







# A Large-scale Robustness Analysis of Video Action Recognition Models

WED-PM-007



Madeline C. Schiappa<sup>1</sup>



Naman Biyani<sup>3</sup>



Prudvi Kamtam<sup>1</sup>



Shruti Vyas<sup>1</sup>



Hamid Palangi<sup>2</sup>



Vibhav Vineet<sup>2</sup>



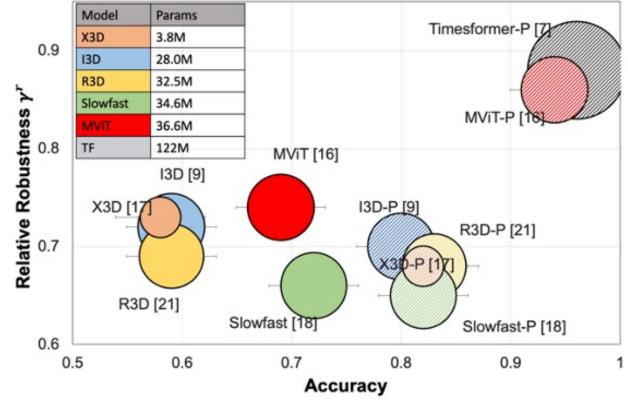
Yogesh S. Rawat<sup>1</sup>

University of Central Florida<sup>1</sup>, Microsoft Research<sup>2</sup>, IIT Kanpur, India<sup>3</sup>

# Summary

- Benchmark action-recognition models on corrupted video
  - UCF101-P, HMDB51-P Kinetics-P, SSv2-P, UCF101-DS
  - 90 Perturbations: Noise, Camera, Compression, Temporal, Blur
- Findings:
  - Pre-trained typically more robust than scratch
  - Robust to time for most datasets, but not robust when reversible actions possible.
  - Transformer-based typically more robust
  - CNN-based models typically more robust than transformer-based models when trained on corruptions

#### UCF101-P









## Motivation

"How is performance impacted by a natural distribution shift?"

#### **Curated**







#### **Simulated**









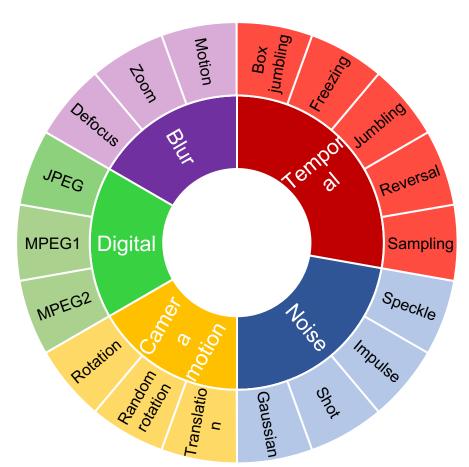








## **Perturbations**







Impulse Noise

Random Rotation





**Motion Blur** 







## **Severities**

Sev. 1



Images from SSv2 dataset.







