PreDisM: Pre-Disaster Modeling With CNN Ensembles for At-Risk Communities

NEURAL INFORMATION PROCESSING SYSTEMS

Vishal Anand
vishal.anand@columbia.edu

Yuki Miura
yuki.miura@columbia.edu

NeurIPS: Tackling Climate Change with Machine Learning, 2021

Natural Hazards amidst Climate Change






Natural Hazards amidst Climate Change

Need to adapt to the threats by implementing proper mitigation

Lack of Data

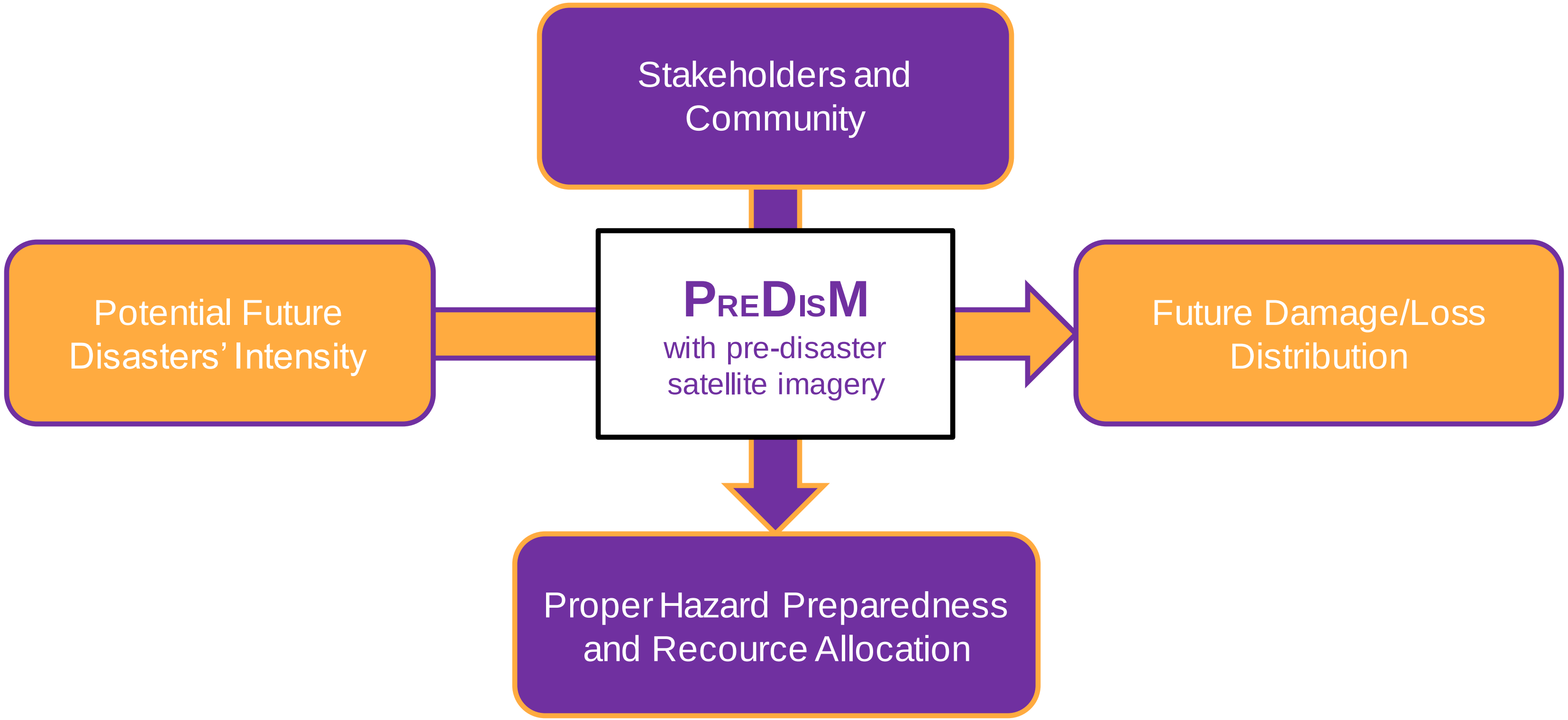
Pre-Disaster

Regions without Previous Hazards

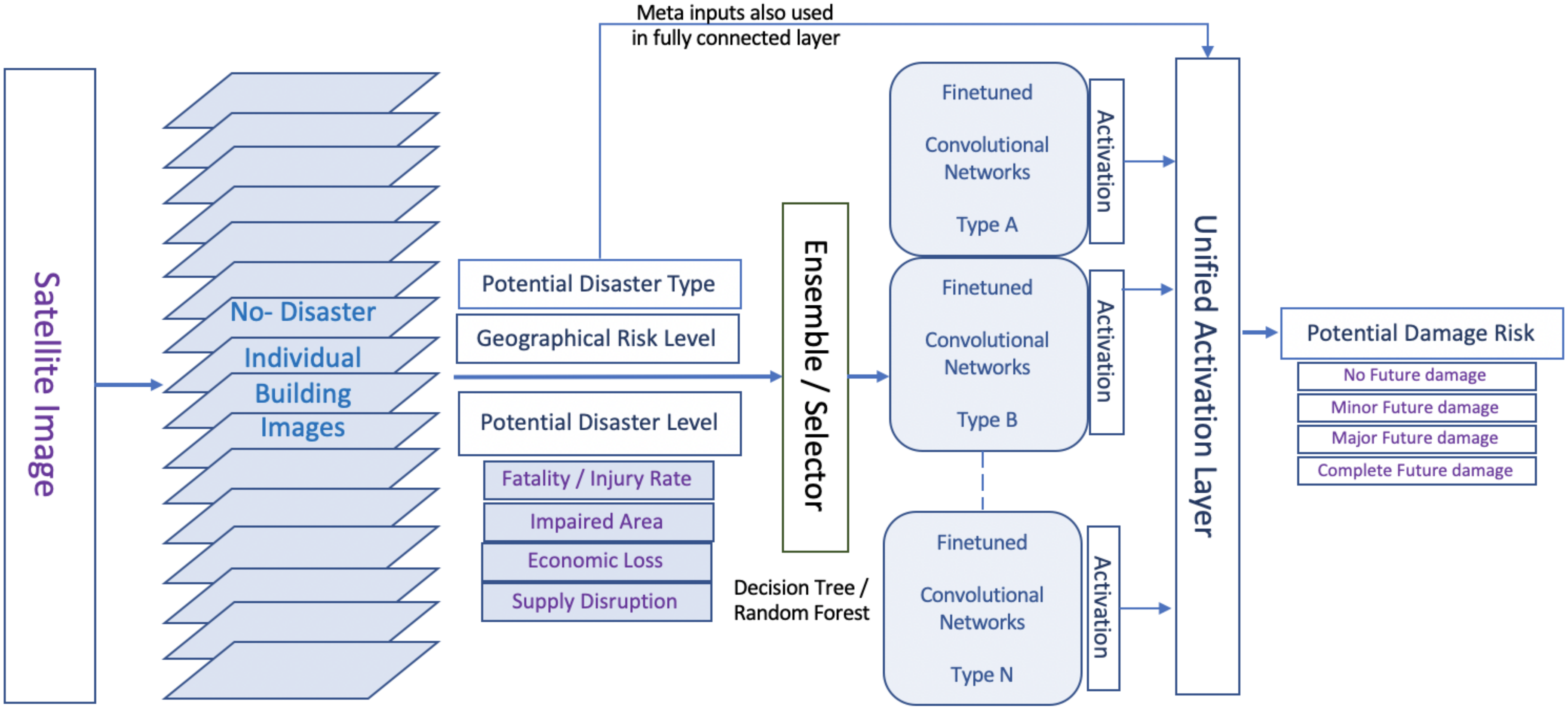
PreDisM

Pre-Disaster Modeling of Damages to Civilization

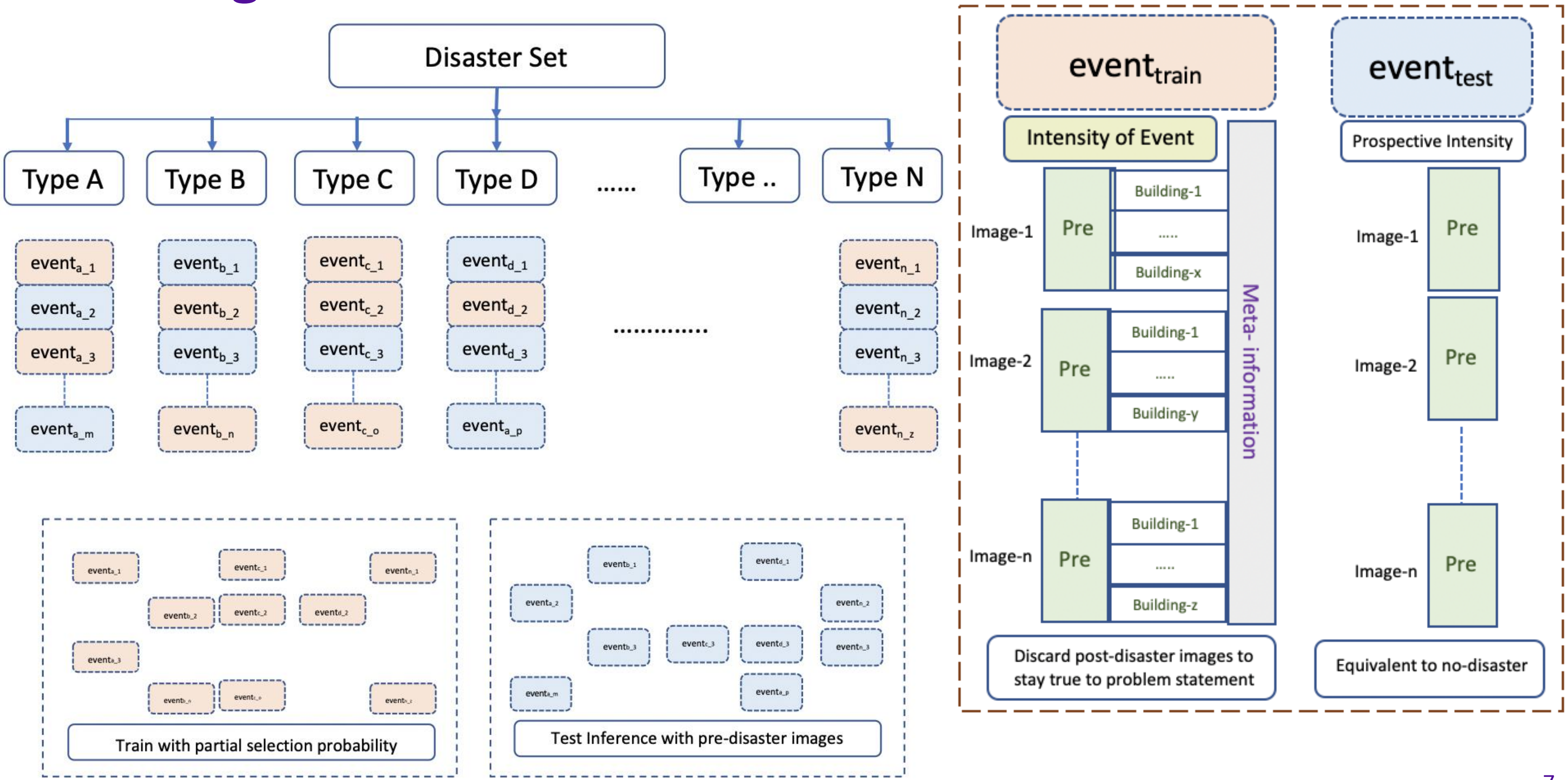
Problem Introduction and Motivation



