)
- Image Tagging: Author tagged collected image sets
- NN Training/Validation

Automated Reconnaissance Maps

- Convert NN Output to ArcGIS Compatible File: Author created the automation process from NN output
- Creation of ArcGIS Maps: Author developed prototype map

2. Related Work

2.1 Neural Network and Machine Learning

Patterson et al. [9] describes a neural network (NN) as a complex network of artificial neurons in which each individual neural executes a singular simple task and provides the output to the next neuron in the series. In the case of image identification, each layer of neurons identifies and assigns weights to different higher-level features in the image. Once each layer is connected the NN can then classify objects in an image. The number of provided layers correlates to the level of functionality of the NN. A deep learning (DL) algorithm (such as the one being trained in this project and in Patterson et al. [9]), uses many layers to provide output from a very complex image.

Rafiei et al. [10] provides an overview of different NN approaches to identify concrete compressive strength. A simplified model called the backpropagation neural network (BPNN) uses a series of inputs and multiple iterations to develop a singular output, which is similar to the NN used in this project however on a simplified scale. Figure 1 from [10] provides a visualization of the process used to classify concrete compressive strength from seven inputs. Lai and Serra [11] reported an error of 9.2% using the BPNN method given eight concrete properties, such as water cement ratio, as the inputs.

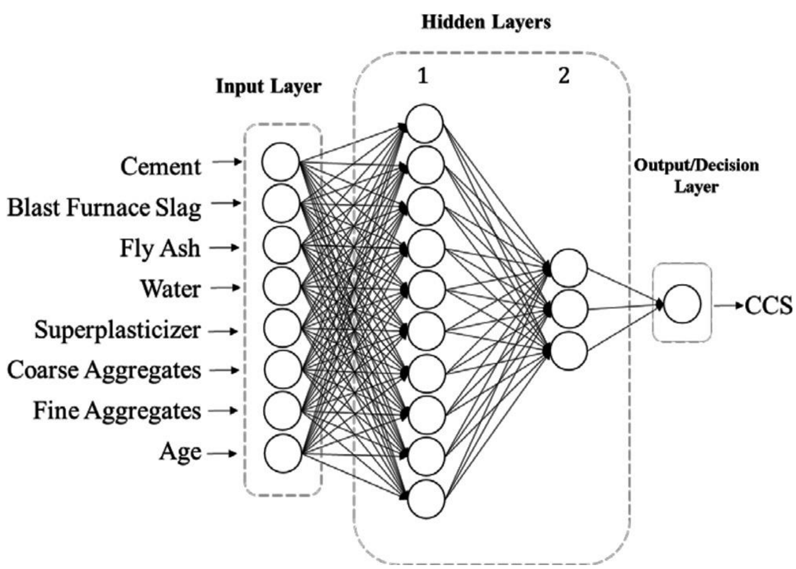


Figure 1: BPNN Visual Model [17]

Pelt and Sethian [12] go into depth between the difference of a simplified NN such as the one used in [10] and the DL algorithm that is being developed in this project. The DL algorithm is vastly more complex than then a simplified model such as the BPNN. The principal difference is the number of layers that a BPNN and a DL algorithm uses. In addition, the BPNN model uses the output of the previous layer, or neuron, in the next layer like a linear process. The DL algorithm can upscale and downscale previous layers to provide more definitive output. Figure 2 from [12] provides a model of the down and upscaling process in what they refer to as "deep convolutional neural networks" (DCNNs). The primary drawback of using a DL algorithm is the lengthy and difficult training process. Since there are many layers the DL algorithm must go through a large iterative process which requires a large training set.

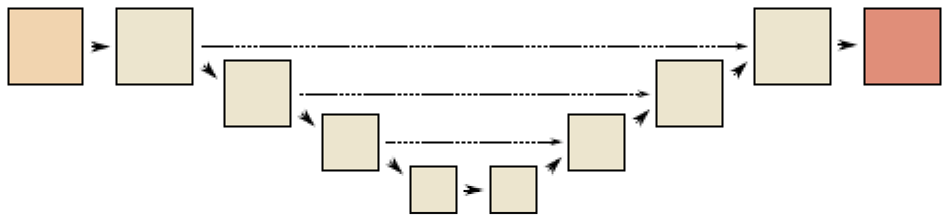


Fig. 2. A schematic representation of a common DCNN architecture with scaling operations. Downward arrows represent downscaling operations, upward arrows represent upscaling operations, and dashed arrows represent skip connections.

Figure 2: DCNN Visual Model [19]

A NN developed by Devries et al. [13] uses a DL algorithm using a pair input system, just like the NN described in this project, to predict the location of aftershocks following an earthquake. Their network trained on over 131,000 pairs were able to predict the location of an aftershock without prior fault data to 85% accuracy on 30,000 test pairs. The NN model used has six layers with 50 neurons per layer.

Y. Chul et al. [14] deploys a CNN to extract targeted content from collected images following a seismic event. The research team is focusing on image classification and object detection which identifies damaged parts of a structure. In this case the CNN has been used thus far to detect spalling in concrete and a total collapse of a building. Classifying the image allows the CNN to categorize the image and narrow the possible objects that will be in an image. For example, an image of a basketball game will be classified as having no damaged structure and the algorithm will not attempt detection of any specified objects. In this way the image can be classified as having a complete collapse or only being damaged, whereas the later case will follow the next step to object detection. Object detection uses a variety of image manipulation techniques to search for a specified input occurrence, i.e. concrete spalling. If the object in question is in the image the algorithm will tag it within a trained range. Figure 3 from Y. Chul et al. demonstrated the process of this CNN.

