



Università  
di Catania

NEXT VISION

Spin-off of the University of Catania



# Hand-Object Interactions in Egocentric Vision

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# Agenda

## 1. Introduction to Hand-Object Interactions Detection

- Human-Object Interaction vs Hand-Object Interaction
- Definition and importance of Hand-Object Interactions
- Applications in AR/VR, robotics, industrial monitoring, and assistive systems

## 2. Datasets and Benchmarks for Hand-Object Interactions in Egocentric Vision

- Overview of popular datasets
- Challenges in dataset collection and annotation
- Synthetic datasets

## 3. Models and Architectures for Hand-Object Interactions Detection

- Evaluation Protocols
- Understanding Human Hands in Contact at Internet Scale
- Exploiting multimodal synthetic data for egocentric human-object interaction detection in an industrial scenario
- Are synthetic data useful for egocentric hand-object interaction detection?

## 4. Open Challenges

- Standardization of evaluation protocols and task definitions
- Updating and improving pre-existing architectures
- Handling occlusions and complex interactions
- Integration of multimodal data

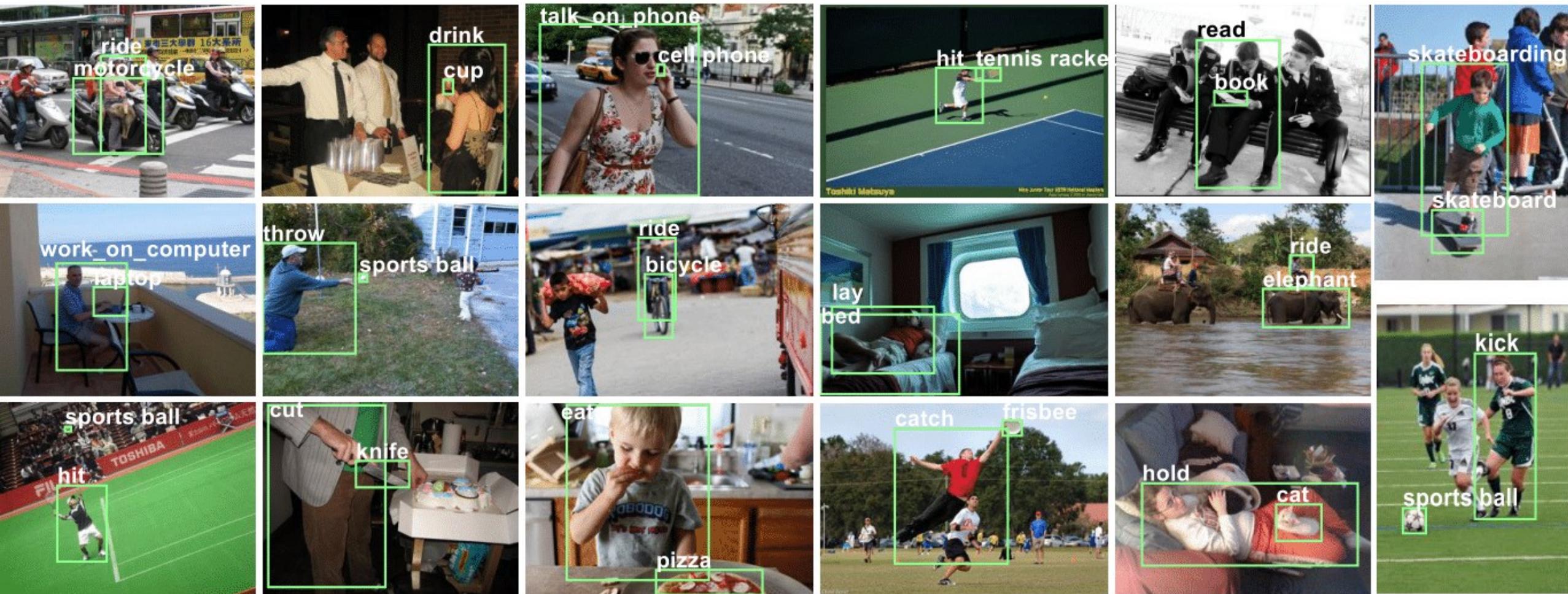


# 1. Introduction to Hand-Object Interactions Detection

# Human-Object Interactions



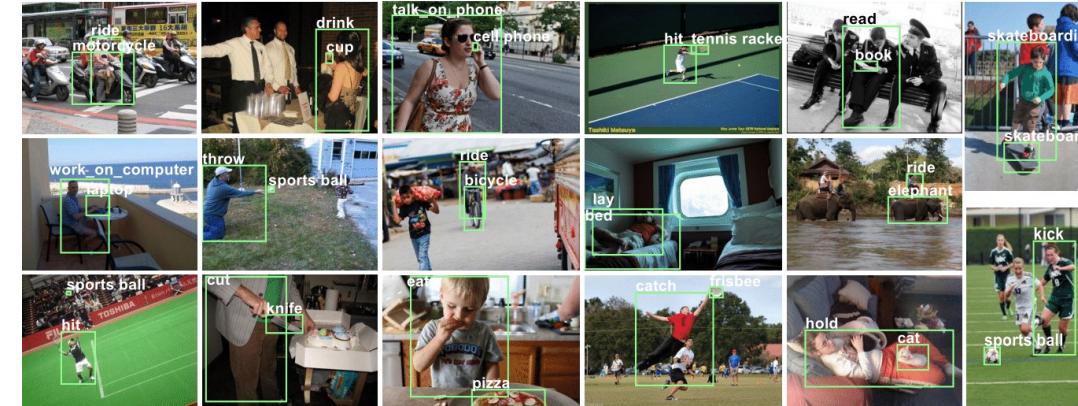
# Human-Object Interactions



The set of actions or relationships that occur when a human interacts with an object, typically described as a **(human, action, object)** triplet.

- Gupta Saurabh and Jitendra Malik. "Visual semantic role labeling" arXiv preprint arXiv:1505.04474 (2015)

# Human-Object Interactions



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- Chao Yu-Wei, et al. "Hico: A benchmark for recognizing human-object interactions in images." *Proceedings of the IEEE international conference on computer vision*. 2015.
- Chao, Yu-Wei, et al. "Learning to detect human-object interactions." *2018 ieee winter conference on applications of computer vision (wacv)*. IEEE, 2018.
- Gkioxari, Georgia, et al. "Detecting and recognizing human-object interactions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.
- Gao, Chen, Yuliang Zou, and Jia-Bin Huang. "ican: Instance-centric attention network for human-object interaction detection." *arXiv preprint arXiv:1808.10437* (2018).
- Kim, Bumsoo, et al. "Hotr: End-to-end human-object interaction detection with transformers." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2021.

# Humans Manipulate The World With Their Hands



Shan Dandan, et al. "Understanding human hands in contact at internet scale" (CVPR 2020)

