# Human-Machine Collaboration Framework for Structural Health Monitoring

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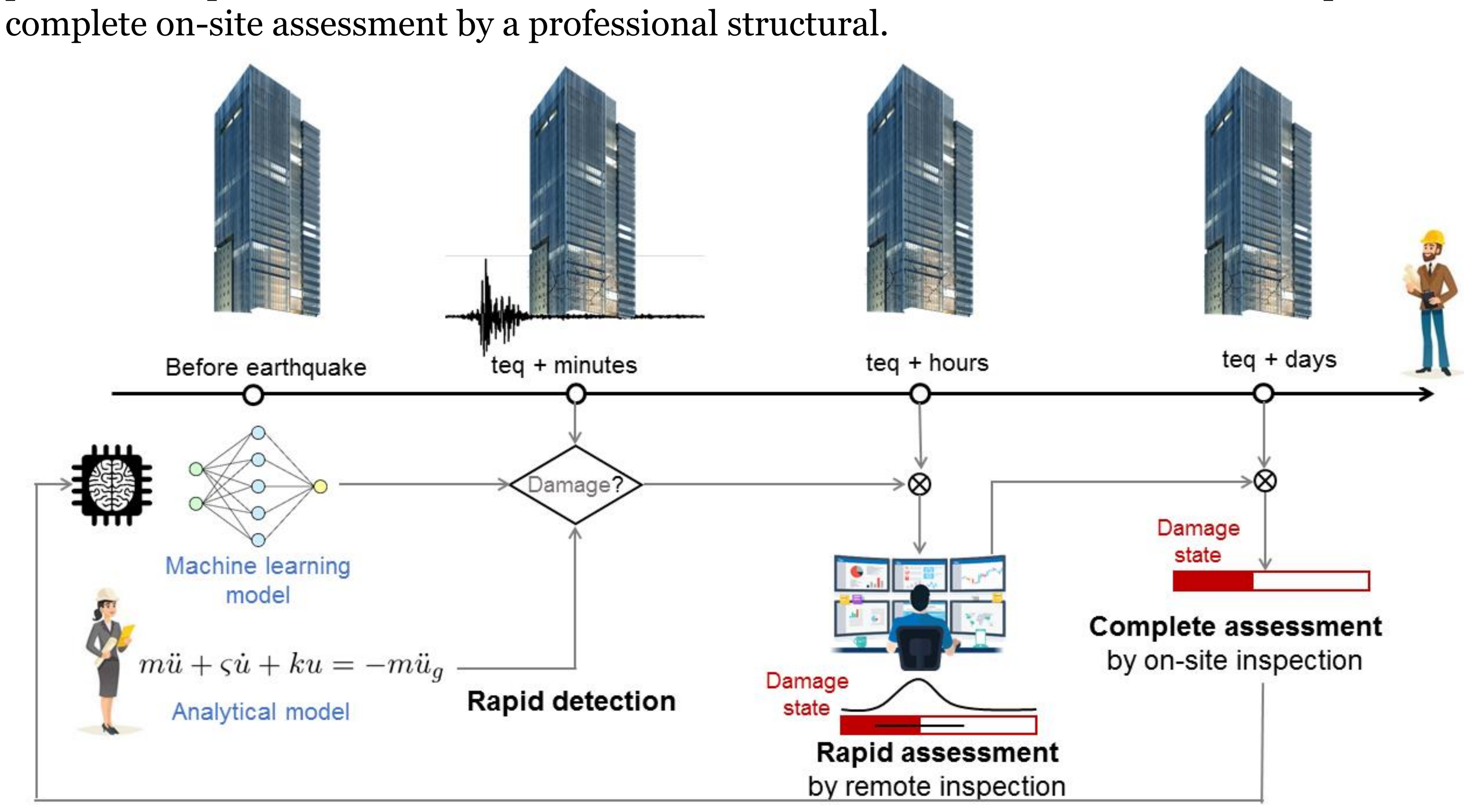
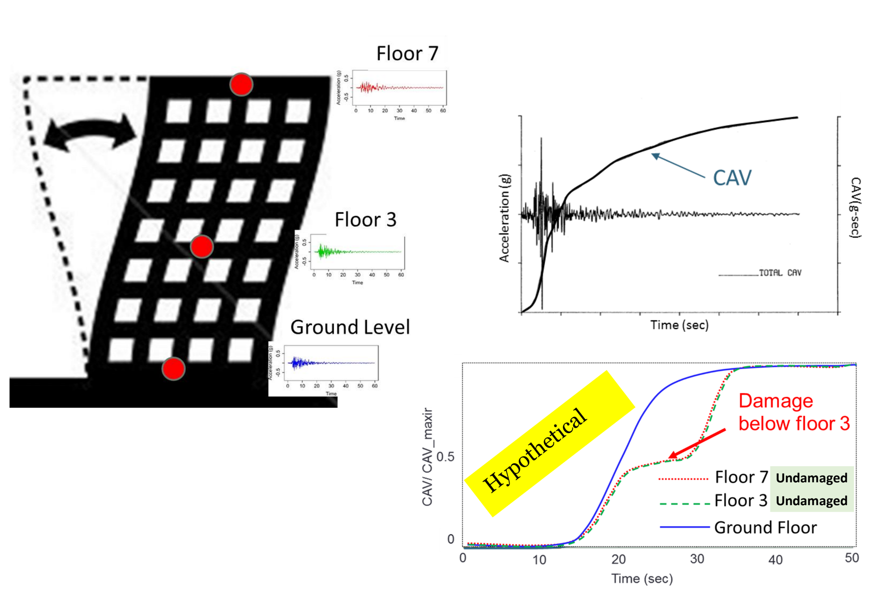
## INTRODUCTION