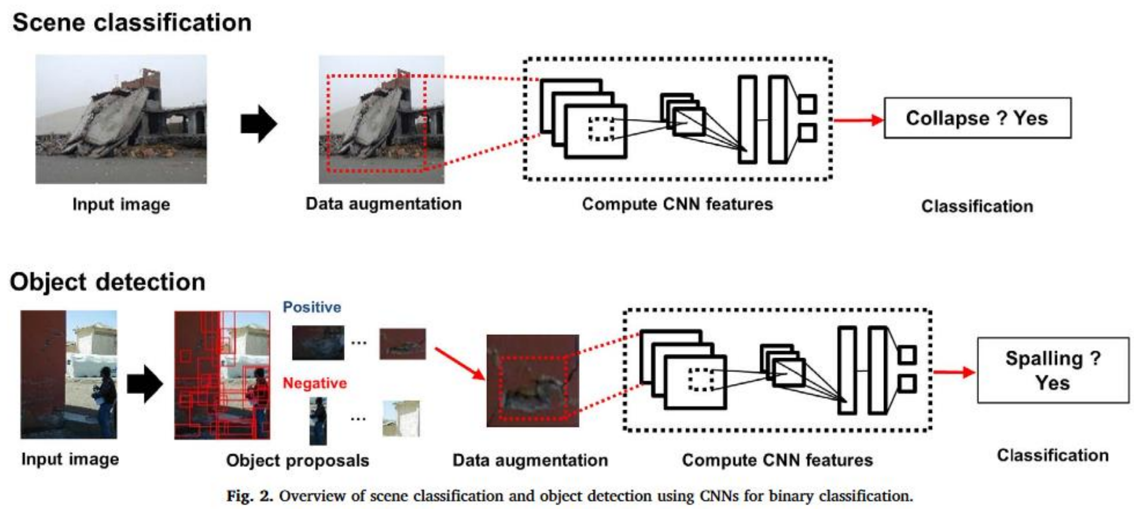


Figure 3: CNN Building Damage Model [14]

2.2 Automated Data Mapping

The combination of a NN and mapping software, ArcGIS in this case, has been used in other studies to quantify and display data analyzed by a NN. Bi et al. [15] used a simple NN model to predict probability landslide occurrences in certain areas of Xiangxi China. The NN consisted of several inputs (lithology, slope angle, river networks, etc.) to output landslide susceptibility. This output information is then paired with ArcGIS to present and quantify the data in the entire Xiangxi catchment. Results showed that 70% of landslides were correctly identified and placed in the ArcGIS map. *Figure 3* shows the landslide susceptibility data.

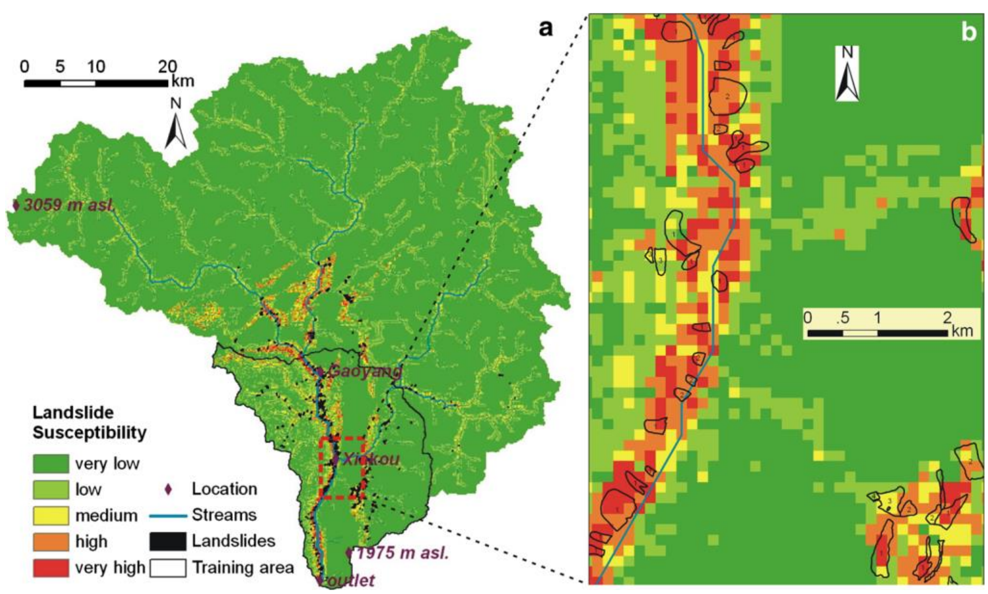


Figure 4: Landslide Susceptibility [21]

Junjie et al. [16] uses a NN to determine the severity of damage to multistory buildings during an earthquake. The output is then coupled with GIS information to demonstrate spatial variation in earthquake damage and reflect the degree of damage visually. The NN they utilized included building height, mortar grade, wall area ratio, etc., as inputs to produce a series of outputs depending on the degree of damage, ranging from largely intact to collapse. The output data is coupled with GIS data and filtered into a mapping software to visually present the degree of damage using colored pins. The GIS software allowed [16] to offer an easily accessible platform for spatial analysis which was automatically filtered through the NN to solve engineering and disaster mitigation issues.

2.3 State of Practice in Post – Earthquake Structural Damage Mapping

Currently interactive data maps following a seismic event are just beginning to become commonplace. Following the Puebla, Mexico earthquake in 2017, EERI LFE [3] published an interactive map using ArcGIS to mark impacted areas. The maps data pins ranged from imaged of damaged building to safe areas for shelter. Most of the information marked was done through a grassroots effort since the map was available for the public to edit. Some of the images collected through reconnaissance were uploaded automatically and marked with GPS coordinates, however any associated information about the structure was dumped into the description, which was manually written by the reconnaissance professional. In addition, the layers of the map were separated arbitrarily by the uploaded content, so there is no way to classify the type of structure damage visually. While there are marked structures on the map there is no easy way to navigate information regarding the type and severity of the damage done to the structure.

3. Neural Network Development:

Before damage mapping can be initialized, the NN must be fully functioning to identify many damage – structure pairs. The post-earthquake civil infrastructure damage images used to train the NN are collected from existing online reconnaissance databases of previous seismic events [1,2,3,4] as well as various formal and social media platforms. This section includes a discussion of each step necessary for the neural network development: (1) human training, (2) image collection, (3) image tagging, and (4) NN training/validation.

