

## 2 *Supplementary Material*

### 1 SUPPLEMENTARY MATERIAL FOR “TOWARDS FINE-GRAINED OBJECT-LEVEL DAMAGE ASSESSMENT DURING DISASTERS”

#### 3 1.1 User Interface

4 To assist the human assessment of disaster object detected or missed by the model, a user interface was  
5 carefully designed to gather qualitative feedback from volunteers, as seen in Fig. S1 of the paper. Each of  
6 the eight volunteers was given individual page links with unique images to be assessed. For each image,  
7 the volunteers were instructed to analyze all the objects detected by the model and for any objects missed  
8 by the model to gather the following information for each object:

- 9 1.Damage: Whether the object shows any sign of damage or not, where the user has to select either ‘Yes’  
10 or ‘No’.
- 11 2.Human Detection: How easy it is to detect the object by the human eye, where the user has to select one  
12 of the following: ‘Easy’, ‘Relatively Easy’, ‘Difficult’, or ‘Very Difficult’.
- 13 3.Model Detection: How accurate the model detected the object, where the user has to select one of the  
14 following: ‘Correct’, ‘Partially Correct’, ‘Incorrect’, or ‘Missed’.
- 15 4.Feedback: User feedback on the overall assessment of the object, where the input field has no word limit.
- 16 5.Mission Area Focus: Identifying whether an object impedes response operations, where the user can  
17 select ‘Transportation’ and/or ‘Debris Management’. The user also has the option to select ‘Unable to  
18 Determine or N/A’.

19 Once the user fills in their evaluation for an object and clicks the submit button, their response gets saved  
20 to Redis, a NoSQL database. Once the insertion is complete, a retrieval request is made to immediately  
21 visualize the saved responses in the table below. Users also have the option to edit and delete their responses.  
22 The following features have been implemented to ensure maximum usability:

- 23 • Clicking on the original or model image opens the image in a new tab so users can easily zoom in.
- 24 • List of detected objects summarized under the model image.
- 25 • Page number is a dropdown field to not only show the current page but to allow users to easily navigate  
26 to any page/image they desire
- 27 • The “Go To Last Analyzed Image” button takes the user to where they last left off
- 28 • The “Check Progress” button opens a new window showing an “Assessed” and “Not Assessed” column.  
29 “Assessed” shows all the page numbers where they have inputted at least one record, whereas “Not  
30 Assessed” shows all the page numbers which have been untouched. This will help in identifying any  
31 missed pages.

#### 32 1.2 Strengths and Weaknesses

33 This section extensively lists the strengths and weaknesses identified through the analysis of all the  
34 volunteer assessments on 946 images. Whilst the model was trained on an existing dataset which is not  
35 tailored to disaster objects, there are a few limitations that were identified.