Model


Meta inputs also used
in fully connected layer
Satellite Image
No- Disaster
Individual
Building
Images
Potential Disaster Type
Geographical Risk Level
Potential Disaster Level
Fatality / Injury Rate
Impaired Area
Economic Loss
Supply Disruption
Ensemble / Selector
Decision Tree /
Random Forest
Finetuned
Convolutional
Networks
Type A
Activation
Finetuned
Convolutional
Networks
Type B
Activation
Finetuned
Convolutional
Networks
Type N
Activation
Unified Activation Layer
Potential Damage Risk
No Future damage
Minor Future damage
Major Future damage
Complete Future damage

Model Usage



Disaster Set
Type A
Type B
Type C
Type D
......
Type ..
Type N
event_{a_1}
event_{a_2}
event_{a_3}
event_{a_m}
event_{b_1}
event_{b_2}
event_{b_3}
event_{b_n}
event_{c_1}
event_{c_2}
event_{c_3}
event_{c_o}
event_{d_1}
event_{d_2}
event_{d_3}
event_{a_p}
....
event_{n_1}
event_{n_2}
event_{n_3}
event_{n_z}
Train with partial selection probability
Test Inference with pre-disaster images
$\text{event}_{\text{train}}$
Intensity of Event
Meta- information
Image-1
Pre
Building-1
.....
Building-x
Image-2
Pre
Building-1
.....
Building-y
Image-n
Pre
Building-1
.....
Building-z
Discard post-disaster images to stay true to problem statement
$\text{event}_{\text{test}}$
Prospective Intensity
Image-1
Pre
Image-2
Pre
Image-n
Pre
Equivalent to no-disaster