3.1 Human Training

The first step of training the NN is to ensure that each person collecting images becomes knowledgeable about their target damage-structure pair based on visual identification standards from a reliable body of existing reconnaissance documents. For instance, if a researcher is collecting images on shear damage of captive (short) reinforced concrete columns, they must be educated on the visual markers of shear damage and the differences between a captive and slender column. The human training step is critical since many of the research team members are undergraduates or early graduate students, and the damage-structure pairs they assign to images must be consistent with classifications from industry/academic reconnaissance experts.

The author has created a sample training document, an excerpt of which is in Appendix A, on earthquake damage types for roadways and railways. This document summarizes information from online earthquake databases, reconnaissance reports, textbooks, and includes input from engineering faculty [1,2,3,17]. The document was used in the Winter 2018 quarter by graduate students on the research team to set standards to identify severity of cracking in damaged roadways, allowing them to collect and tag 200+ images for each of the three severity categories (cracking, fracture, and fissure).

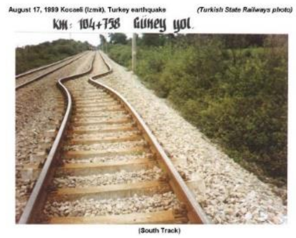
3.2 Image Collection

The research team has determined that a minimum of 200 images clearly demonstrating the target damage-structure pair is required in order to adequately train the NN (accuracy ≥75%). The images must be high resolution; confirmed to be damage resulting from an earthquake, rather than another type of hazard event; and contain enough visual reference information to accurately determine the structure type. When collecting images, the research team uses an Excel sheet to record image metadata such as damage notes, GPS coordinates, and image URL.

A greater number of images will improve NN performance; however, finding reliable, publicly available post-earthquake infrastructure damage images for a specific damage-structure pair has been a major challenge. Neural networks are often trained on much larger image sets such as the ImageNet repository with over 14 million classified images [18]. There are limited public images for the current research work due to: a wide variety of building types and plans that causes distinct damage in each structural system; the relative infrequency of major seismic events; and the incompleteness of public repositories since not all reconnaissance teams will upload or organize their collected data.

The research team has collected image sets for five damage-structure pairs, shown in Figure 1. Of the collected sets the author collected collapse of infill walls in reinforced concrete (RC) framed buildings and landslide over roadway, as indicated by the red outline.

Cracking
Roadway



Horizontal Offset
Railway

Landslide
Roadway

Infill Collapse
RC Frame

Shear Damage
Short Column

Figure 5: Collected Image Sets

3.3 Image Tagging

After collecting an image set for a damage-structure pair, the research team uses a tagging tool developed by the computer science group to identify the damaged area of each image with a bounding box as shown in Figure 2. The tagging tool then saves a screenshot of the tagged image and writes a Pascal Visual Object Class (VOC) .xml file which includes the image dimensions and each assigned damage-structure pair with the pixel coordinates of bounding box corners. The .xml file, shown in Figure 3, is passed along to the NN for training and used in the automated generation of reconnaissance maps. Additional information on the image tagging tool can be found in Behrouzi & Pantoja [19]. The author has tagged three image sets: infill wall collapse, roadway cracking, and landslide failure over roadways.

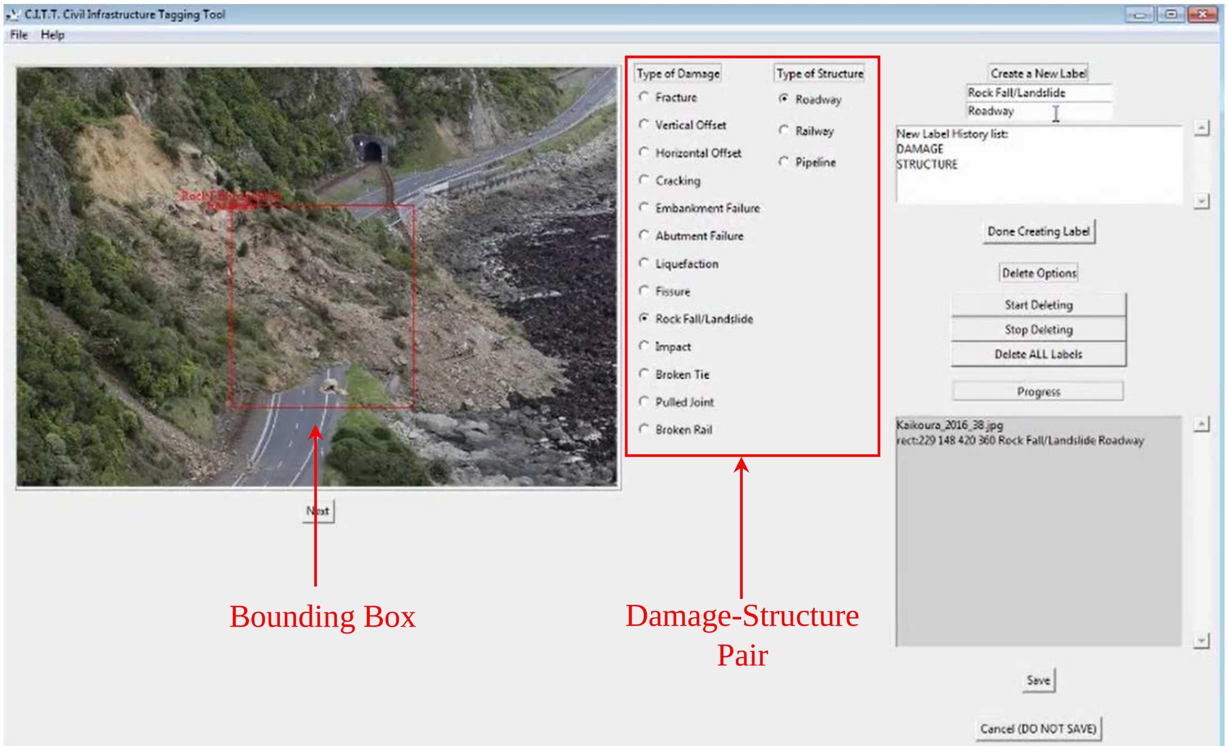


Figure 6: Image Tagging Tool Interface

```
<annotation verified="yes">
        <folder>Infrastructure</folder>
        <filename>Kaikoura 2016 15.PNG</filename>
        <size>
                <width>300</width>
                <height>224</height>
                <depth>3</depth>
        </size>
        <segmented>0</segmented>
        <object>
                <name>Rock Fall/Landslide Roadway</name>
                <bndbox>
                        <xmin>130</xmin>
                        <ymin>106</ymin>
                        <xmax>168</xmax>
                        <ymax>140</ymax>
                </bndbox>
        </object>
</annotation>
```