The human-machine collaboration (**H-MC**) is a model in which humans co-work with artificial intelligence to complete specific tasks. The H-MC for structural health monitoring (SHM) uses the speed of machine learning techniques and expertise of structural engineers for rapid post-earthquake damage assessment. In this framework, response data from undamaged structures can be used to develop an ML model. Concurrently, analytical models can be developed by the domain experts. Both these processes will happen before an earthquake. During an earthquake, ML tools can rapidly generate damage-sensitive features and using the simplified analytical model of the structure developed by a domain expert, rapid damage detection can be made within seconds after an event. Detailed analytical models along with ML tools can provide a rapid assessment within minutes. However, if a detailed model is missing, the response data can be reviewed by a skilled human counterpart to provide a rapid assessment within hours after an event. This can be followed up with a complete on-site assessment by a professional structural.




## RESEARCH MOTIVATION & BACKGROUND

Motivation of this project stems from a previous study where CAV analysis successfully detected and located damage. Result from a subsequent study indicated that CAV and $R_{CAV}$ are good damage features to be utilized in ML tools

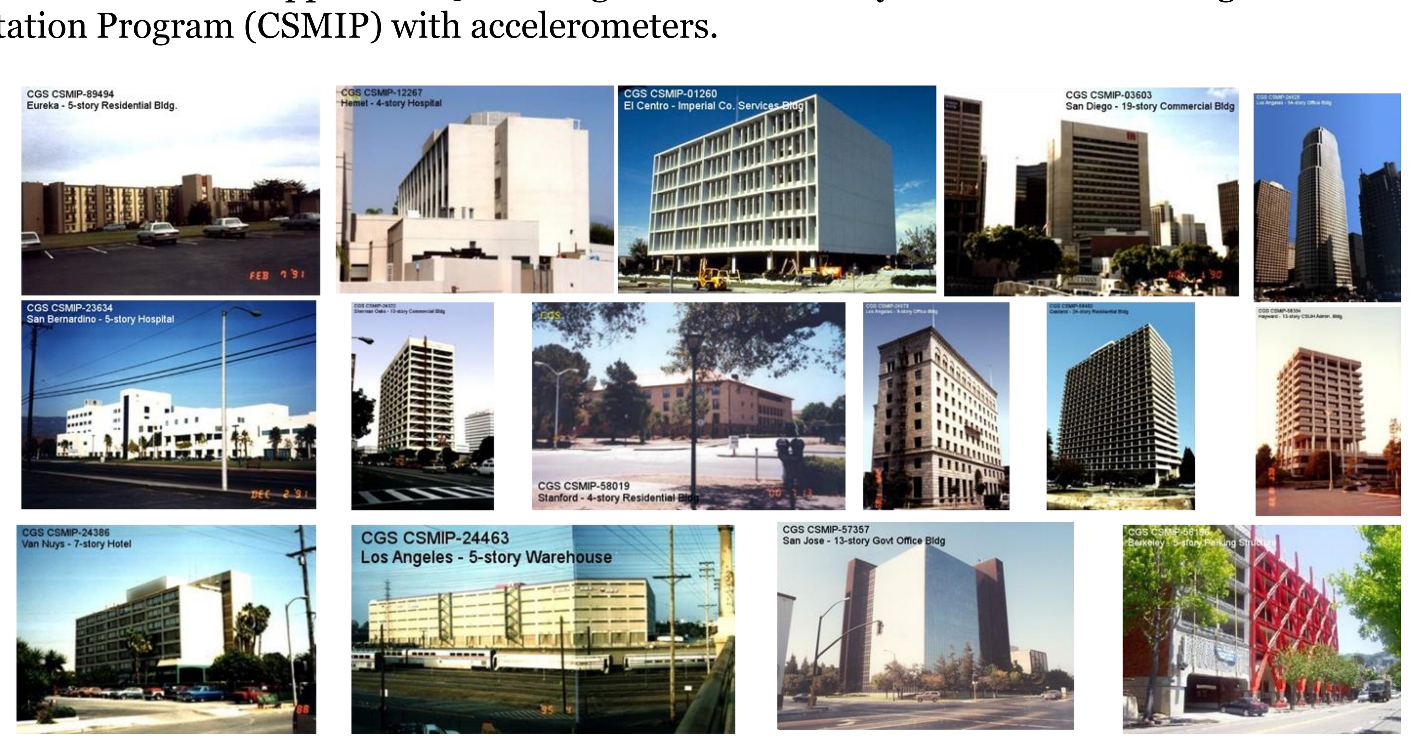



| | |
|---|---|
| Value at a sensor | $CAV = \int_0^T \lvert\ddot{u}(t)\rvert dt$ |
| Normalized w/ linear response | $R_{CAV} = \frac{CAV_s}{CAV_l}$ |

| Input Features | OLR | LR | ANN_10 | ANN_100 | SVM |
|---|---|---|---|---|---|
| CAV | 80.54 | 82.88 | 80.54 | 81.71 | 79.38 |
| $R_{CAV}$ | 87.16 | 86.72 | 88.72 | 89.49 | 88.33 |
| $\Delta_{CAV}$ | 75.10 | 75.10 | 75.10 | 77.04 | 75.10 |
| CAV, $R_{CAV}$ | 90.27 | 89.44 | 88.72 | 90.66 | 91.05 |
| $R_{CAV}$, $\Delta_{CAV}$ | 86.77 | 84.72 | 89.11 | 87.94 | 87.94 |
| CAV,$\Delta_{CAV}$ | 80.54 | 83.27 | 80.54 | 81.32 | 79.38 |
| CAV, $R_{CAV}$, $\Delta_{CAV}$ | 90.27 | 89.05 | 90.27 | 90.66 | 89.88 |

## BUILDING PORTFOLIO

The proposed framework is applied to 15 buildings instrumented by the California Strong Motion Instrumentation Program (CSMIP) with accelerometers.