Data

Hazard Type	Location/Name	Year
Earthquake	Mexico City	2017
Wildfire	Santa Rosa, CA	2017
	Pinery	2015
	Portugal	2017
	Woolsey, CA	2018
Flood	Midwest, US	2019
	Nepal	2017
Hurricane	Florence	2018
	Harvey	2017
	Matthew	2016
	Michael	2018
Tornado	Joplin, MO	2011
	Moore, OK	2013
	Tuscaloosa, AL	2011
Tsunami	Palu, Indonesia	2018
	Sunda, Indonesia	2018
Volcanic Eruption	Guatemala	2018
	Lower Puna	2018

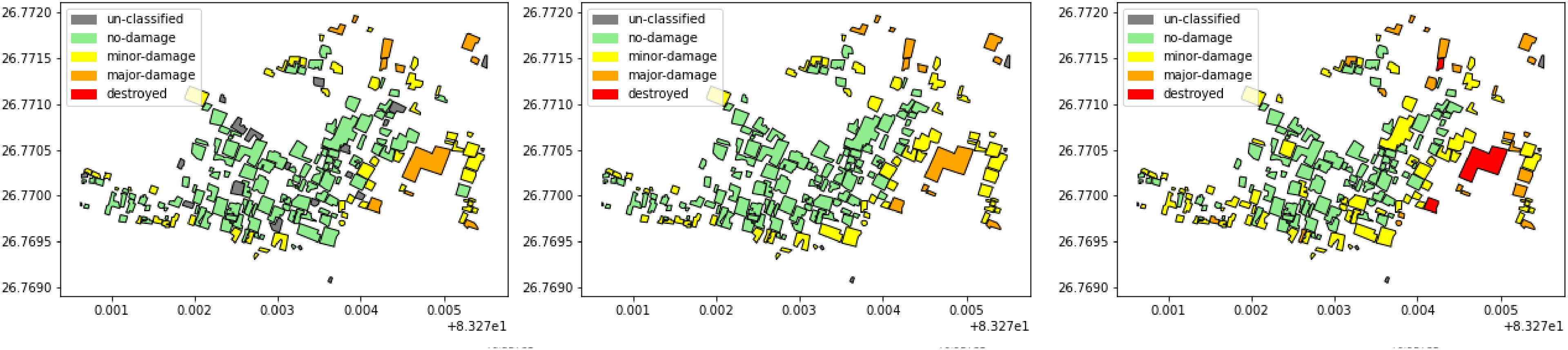
xBD Dataset. Gupta et al.

Hazard Level Metric

Hazard Levels as a function of attributes

Attributes	Hazard Level				
	5	4	3	2	1
Fatality	>10000	>1000	>100	>10	>1
Injury	>100000	>10000	>1000	>100	>10
Land Impaired (km^2)	>500	>100	>50	>10	>1
Direct Damage (billion USD)	>100	>10	>1	>0.1	>0.01
Indirect Damage (billion USD)	>100	>10	>1	>0.1	>0.01
Water Disruption (days)	>30	>14	>7	>3	>1
Energy Disruption (days)	>30	>14	>7	>3	>1

Example of Model Output



(a) Hazard Level 3 (b) Hazard Level 4 (c) Hazard Level 5

Qualitative flooding damage prediction (x =lat, y =lng) without earlier disasters: Nepal

Results

MODEL	LOSS-FUNCTION	ACCURACY
$\text{PREDISM}_{\text{RESNET-18}}$	Cross-Entropy	78.38 %
$\text{PREDISM}_{\text{RESNET-34}}$	Cross-Entropy	79.24 %
Chen_{post}	Cross-Entropy	59.50 %
	Ordinal Cross-Entropy	64.20 %

Prediction inference on non-disaster images

Takeaways

PreDisM can help society prepare for future hazards amidst climate change (stakeholders, residents, insurance, among others)

Future Work

1. Adding protective strategies will quantifiably minimize loss
2. Ablation studies on pre-disaster image sets spread across decades
3. Add crowd-sourced data to better process geographical features

PreDisM: Pre-Disaster Modelling With CNN Ensembles for At-Risk Communities

NEURAL INFORMATION PROCESSING SYSTEMS

Vishal Anand
vishal.anand@columbia.edu

Yuki Miura
yuki.miura@columbia.edu

NeurIPS: Tackling Climate Change with Machine Learning, 2021