Image name

Bounding box dimensions

Damage structure pair

Bounding box coordinates

Figure 7: Pascal VOC (.xml) Output File

3.4 Neural Network Training/Validation

After an image set has been collected and tagged properly, it is sent to the computer science group to be trained on the NN to identify if and where damage is located in an image so it can independently tag damage without human assistance. The tagged images are split into two groups, a training set for input into the algorithm and a validation set to test the algorithm for accuracy. During the training process error/loss functions are calculated during each iteration to determine accuracy, and certain parameters are modified to correct found errors [20]. Figure 5 is an example of the output from the trained NN tagging images for the shear damage-short column type damage-structure pair.

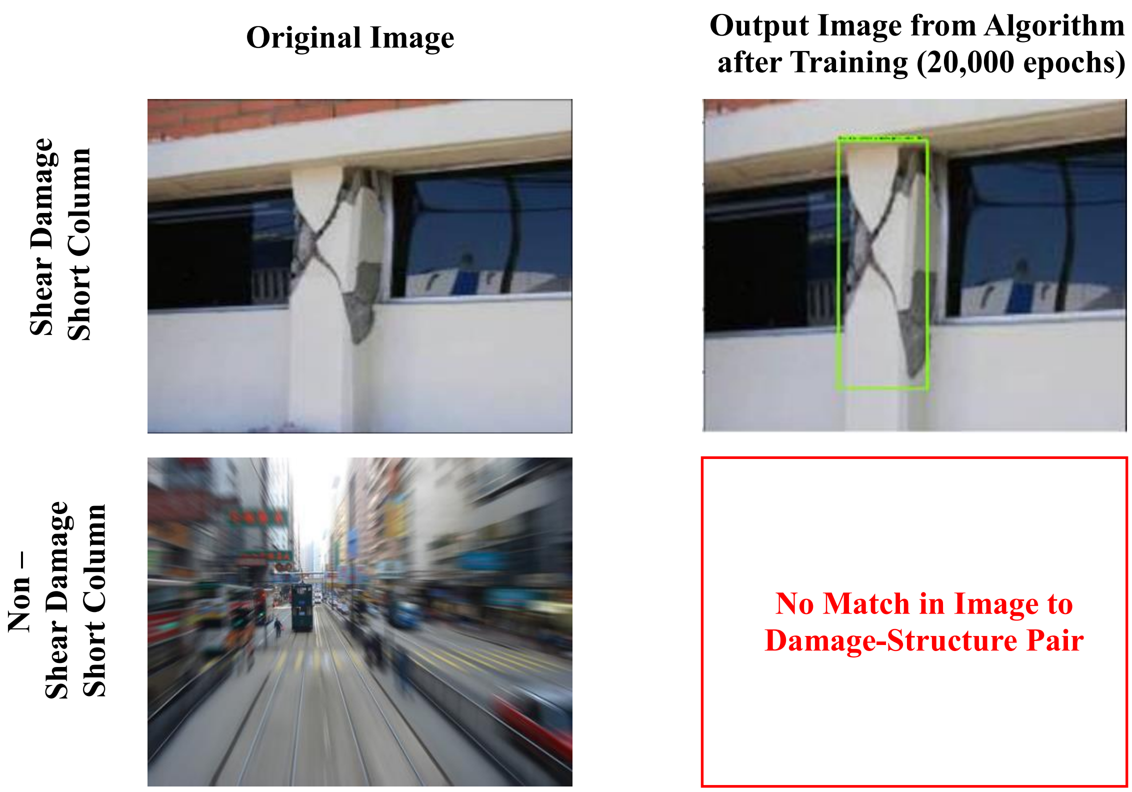


Figure 8: Neural Network Identification Process [13]

The research team has attempted to train NNs on four of the damage-structure pairs shown in Figure 1. The accuracy is as follows: (1) shear damage of short RC columns (77% accuracy), (2) cracking in roadways (92% accuracy), (3) horizontal offset of railways (80% accuracy), and (4) infill collapse in reinforced concrete frames (attempted, but unsuccessful). Additional details on this work can be found in Behrouzi & Pantoja [20] and Patterson et al. [9].

Training the NN on collapse of infill walls posed a challenge since many images included complete collapses of infill walls that left the RC frame entirely bare without any indication that an infill wall had previously existed in the opening. The research team is currently working on this particular challenge and training on other unreinforced masonry (URM) damage types via a collaboration with faculty at the University of Auckland who have a conducted several recent reconnaissance missions to survey and collect URM damage data.

3. Automated Reconnaissance Maps:

After presenting the development progress of the NN to industry professionals [21], objectives of the research team were expanded to include creating automated reconnaissance maps from the classified civil infrastructure damage images. Generating automated maps in a software tool like ArcGIS [22] can be a visually meaningful way to present localized building damage and severity, highlight distributed damage to railways and roadways, as well as outline fault lines and geotechnical soil zones. After importing all this data into a map it is then possible for the user to filter for specific site and earthquake damage information based on their preferences. This can help inform immediate response by municipalities after an earthquake or to enable the type of geo-spatial data analysis necessary to improve seismic design practice. Automation of these maps from the NN outputs only requires a few extra steps which are outlined in Section 3.1.

3.1 Convert NN Output to ArcGIS Compatible File

Creating location-specific map pins to represent damaged infrastructure on a reconnaissance map requires: (i) damage image information from the NN output or the image tagging tool (.xml file shown previously in Figure 3), (ii) GPS coordinates, and (iii) additional metadata such as image URLs, extent (length or area) and severity of damage to effected infrastructure. All of this information is combined using a MATLAB script (Appendix B) that creates a comma delimited (.csv) file shown in Figure 6 which is then used as an input attribute table to ArcGIS. A set of map pins with an associated damage-structure pair constitutes one sheet on the .csv Excel file.