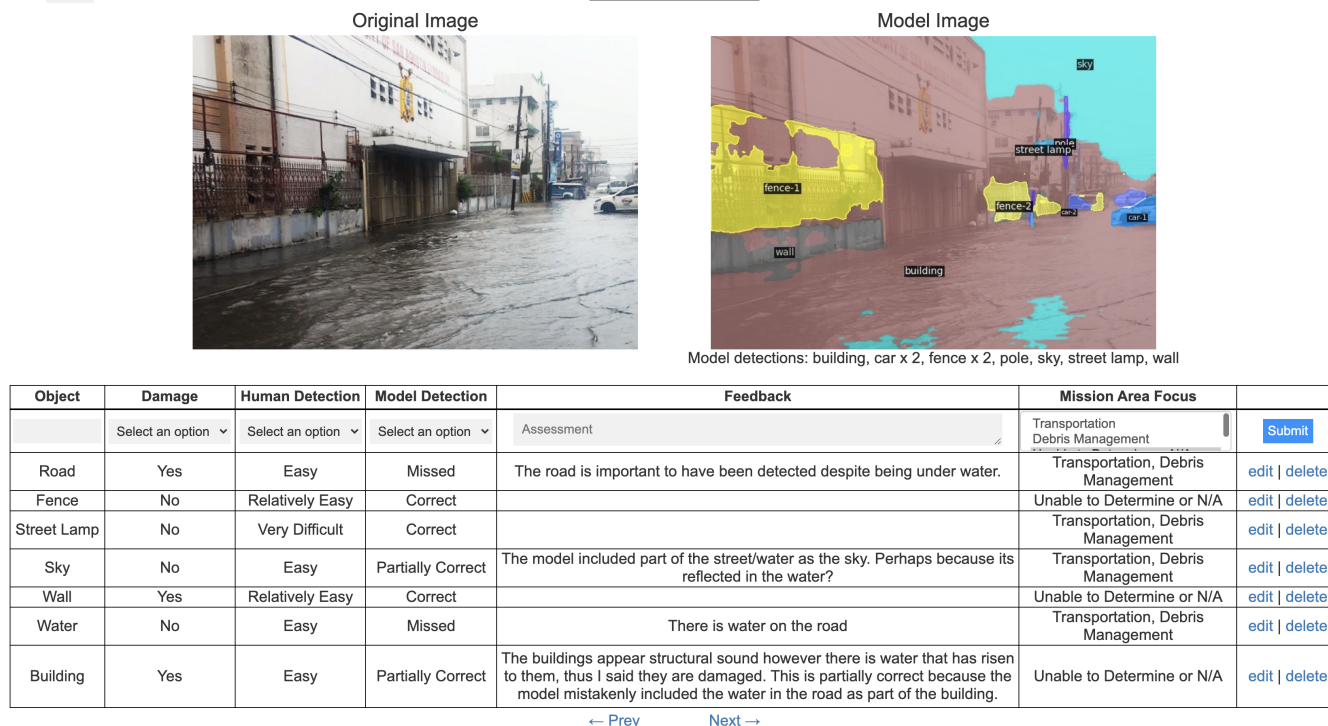


Figure S1: Web user interface

### 1.2.1 Strengths

1. Buildings which are easy to detect by humans and has zero to medium damage, are accurately predicted by models whether the building is in far distance or nearby.
2. In most cases undamaged vehicles are accurately predicted (at certain angles when the whole vehicle is seen) by the model whether the object is in the foreground or in a very far distance (where the object is very small).
3. Model can correctly predict undamaged/slightly damaged road in the presence of road markings, separator, guardrail and vehicles.
4. Model can successfully predict and differentiate between different types of agriculture (e.g trees, palm trees, grass, plant etc.).
5. Mountains in the far distance (and have clear sky) are usually predicted accurately by the model
6. If the nearby damage is not severe, model can correctly identify the pole, even if it is a bit damaged itself.
7. Model is able to detect boats in the sea even if the view is distant.
8. Model can correctly identify partially submerged cars.
9. The model is able to partially detect sea or river in images.
10. Model can partially detect the water during hurricane.

### 1.2.2 Weaknesses

1. Debris prediction causes other object predictions to be inaccurate.
2. Larger objects can overshadow the prediction of other relatively smaller objects.
3. Due to higher variations in flood water, e.g muddy water, clear water, water with debris etc. model predictions are not always correct.

4. Vehicles and other objects almost fully submerged in water makes it hard for the model predictions.
5. Damage level to the object affects the performance of the model prediction, higher the damage, poorer the performance.
6. Model misses to detect vehicles (car, motorbike) under debris and mispredicts as ground.
7. Certain angles i.e. front view i.e. back half makes it difficult for the model to predict light vehicles like bicycles and motorbikes.
8. If a portion of a light vehicle is shown i.e. the back half of a bicycle, the model tends to miss the object
9. The model tends to miss light vehicles in the far distant due to the very small size of the object
10. Inclined poles which represents a damaged pole is more often missed by the model as compared to straight, undamaged poles.
11. The model tends to miss poles in front of buildings as the pole gets added to the building prediction, possible due to the similar coloring
12. Highly ruptured roads are not correctly detected by the model, as it tends to confuse the deep creeks with mountain or ground.
13. The model detection of sidewalks is rarely accurate due to the presence of crowds in the image.
14. Trees next to each other are predicted as one tree
15. The model does not identify any animal.