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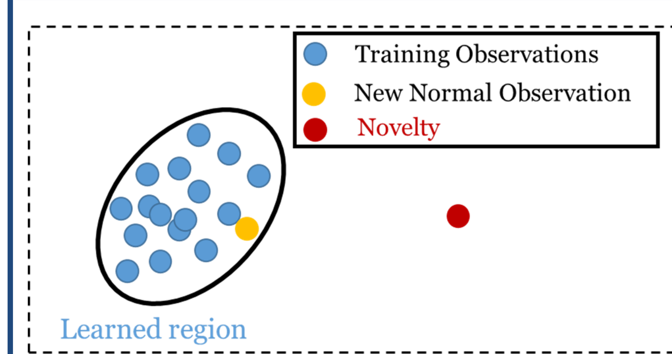
## METHODOLOGY

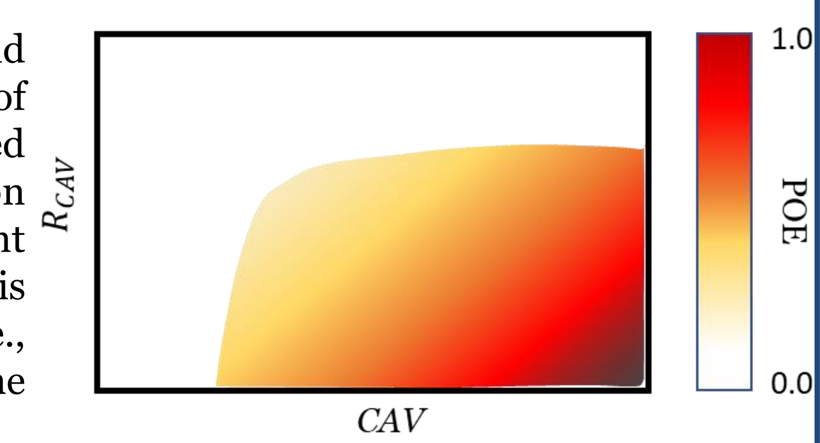



### NOVELTY DETECTION

In between supervised and unsupervised learning falls novelty detection when responses from an undamaged structure are available only. The novelty model uses the CAV and the RCAV response of an undamaged structure as training data to learn about the region belonging to the undamaged structures (black oval). It uses a distance measure of 1.5 times interquartile range (IQR) to identify novelty, i.e., the new data is a novelty if it exists more than 1.5 interquartile ranges above the upper quartile or below the lower quartile (red dot).