	A	B
1	Street	Harris Lane
2	District	Kaikoura Flat
3	City	Kaikoura 7371
4	Country	New Zealand
5	Image Name	Kaikoura_2016_15.PNG
6	Roadway Damage?	NO
7	Damage-Structure Type_1	Embankment Failure Roadway
8	Damage-Structure Type_2	Fracture Roadway
9	Damage-Structure Type_3	Rock Fall/Landslide Roadway
10	Image URL	http://www.eqclearinghouse.org/map/photos/8e170f13-9444-4f45-ba69-5ca80dad9475.jpg
11	Link URL	http://www.eqclearinghouse.org/2016-11-13-kaikoura/maps-and-photos/photo-gallery/

Figure 9: Comma Delimited (.csv) File Input for ArcGIS Software

3.2 Creation of ArcGIS Maps

ArcGIS reads the information from the comma delimited attribute table file and creates a map pin for each damaged structure at the physical address or set of GPS coordinates, sample pins are shown in Figure 7. It is possible to modify text and image/URL metadata from the attribute table that is visualized when hovering over a map pin. After assigning all pins to a map, the user can set visibility distance for the pins or apply filters that sort structures by damage type or severity. The ability to modify and filter visualized data through pins allows the user to identify meaningful patterns in earthquake damage to civil infrastructure including relationships between frequency of a damage type and locations where damage is most concentrated and severe.

The civil infrastructure damage information produced by the neural network and visualized in the map can be supplemented by existing open-source GPS files or built-in ArcGIS base maps like roadway coordinates, fault lines, or satellite imagery. In Figure 9, roadway coordinates paired with landslide damage data can be informative to highlight effected areas of routes (red line). Also, in Figure 9, the ability for ArcGIS to overlay built-in base maps made it possible to upload external shapefiles of the Kaikoura fault lines from canteburymaps.govt.nz (orange lines) [23]. Other possible uses of shapefiles include shading regions that have varying geo-spatial information to identify different soil zones or population density to cross-identify these variables with highly damaged areas. Particularly relations between population density and damage can assist rescue and relief efforts following an event.

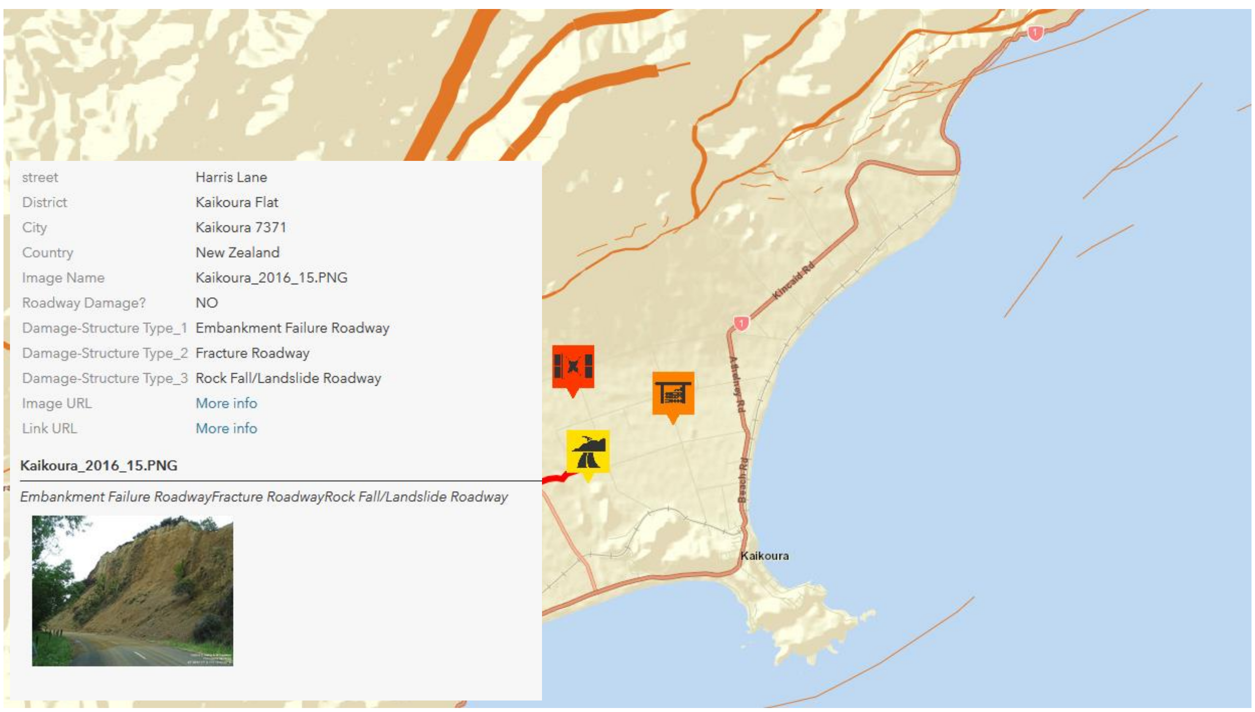


Figure 9: Sample Map with Pin Attributes

The author collaborated with a graphic arts student to design map pins shown in Figure 8 for three damage-structure pairs (shear damage to captive columns; infill wall collapses in RC frame buildings; and landslides blocking roadways) and severities (low; moderate; high). These new map pins can be implemented in ArcGIS via the comma delimited attribute table file.