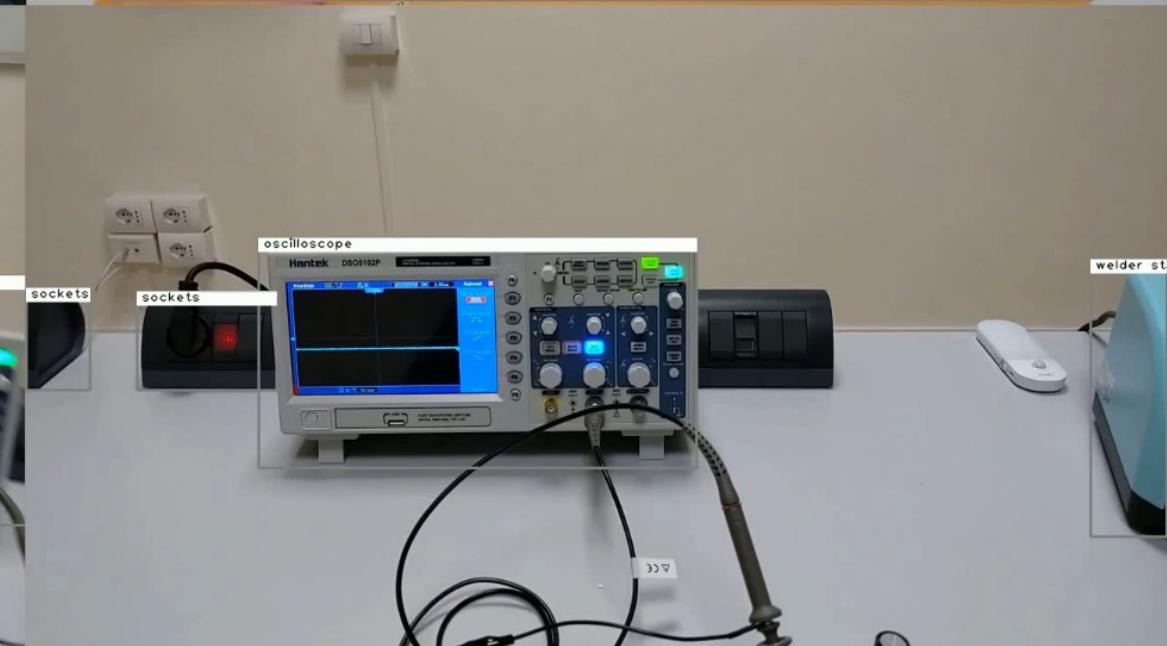
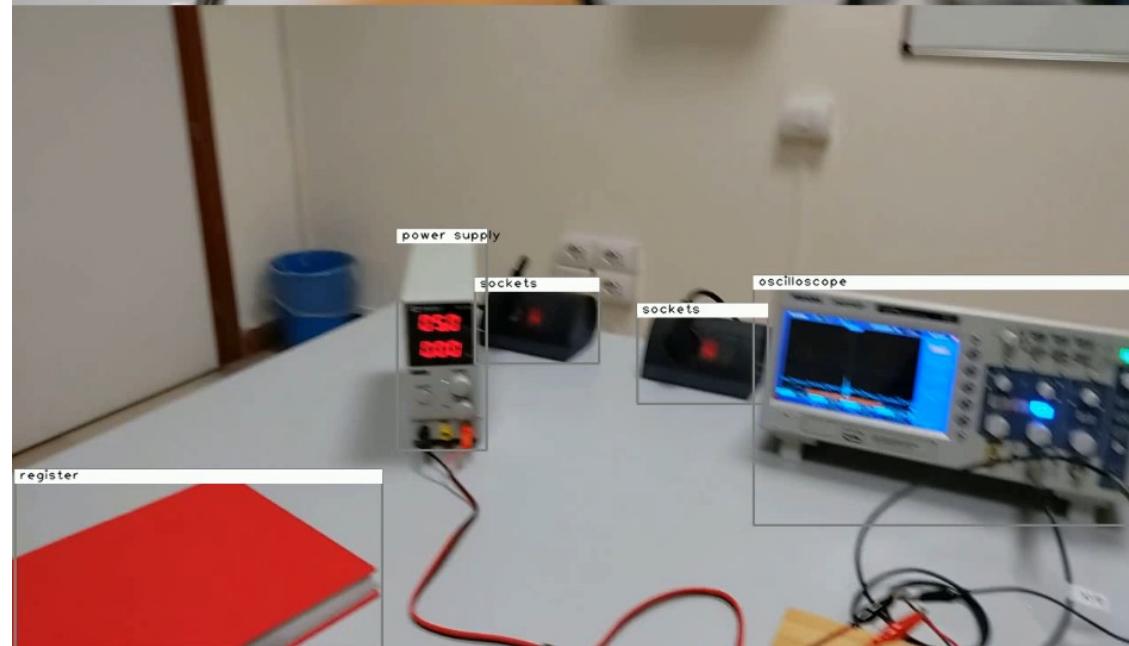