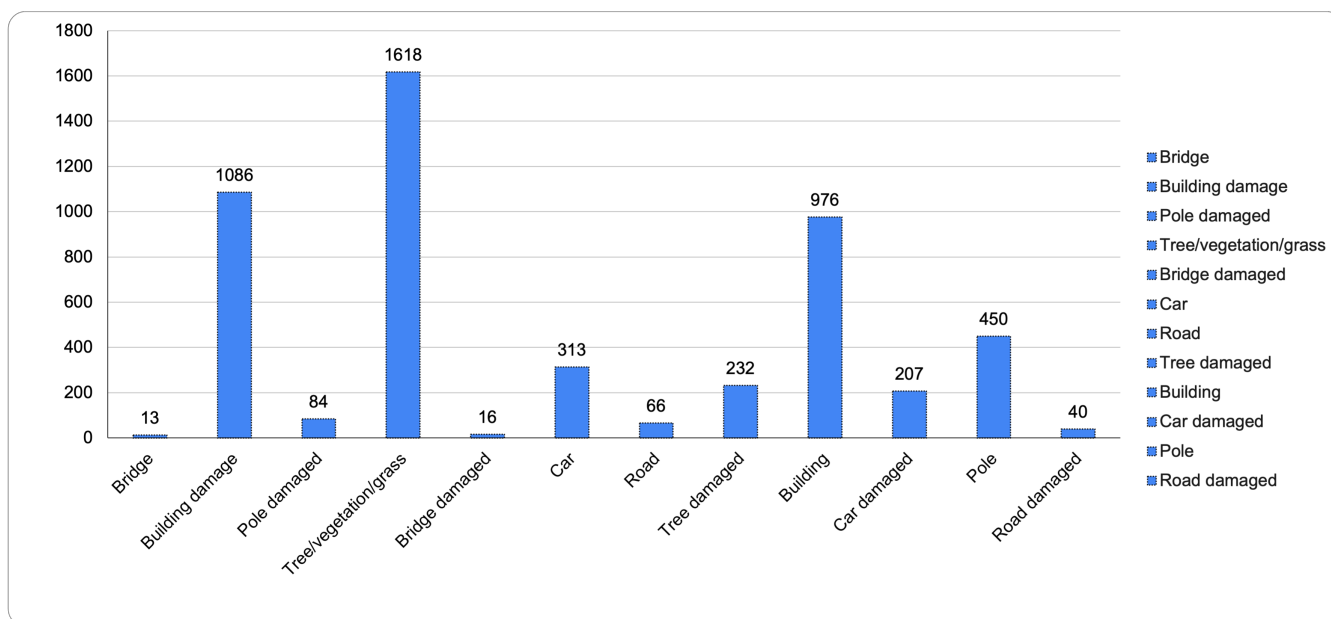
### 1.2.3 Limitations

Deep learning models are trained with fixed number of objects. If a model fails to identify an object, not part of its training taxonomy, it can not be considered as the failure of model, rather it is considered as the limitation. Some of the limitations we observed for current state-of-the-art object detection models for disaster object detection are:

1. Model does not identify pipe/conduit.
2. Model does not identify ladders.
3. Model confused bucket/cell phone with box.
4. Model does not identify wheelchair and sometimes confuses wheelchair as bicycle.
5. Model does not identify heavy vehicles like backhoe.
6. Model does not identify all types of wiring such as utility lines, cables, power lines etc.
7. Model also fails to identify power transformers.

## 1.3 Object Count, Differential and Relevance

This section describes the object count, differential and relevance for each object included in the proposed taxonomy. Table S1 provides the details for the Natural and Living class, Table S2 includes details for the Transportation, Infrastructure and Utilities class, Table S3 provides the details for the Debris Removal, Response, and Shelter class and Table S4 include the list of objects excluded from final taxonomy. The counts for each object across both disaster are recorded where the total count is also recorded. With regards to differentials, objects that appear 50% or greater in one disaster type versus the other are highlighted in bold as being noteworthy. However, if an object appeared less than 10 times in a disaster type and 0 times in the other disaster type, it was not highlighted due to the infrequency of its appearance in the overall 946 images. Object differentials highlighted in bold can be positive or negative, where the positive values indicate that the earthquake disaster has far more objects as compared to hurricanes. The opposite applies for negative values, where the object appears much frequently in hurricane images as compared to earthquake images. Moreover, a relevance score was assigned to each object by the CEM<sup>®</sup> where the following scale was used: 3 = relevant to both transportation and debris removal; 2 = relevant to either



**Figure S2:** Distribution of instances of each object in Training Dataset

100 transportation or debris removal; 1 = relevant to another support function other than transportation and  
 101 debris removal; 0 = irrelevant to any disaster support function.