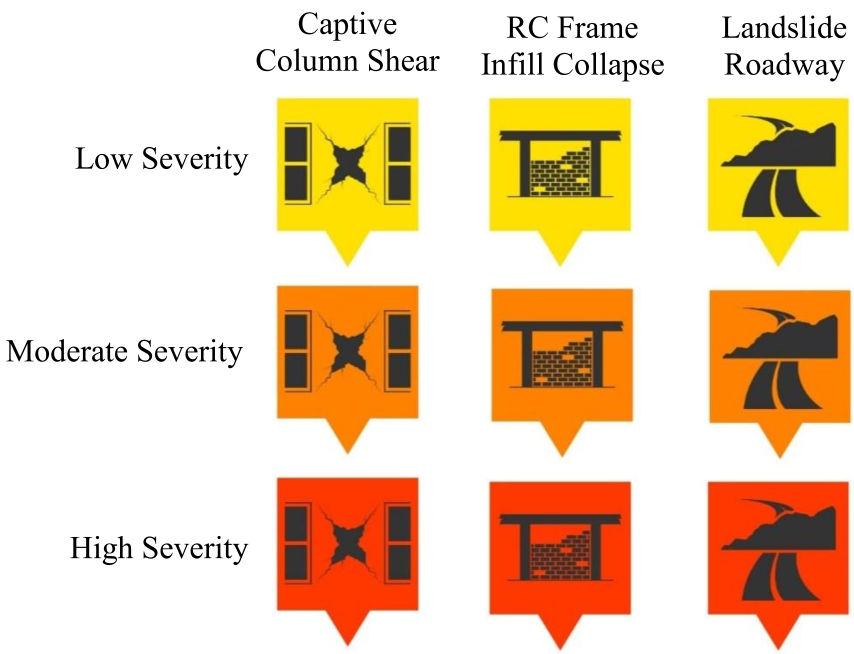


Figure 10: Damage Structure Pair Pins

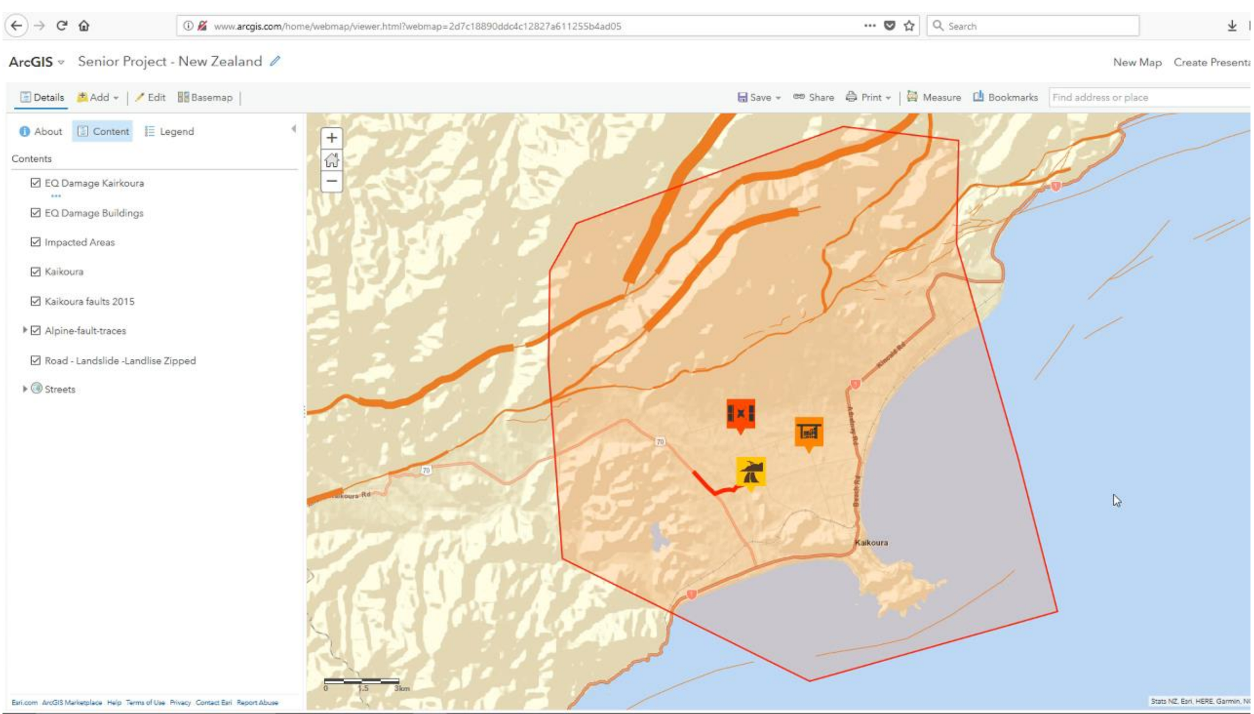


Figure 11: Sample Automated Reconnaissance Map

3.3 Future ArcGIS Work

Beyond the capabilities discussed in Section 3.2, in the future the automated reconnaissance maps should provide real time updates regarding an earthquake event by cross-referencing different databases of information to create “hotspots”. These hotspots can consist of areas that have a high amount of civil infrastructure damage coinciding with a high population density. In this way the maps can be very effective in the short term by helping emergency/rescue, repair, and recovery teams coordinate their efforts in areas that require the most urgent attention.

In the long term these maps can serve as an organized visual summary of information for earthquakes over the course of many years in any given location. Once the maps contain a large dataset for an extended time history, researchers and professionals can track the effectiveness of civil infrastructure improvement in a city over time, or across nations around the world. The ability to examine infrastructure damage from a geo-spatial and timewise perspective has a powerful role in developing important earthquake safety measures.

4. Conclusion:

The main purpose of the research team’s work is to efficiently and effectively communicate the information gathered from earthquake reconnaissance. By automating the classification and identification process of post-earthquake infrastructure images, the neural network saves a significant amount of time that would otherwise have to be done manually by a professional. The information the neural network provides can be used to analyze damage patterns from any earthquake that has sufficient image metadata through use of automated reconnaissance maps. The NN output can be used to create reconnaissance maps which allow the user to identify patterns through visual presentation and filtered information.

In order to effectively create a virtual reconnaissance neural network, there are limitations which must be met to meet the ultimate goal of a completely automated hazard identification tool. First, a large amount of image metadata has to be collected and tagged by a knowledgeable expert to ensure the NN is being trained accurately. Second, standards of practice must be established and adhered to so the NN is consistent in identify any one damage or structure type. For example, a short column must be established as so, rather than a “captive column” or “spandrel element”. Lastly, all metadata gathered has to be meticulously recorded and verified on a specific seismic event. This ensures the accuracy of the image information being used on the NN and provides sufficient data to be paired with NN output for the automated reconnaissance maps.