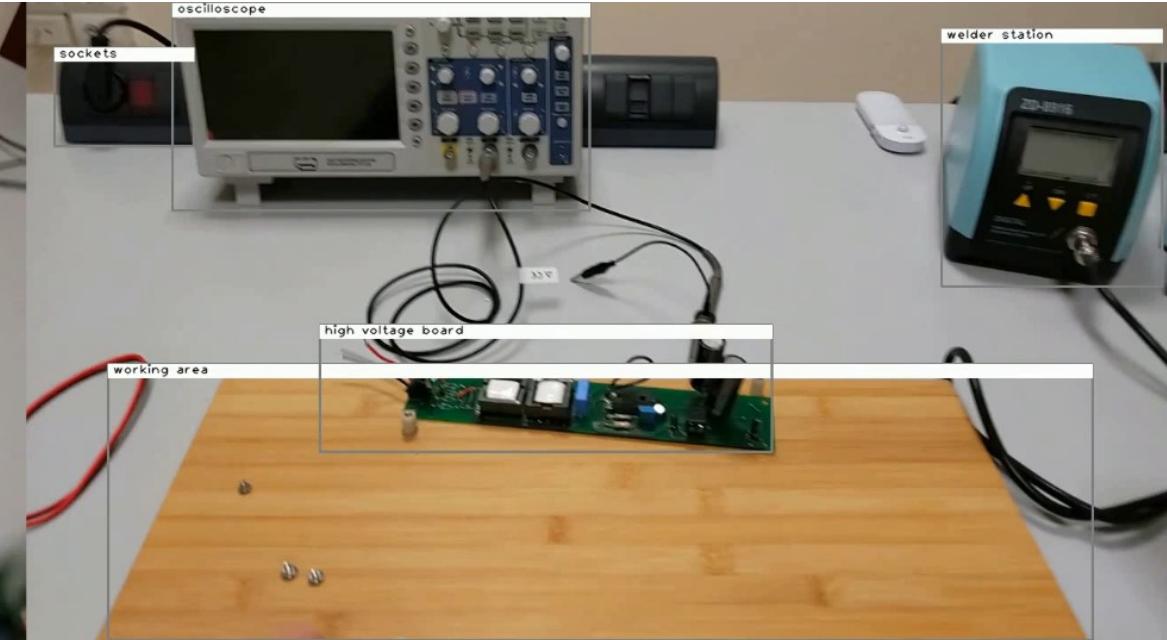
# Hand-Object Interactions