**Table S1.** Differentials and Relevance for Natural and Living Classes

	Object Classes	Earthquake Count	Hurricane Count	Total	Differential	Relevance
	<b>Natural &amp; Living</b>					
<b>Natural</b>	sky	310	248	558	62	3
	mountain	29	28	57	1	1
	sea	3	28	31	-25	3
	water	5	159	164	-154	3
	ground	208	167	375	41	3
	tree	220	424	644	-204	3
	sand	0	13	13	-13	1
	river	0	5	5	-5	3
	path	0	5	5	-5	3
	hill	0	1	1	-1	1
	creek	1	0	1	1	2
<b>Living</b>	person	174	78	252	96	1
	victim	2	0	2	2	1
	animal	4	3	7	1	1
	dog	8	0	8	8	1

## 2 DATASET FOR QUANTITATIVE ANALYSIS

### 102 2.1 Taxonomy

103 This section provides the full hierarchical diagram of taxonomy in Figure S3, where the human-identified  
 104 objects are highlighted with an asterisk and the objects are color coded based on the relevancy score.

**Table S2.** Differentials and Relevance for Transportation, Infrastructure and Utilities Classes

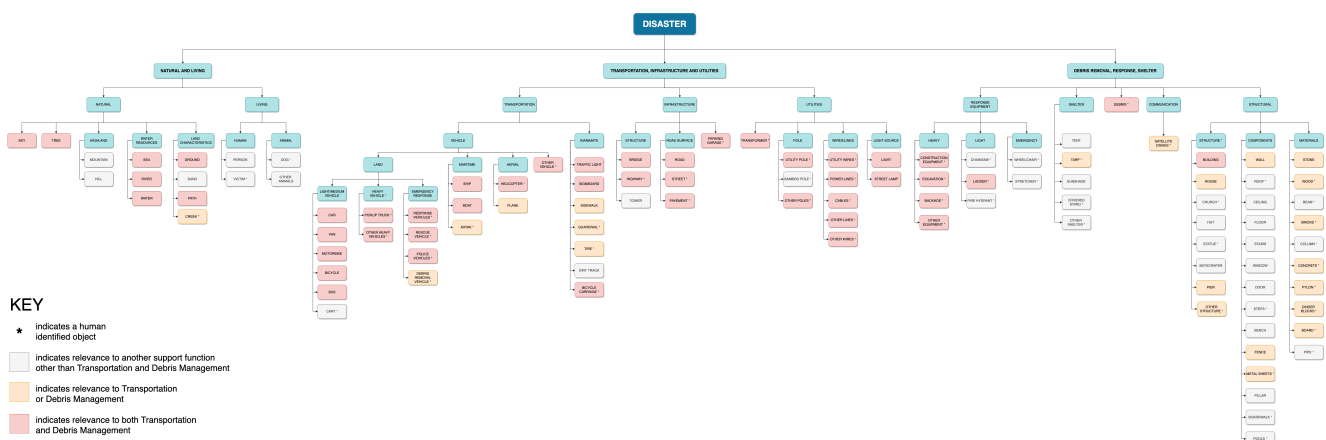
	Object Classes	Earthquake Count	Hurricane Count	Total	Differential	Relevance
		<b>Transportation</b>		<b>Infrastructure &amp; Utilities</b>		
<b>Infrastructure</b>	road	85	142	227	-57	3
	bridge	2	11	13	-9	3
	tower	7	1	8	6	1
	street	0	1	1	-1	3
	highway	0	1	1	-1	3
	pavement	0	1	1	-1	3
	parking garage	0	1	1	-1	3
<b>Transportation</b>	guardrail	2	1	3	1	2
	sidewalk	24	28	52	-4	2
	car	71	122	193	-51	3
	vehicle	13	6	19	7	3
	response vehicles	1	0	1	1	3
	rescue vehicle	1	0	1	1	3
	police vehicles	0	1	1	-1	3
	heavy vehicle	2	13	15	-11	3
	motorbike	11	6	17	5	3
	van	6	6	12	0	3
	pickup truck	1	0	1	1	3
	ship	1	1	2	0	3
	helicopter	1	0	1	1	3
	bus	1	4	5	-3	3
	boat	1	40	41	-39	3
	bicycle	16	13	29	3	3
	bicycle carriage	1	0	1	1	3
	debris removal vehicle	2	0	2	2	2
	traffic light	3	2	5	1	3
	signboard	44	69	113	-25	3
	plane	0	2	2	-2	2
	kayak	0	2	2	-2	2
	cart	3	0	3	3	1
	tire	1	1	2	0	2
	dirt track	7	0	7	7	1
<b>Utilities</b>	pole	97	118	215	-21	3
	utility pole	7	0	7	7	3
	bamboo pole	1	0	1	1	1
	street lamp	19	30	49	-11	3
	utility wires	4	0	4	4	3
	wires	9	1	10	8	3
	power lines	4	12	16	-8	3
	transformer	1	2	3	-1	3
	cables	4	0	4	4	3
	line	0	2	2	-2	3
	light	3	0	3	3	3