So far, the research team has successfully trained the NN to identify three damage structure pairs with reasonable accuracy. In addition, the author has transferred NN information paired with database resources to automate the process of creating reconnaissance maps. While progress has been made, there are still important milestones that must be met before the NN reaches fruition.

5. References:

[1] “The Earthquake Engineering Online Archive NISEE e-library,” nisee.berkeley.edu, 2016. [Online]. Available: https://nisee.berkeley.edu/elibrary/

[2] “Learning from Earthquakes Reconnaissance Archive,” eeri.org, 2016. [Online]. Available: https://www.eeri.org/projects/learning-from-earthquakes-lfe/lfe-reconnaissance-archive/

[3] “Reconnaissance Reports,” geerassociation.org, 2015. [Online]. Available: http://www.geerassociation.org/reconnaissance-reports

[4] “Resources: Databases,” datacenterhub.org, 2014. [Online]. Available: https://datacenterhub.org/resources/databases

[5] “Puebla, Mexico Earthquake Clearinghouse” eeri.org, 2017. [Online]. Available: http://learningfromearthquakes.org/2017-09-19-puebla-mexico/

[6] Diaz, A. Murren, P. Walker, S. 32 years after Michoacán: Preliminary Reconnaissance Observations in the Aftermath of the September 19, 2017 Puebla-Morelos Earthquake, in EERI LFE Puebla Mexico Clearinghouse, Resources, Available: http://learningfromearthquakes.org/2017-09-19-puebla-mexico

[7] Y. Chul, S.J. Dyke, and J. Ramirez, “Visual Data Classification in Post-Event Building Reconnaissance”, Engineering Structures, vol. 155, p. 16-24, 2018.

[8]. Y. Chul, S.J. Dyke, 2015. Vision-Based Automated Crack Detection for Bridge Inspection. Computer-Aided Civil and Infrastructure Engineering, 30: 759-770. doi:10.1111/mice.12141

[9] Patterson B, Leone G, Pantoja M, Behrouzi A. “Deep learning for automated image classification of seismic damage to built infrastructure, ” Proceedings of the 11th National Conference in Earthquake Engineering 2018.

[10] Rafiei, M., Khushefati, W., Demirboga, R., & Adeli, H. (2016). Neural Network, Machine Learning, and Evolutionary Approaches for Concrete Material Characterization. *ACI Materials Journal, 113*(6), 781-789.

[11] Lai, S., and Serra, M., “Concrete Strength Prediction by Means of Neural Network,” Construction and Building Materials, V. 11, No. 2, 1997.

[12] Pelt, D., & Sethian, J. (2018). A mixed-scale dense convolutional neural network for image analysis. *Proceedings of the National Academy of Sciences of the United States of America, 115*(2), 254-259.

[13] Devries, P., Viégas, F., Wattenberg, M., & Meade, B. (2018). Deep learning of aftershock patterns following large earthquakes. *Nature, 560*(7720), 632-634.

[14] Y. Chul, S.J. Dyke, and J. Ramirez, “Visual Data Classification in Post-Event Building Reconnaissance”, Engineering Structures, vol. 155, p. 16-24, 2018.

[15] Bi, Renneng, Markus Schleier, Joachim Rohn, Dominik Ehret, and Wei Xiang. "Landslide Susceptibility Analysis Based on ArcGIS and Artificial Neural Network for a Large Catchment in Three Gorges Region, China." Environmental Earth Sciences 72, no. 6 (2014): 1925-938.

[16] Junjie, Wang, Gao Huiying, and Xin Junfeng. "Application of Artificial Neural Networks and GIS in Urban Earthquake Disaster Mitigation." *Intelligent Computation Technology and Automation (ICICTA), 2010 International Conference* (2010): 726-29.

[17] Elnashai, Amr S.;Di Sarno, Luigi. *Fundamentals of Earthquake Engineering*. Wiley, 2015.

[18] L. Fie-Fie, K. Li, “ImageNet,” image-net.org, 2016. [Online]. Available: http://imagenet. org/index

[19] Behrouzi A, Pantoja M (2018). Photo Tagging Tool for Rapid and Detailed Post-Earthquake Structural Damage Identification. Proceedings of the 11th National Conference in Earthquake Engineering (11NCEE).

[20] Behrouzi A, Pantoja M (2018). Software Toolset to Enable Image Classification of Earthquake Damage to Above-Ground Infrastructure. Proceedings of the 16th European Conference on Earthquake Engineering (16ECEE).

[21] Behrouzi A, Pantoja M, Bergquist J (2017). Application of Automated Image Classification Tool for Post-Earthquake Assessment of Concrete Structures. Presentation at the Fall 2017 American Concrete Institute Convention (ACI 2017).

[22] “ArcGIS Online,” arcgis.com, 2017. [Online]. Available: https://www.arcgis.com/home/index.html

[23] “Canterbury Maps Kaikoura Faults,” canterburymaps.govt.nz. [Online]. Available: http://opendata.canterburymaps.govt.nz/datasets/kaikoura-faults-2015.

6. Other Senior Project Deliverables:

This document only represents part of the author's senior project deliverables, other significant work includes:

- Presenting on the functionality of the image tagging tool at the Fall 2017 American Conference Institute Convention in the ACI 133 Disaster Reconnaissance committee meeting and Research in Progress session [13]. The presentation included the progress made on the NN and the motivation behind its creation. The author prepared a demonstration video on the use of the tagging tool to prepare training images for the NN.
- Serving as first author on a paper for the American Society of Engineering Education (ASEE) titled, "Multidisciplinary Research Efforts in Post-Earthquake Civil Infrastructure Reconnaissance," which discusses the coordination and positive and negative effect of working on a multidisciplinary research team for both the faculty and students. The paper includes student and faculty interviews/questionnaires which gather input into how each member perceives progress and development of both the project and their development as engineering students. (abstract in Appendix C*);*
- Assisting with preparation of school damage information documents for the Mexican governmental agency Instituto Nacional de la Infraestructura Físicia Educativa (INIFED) under NSF RAPID Award # 1811084 following the 2017 Puebla Mexico Earthquake.