#### **Datasets**

#### • UCF101-P

- 101 action classes.
- ~350K videos

#### • HMDB51-P

- 51 action classes
- ~140K videos

#### Kinetics400-P

- 400 action classes
- ~1.6M videos

#### SSv2-P

- 174 action classes
  - ~2.2M videos



Jumble UCF101-P



JPEG Compression HMDB51-P



Defocus Blur Kinetics400-P



Freeze SSv2-P



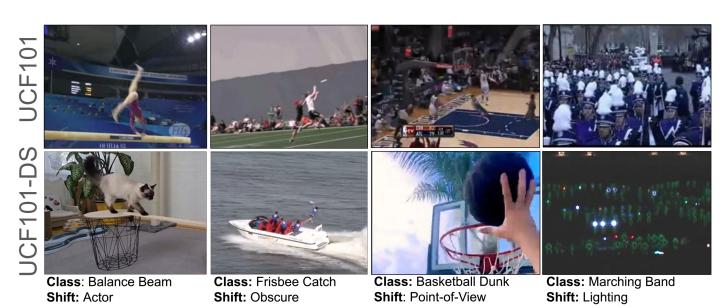


### UCF101-DS

- Real distribution shifts
  - 4,708 clips
  - 47 action classes from UCF101

- Keywords for query
  - e.g. "bike riding+fog"
- Higher level categories









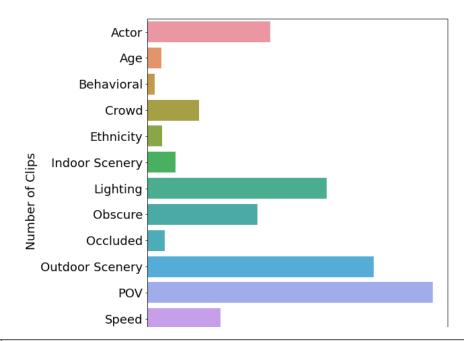




## UCF101-DS

- Real distribution shifts
  - 4,708 clips
  - 47 action classes from UCF101

- Keywords for query
  - e.g. "bike riding+fog"
- Higher level categories



Category	Distribution Shift
Actor	[animal, costume, toy]
Age	[kids, old_person]
Behavioral	[caught_on_cam!, prank, reaction, scary]
Crowd	[crowd]
Ethnicity	[african, asian, black, indian_brown]
Indoor Scenery	[at_home, at_the_club, at_the_gym, indoor, indoors, in_court, in_garage, mirror]
Lighting	[low_light, at_late_night, at_night, dark, low_light_conditions]
Obscure	[unsual, unusual]
Occluded	[obstructed, obstructed_view]
Outdoor Scenery	[at_the_beach, desert, in_backyard, in_garden, in_the_fields, on_the_road, outdoors, outside, underwater]
POV	[camera_angle, camera_angles, go_pro, on_TV, pov, pov_at_night, shaky, tutorial, upside_down]
Speed	[alow_mo, fastest, slowmotion, slow_mo]
Style	[animated, animation, filter, text_on_screen, vintage]
Weather	[fog, in_rain, muddy, rain, snow]





## **Metrics and Evaluation**

#### **Relative Robustness**

Measures relative drop in accuracy

$$\gamma_{p,s}^r = 1 - (A_c^f - A_{p,s}^f)/A_c^f$$

#### **Absolute Robustness**

Measures absolute drop in accuracy

$$\gamma_{p,s}^{a} = 1 - (A_c^f - A_{p,s}^f)/100$$

- p: Perturbation
- s: Severity
- $A_c^f$ : Accuracy on clean video
- $A_{p,s}^f$ : Accuracy on perturbed (p) video at severity s