**Table S3.** Differentials and Relevance for Debris Removal, Response and Shelter Classes

	Object Classes	Earthquake Count	Hurricane Count	Total	Differential	Relevance
	<b>Debris Removal, Response, and Shelter</b>					
<b>Debris</b>	debris	85	39	124	<b>46</b>	3
<b>Response Equipment</b>	construction equipment	3	7	10	-4	3
	equipment	4	1	5	3	3
	excavation	16	0	16	16	3
	backhoe	1	0	1	1	3
	chainsaw	0	1	1	-1	1
	ladder	5	0	5	5	3
	wheelchair	1	0	1	1	1
	stretcher	12	0	12	12	1
	fire hydrant	0	1	1	-1	1
<b>Communications</b>	satellite dishes	2	0	2	2	2
<b>Structural</b>	building	374	276	650	98	3
	structure	6	2	8	4	2
	wall	98	78	176	20	2
	house	4	54	58	<b>-50</b>	2
	church	1	1	2	0	1
	hut	1	2	3	-1	1
	stone	88	15	103	<b>73</b>	2
	metal sheet	13	0	13	<b>13</b>	2
	wood	25	0	25	<b>25</b>	2
	beam	4	0	4	4	1
	bricks	12	0	12	<b>12</b>	2
	column	2	0	2	2	1
	concrete	2	1	3	1	2
	roof	3	1	4	2	1
	ceiling	6	12	18	<b>-6</b>	1
	floor	14	14	28	0	1
	stairs	14	8	22	6	1
	window	10	9	19	1	1
	door	10	7	17	3	1
	steps	1	0	1	1	1
	skyscraper	0	1	1	-1	1
	pillar	0	2	2	-2	1
	pylon	0	1	1	-1	2
	pools	0	1	1	-1	1
	cinder blocks	0	1	1	-1	2
	board	0	1	1	-1	2
	fence	47	88	135	-41	2
	bench	1	3	4	-2	1
	statue	2	2	4	0	1
	pipe	1	1	2	0	1
	pier	0	4	4	-4	2
	boardwalk	0	1	1	-1	1
<b>Shelter</b>	tent	2	2	4	0	1
	tarp	2	0	2	2	2
	sunshade	3	2	5	1	1
	shelter	0	2	2	-2	1
	covered stand	1	1	2	0	1

**Table S4.** Object Differentials and Relevance for Irrelevant Object Classes

	Object Classes	Earthquake Count	Hurricane Count	Total	Differential	Relevance
	Irrelevant					
Irrelevant	irrelevant	4	13	17	-9	0
	news banner	1	1	2	0	0
	liquid tank	1	0	1	1	0
	mailbox	0	3	3	-3	0
	umbrellas	0	2	2	-2	0
	trade name	0	2	2	-2	0
Interior Objects	chair	6	5	11	1	0
	table	3	2	5	1	0
	box	11	4	15	7	0
	bag	6	3	9	3	0
	bottle	3	0	3	3	0
	trash can	1	1	2	0	0
	toy	1	0	1	1	0
	shelf	1	0	1	1	0
	furniture	1	0	1	1	0
	stand	0	1	1	-1	0
	rack of plastic containers	0	1	1	-1	0
	pot	0	1	1	-1	0
	handrail	0	1	1	-1	0
	ball	0	1	1	-1	0
	sconce	0	2	2	-2	0
	cabinet	0	2	2	-2	0
	bucket	1	0	1	1	0
	bell	1	0	1	1	0
	basket	1	1	2	0	0
	picture	2	0	2	2	0
	flag	2	3	5	-1	0
	rail	1	8	9	-7	0
	pails	1	0	1	1	0
	barrel	0	1	1	-1	0



**Figure S3: Proposed Taxonomy for Disaster Object Detection**