The author's involvement in this research team has provided them with valuable experience and engineering development that would otherwise not be seen during traditional coursework. Applying engineering logic and decision making into applications that have direct influence in the industry provided the author with a valuable opportunity to showcase skills learned in Cal Poly's Architectural Engineering program as well as grow as an engineer in training.

7. Acknowledgements:

The author would like to thank Dr. Anahid Behrouzi for her continued guidance and mentorship of the author during their time on the team. Thanks also to Anthony Herring of the University of Nevada Reno for dedicating his time to develop the map pins used on this project. The author would also like to thank their institution for generous funding of the discussed technical research work via two internal grants, Cal Poly CPConnect and Cal Poly RCSA Grant, that support faculty/student salary and travel.

Appendix A: Infrastructure Training Document (Sample)

Note: Various references left out for brevity. Available upon request.

Roads

General Definition of Structural Member:

- Roadways are prevalent in all areas that are inhabited and damage sustained by an earthquake could halt relief efforts.
- To distinguish different damage types, the degree of damage will be measured against how it will affect “normal traffic”. Normal traffic is indicative of a normal commuter car traveling on the road at normal time intervals.
- Most damage examples shown are in paved roads, however the same damage can be exhibited in unpaved roads. The only exception being liquification which can be identified in unpaved roads alone.

Pavement Damage

Cracking

- Cracking is the most common type of damage in roads. To classify cracking, the damage must be small enough where the integrity of the road is not compromised, and normal traffic can continue without repair.

Figure 1. Cracking in Roads

(a) Cracking in Central Italy 2016(reference)

(b) Cracking in Muisne Ecuador 2016 (reference)

Fracture

- Fracture is one step above cracking in that the damage is much larger, and there is obvious separation in the road.
- Fracture is classified separately from cracking in that it will need to be repaired before normal road traffic can resume. A commuter car could drive over a fracture but it would be similar to a large speed bump or possibly even hit the bumpers.

a

Figure 2. Examples of Road Fracture

(a) Fracture in Kaikoura New Zealand 2016 (reference)
(b) Fracture Kaikoura New Zealand 2016 (reference)
(c) Fracture Kaikoura New Zealand 2016 (reference)
(d) Fracture in Central Italy 2016 (reference)

Fissure

- A fissure is the complete failure of a roadway. This damage type included the complete destruction of a portion of roadway where the existing road is completely impassible by normal traffic.
- While this failure includes many of the other failures, such as vertical offset and major fracturing, it is classified separately to indicate complete failure (similar to the total collapse of a building).

Figure 3 Examples of Fissures
(a) Fissure in Kaikoura New Zealand 2016 (reference)
(b) Fissure in Kaikoura New Zealand 2016 (reference)
(c) Fissure in Meinong Taiwan 2016 (reference)

Vertical Offset

- Vertical offset occurs when there is significant differential displacement between planes of the road. This damage type generally has both planes of the road intact on both sides of the failure
- Indicators include the fracture plane being over the majority or full plane of the roadway. To differentiate between a fracture and vertical offset, the offset must be large enough where normal traffic will be impeded.

Figure 4. Examples of Vertical Offset
(a) Vertical offset in Kaikoura 2016 (reference)
(b) Vertical Offset in Kumamoto Japan 2016 (reference)
(c) Vertical Offset in Central Italy 2016 (reference)
(d) Vertical Offset in Dixie Nevada 1954 (reference)

Appendix B: MATLAB Script; Xml to Csv File

XML2CSV.m

```matlab
% User Inputs
% Calls the xml file output from the NN
 file = 'D:\Senior Projects\MAps\Kaikoura_2016_15.xml';

% XML Read
% Reads the information about the damage structure pair found in the xml
s = xml2struct(file);

% Creating a Summary File
% Parses the useful data from the xml into a "summary" file type which can
% be written into a csv filetype.
Summary{1,1}='Image Name';
Summary{2,1}=s.annotation.filename.Text;

for jj=1:length(s.annotation.object)

Summary{1,jj+2}=strcat('Damage-Structure Type_', num2str(jj));

if length(s.annotation.object)==1
Summary{2,jj+2}=s.annotation.object.name.Text;
elseif length(s.annotation.object)>1
Summary{2,jj+2}=s.annotation.object{1,jj}.name.Text;
else
end


%Determine if the word "Roadway" appears in the Damage-Structure Type Tag
Summary{1,2}='Roadway Damage?';

if strcmp(Summary{2,jj+2},'Roadway')
    Summary{2,2}='YES';
else
    Summary{2,2}='NO';
end


end

%CSV Write
xlswrite('Kaikoura.csv',Summary);
```

Appendix C: ASEE Paper Abstract

Title:

Multidisciplinary Research Efforts in Post-Earthquake Civil Infrastructure Reconnaissance

Abstract:

To address existing challenges with filtering and classification of post-earthquake structural damage images, the authors are engaged in a multidisciplinary project to develop and train a machine-learning algorithm that identifies relevant photographs and assigns damage tags to those images. The research team is predominantly comprised of undergraduate students and is led by a structural engineering and a computer science faculty. While machine-learning algorithms have been successfully used for image tagging in a variety of fields (health care, manufacturing, etc.), the extension of this approach for earthquake reconnaissance is only just beginning. As such, the creation and development of this tool is a new and dynamic project-based learning experience for both the students and faculty involved.

This collaborative project emphasizes student initiative and innovation where they are active in all development stages of the tool ranging from collection and tagging of earthquake damage images, coding and testing the machine-learning algorithm, to writing papers for and presenting at conferences. In addition, the unique nature of this project exposes students to a field and possible career path they may not have encountered in their typical course of study. The authors provide a comprehensive discussion of the results of faculty and student surveys/ interviews and conclude by highlighting some of the greatest benefits of the multidisciplinary project. They also point out lessons learned engaging in a project with a large scope, diverse experts (who have limited knowledge of the partnering disciplines), and a number of undergraduate students who began as novices in their respective research area.

Note: Full Conference Paper available on ASEE PEER repository