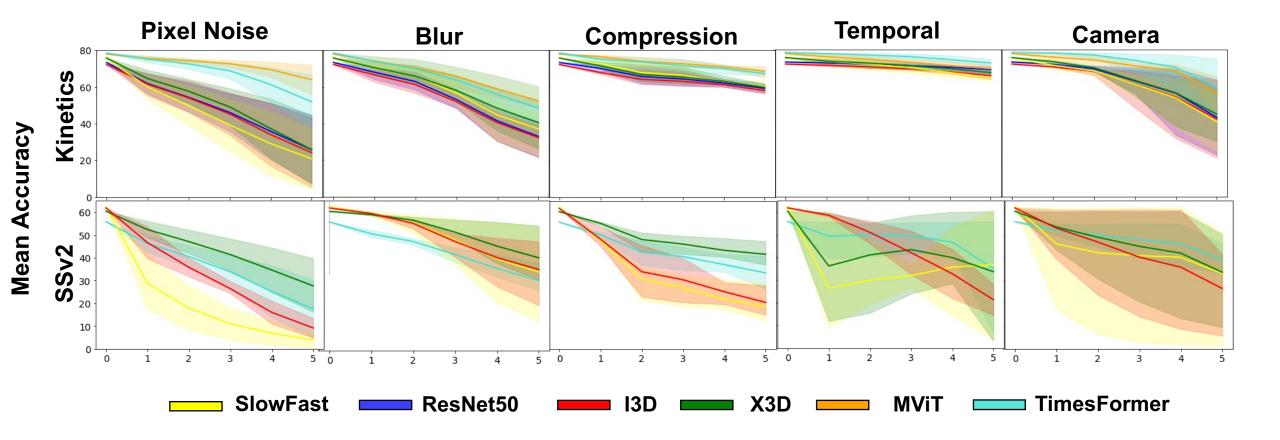
# Findings







## **Overall Results**



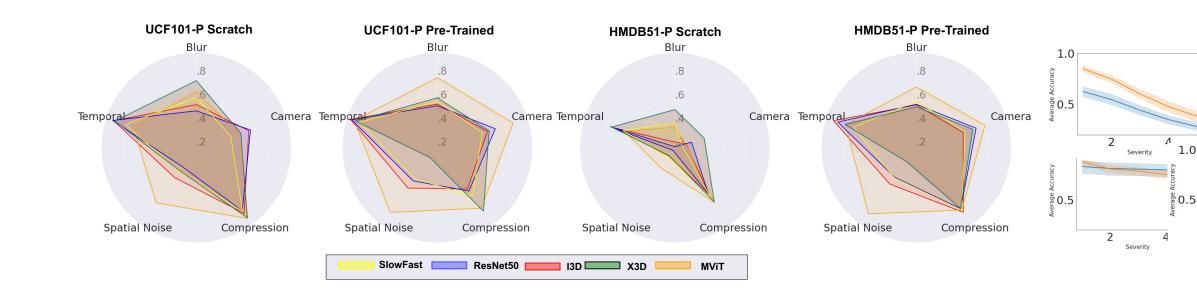






# **Pre-Training**

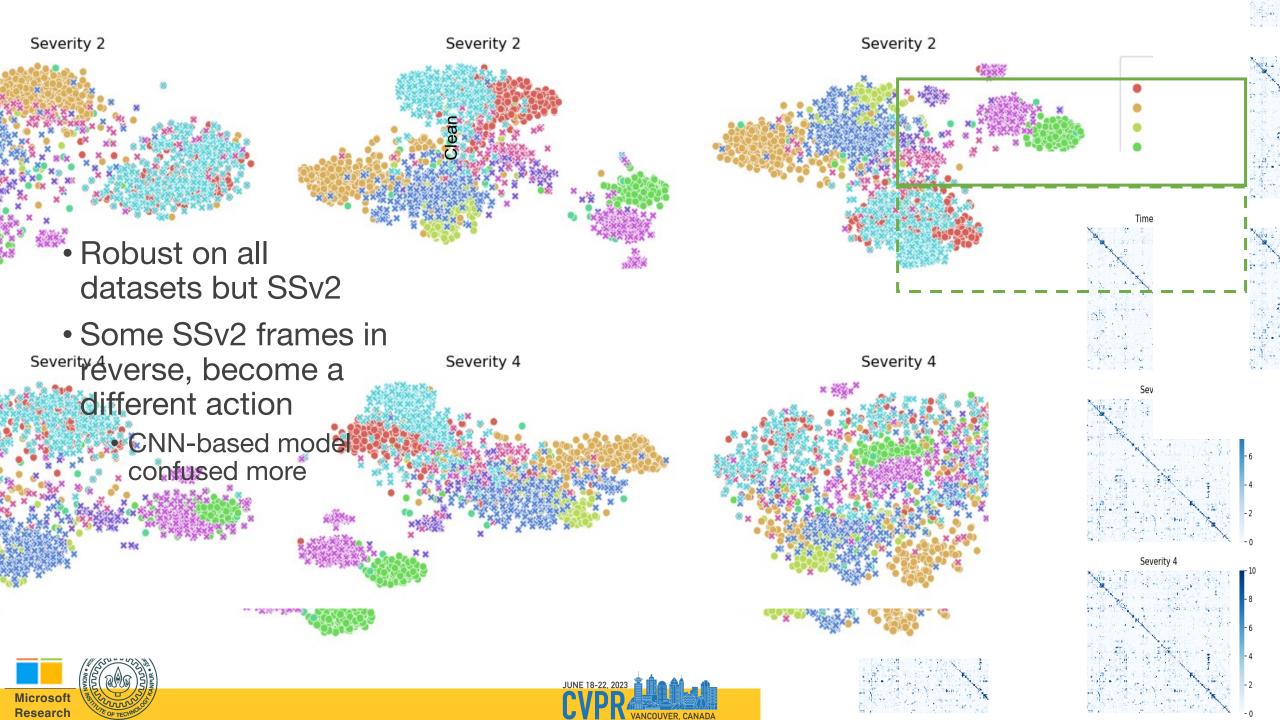
• Pre-training generally improves robustness