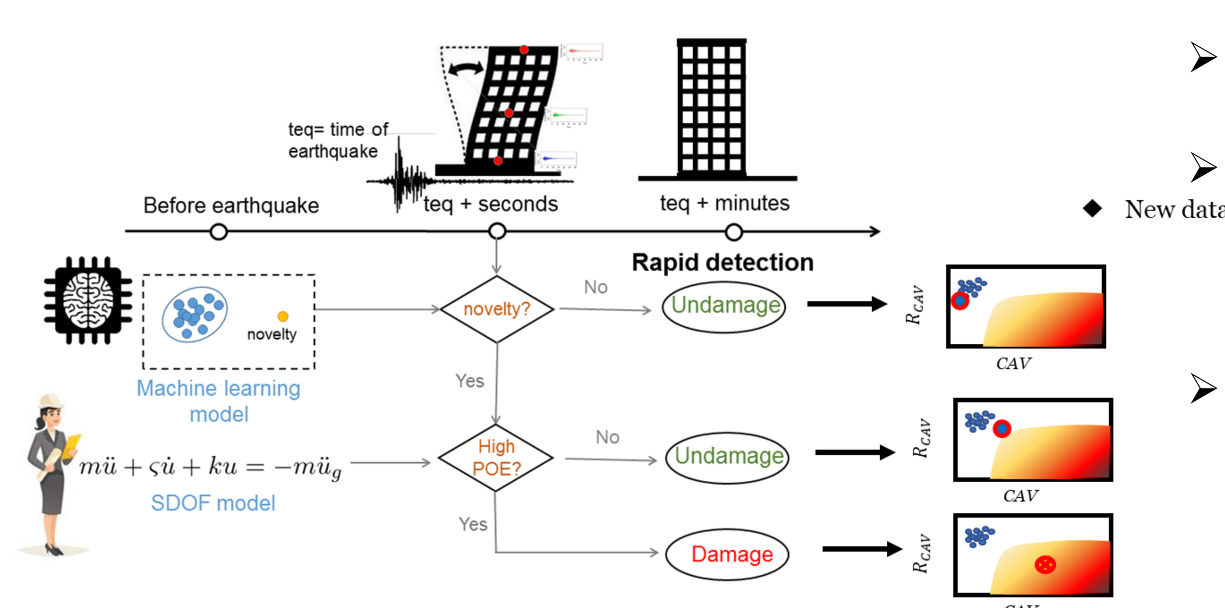
### POE ENVELOPE

Using structure specific SDOF systems and 1710 ground motions from NGA-West2, CAV and $R_{CAV}$ of the roof response of each building is calculated. Using damaged event data, a non-parametric joint cumulative distribution is developed with the kernel-based approach. This joint cumulative distribution represents the POE which is analogous to fragility curves, but with two variables, i.e., fragility surface. The darker the color the higher the probability of damage




### H-MC FOR DAMAGE DETECTION

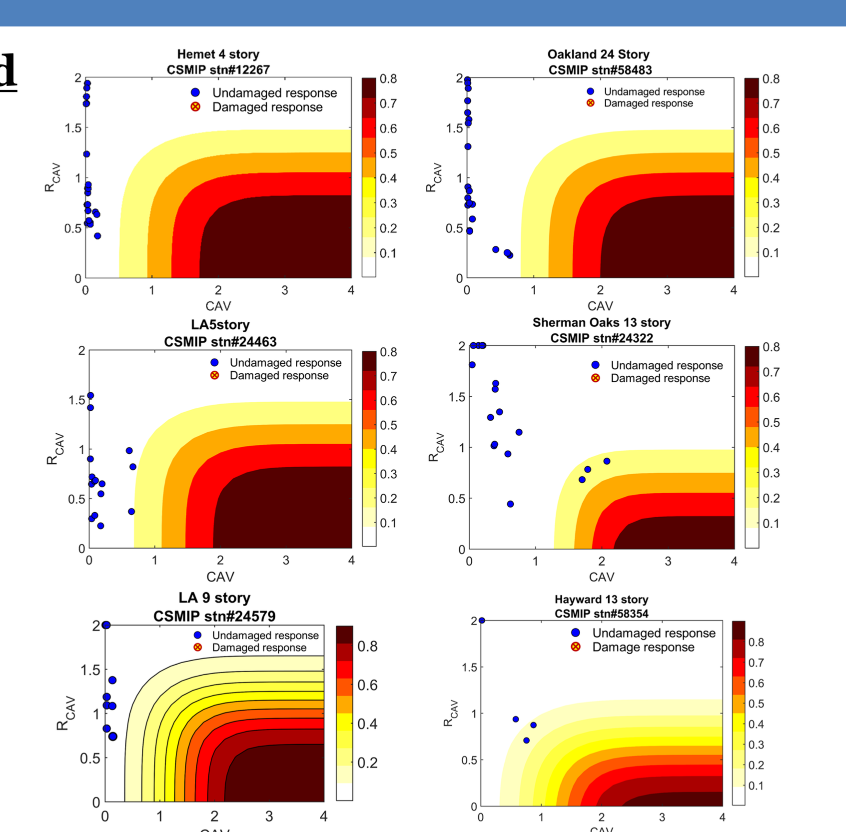
When a new earthquake occurs, the framework will first check if the new data is novelty or not