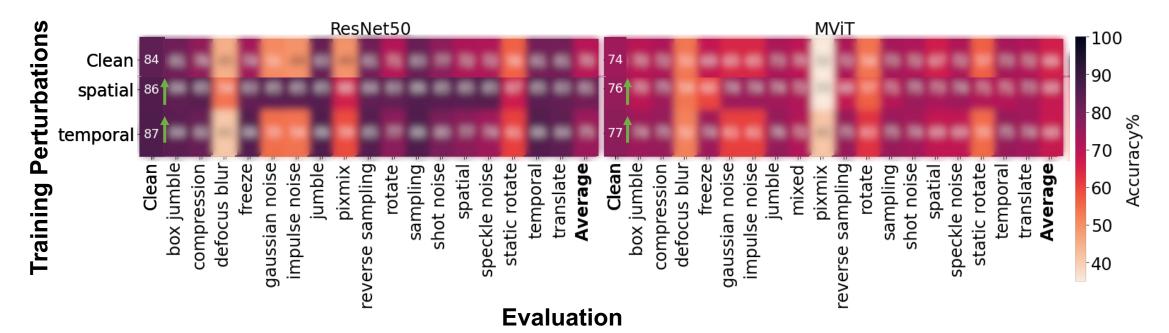






# **Training on Corruptions**

Train foundational models on corruptions



· Helps on original data

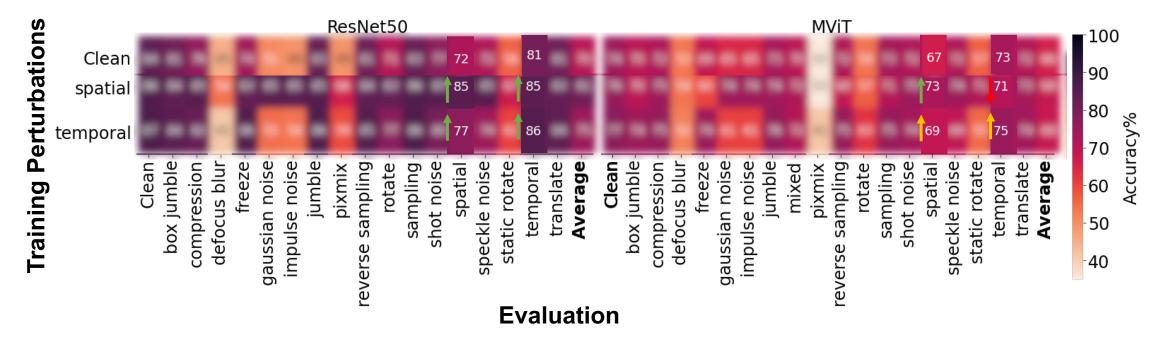






# **Training on Corruptions**

Train foundational models on corruptions



- Helps on original data
- Helps more on CNN-based architecture





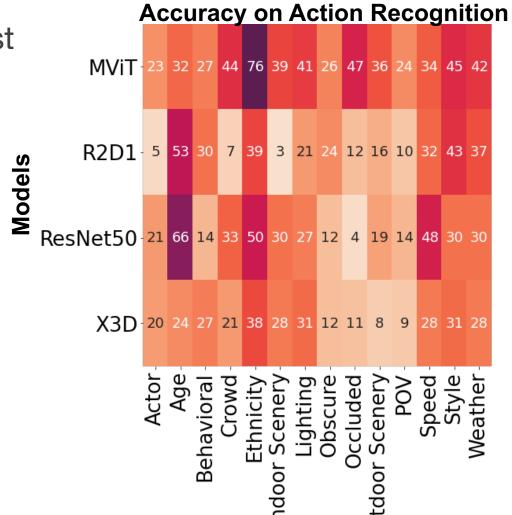


## Real Distribution Shifts: UCF101-DS

Certain architectures more robust











100

90

50

-40

Accuracy











## Thank You!

WED-PM-007



Website



Madeline C. Schiappa<sup>1</sup>



Naman Biyani<sup>3</sup>



Prudvi Kamtam<sup>1</sup>



Shruti Vyas1



Hamid Palangi<sup>2</sup>



Vibhav Vineet<sup>2</sup>



Yogesh S. Rawat<sup>1</sup>

University of Central Florida<sup>1</sup>, Microsoft Research<sup>2</sup>, IIT Kanpur, India<sup>3</sup>