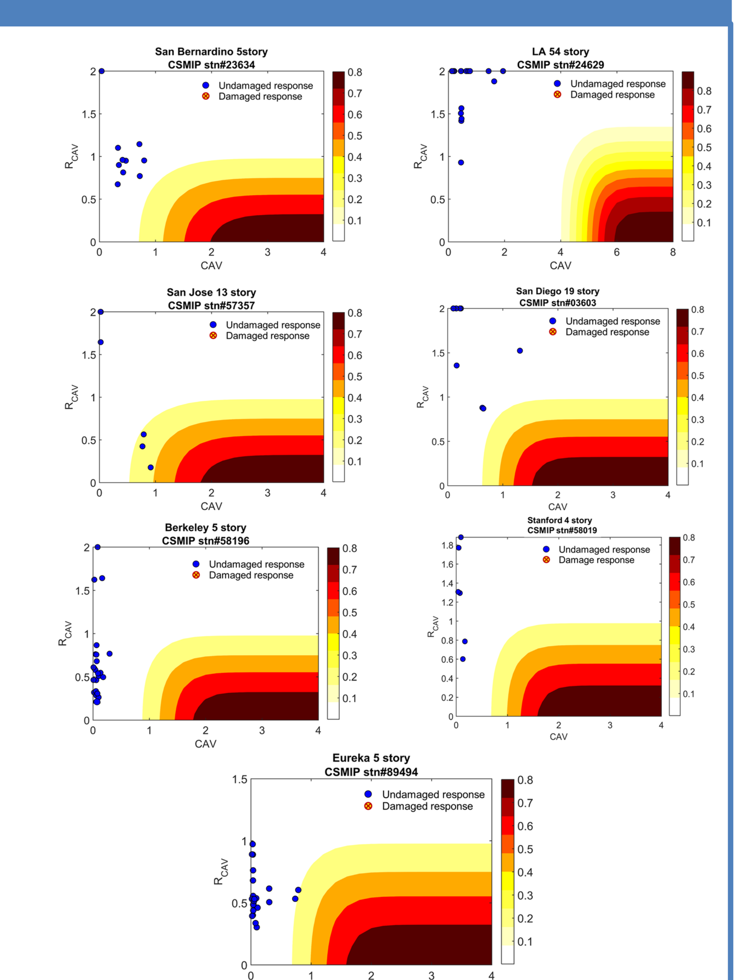



- If it's not novelty, it will be labelled as undamaged
- If it's novelty, but falls outside or in the lower probability part of the POE envelope, it is labelled as undamaged
- If it's novelty and falls inside the higher probability part of the framework, it is labelled as damaged

## RESULTS

### Undamaged structures

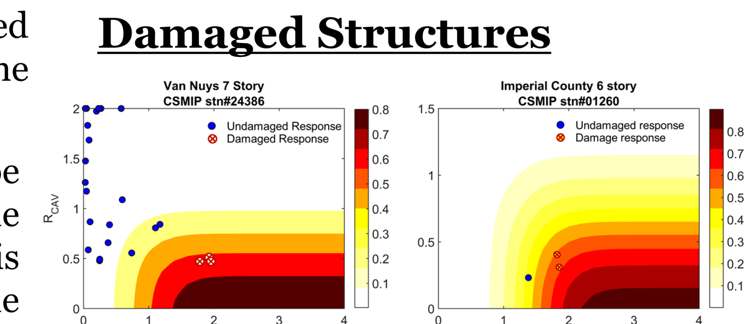



Results show that the undamaged buildings are correctly detected as indeed undamaged by the algorithm. In some cases (such as stations 58483, 24322, 58354, 57357 and 89494) novelty detection or POE envelope alone will result in false positive detection but when used together with ML these false positive results are eliminated successfully. The algorithm accurately detects damage for the damaged buildings detecting both novelty and high POE values.

In these figures, the colored envelope is that for the POE envelope with higher probability shown with darker color. The dots are the response from each sensor installed at the roof level. When the dot is blue (filled) in color, it is detected as an undamaged event. On the other hand, when the dot consists of the red cross mark, it indicates damage has been identified.

### Damaged Structures




## CONCLUSION

- The H-MC framework combines ML capabilities and human expertise for rapid SHM
- It detects damage using data from undamaged condition only.
- Application of this framework to instrumented buildings showed that the framework can correctly label damaged and undamaged buildings eliminating false positive detections.

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