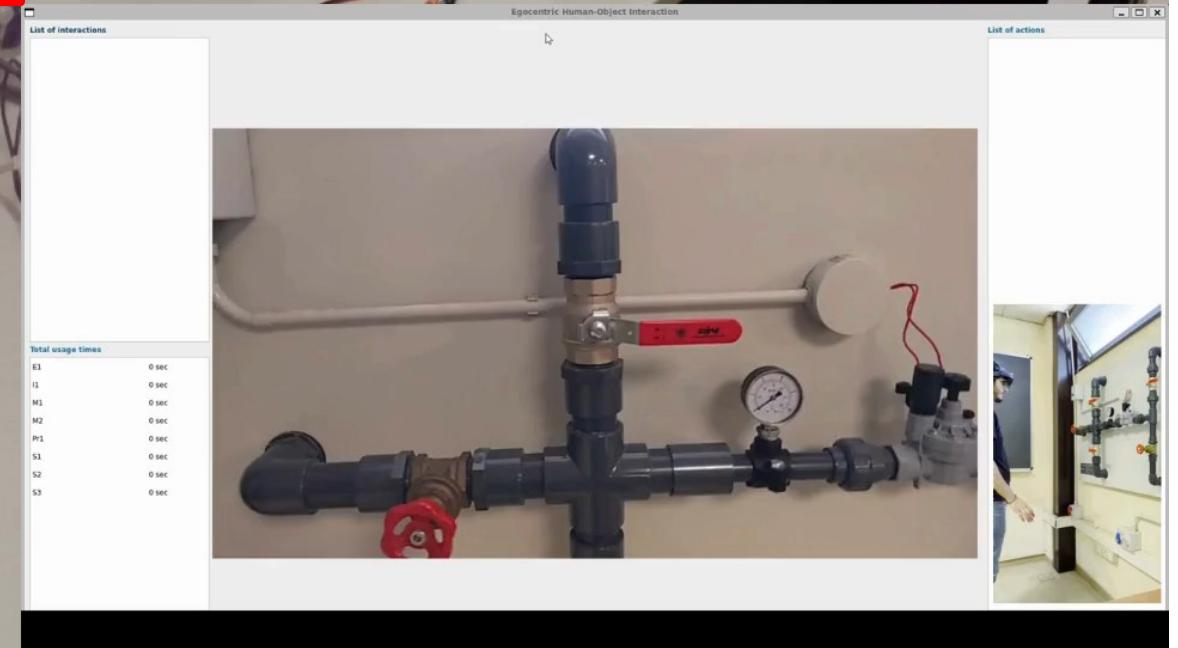
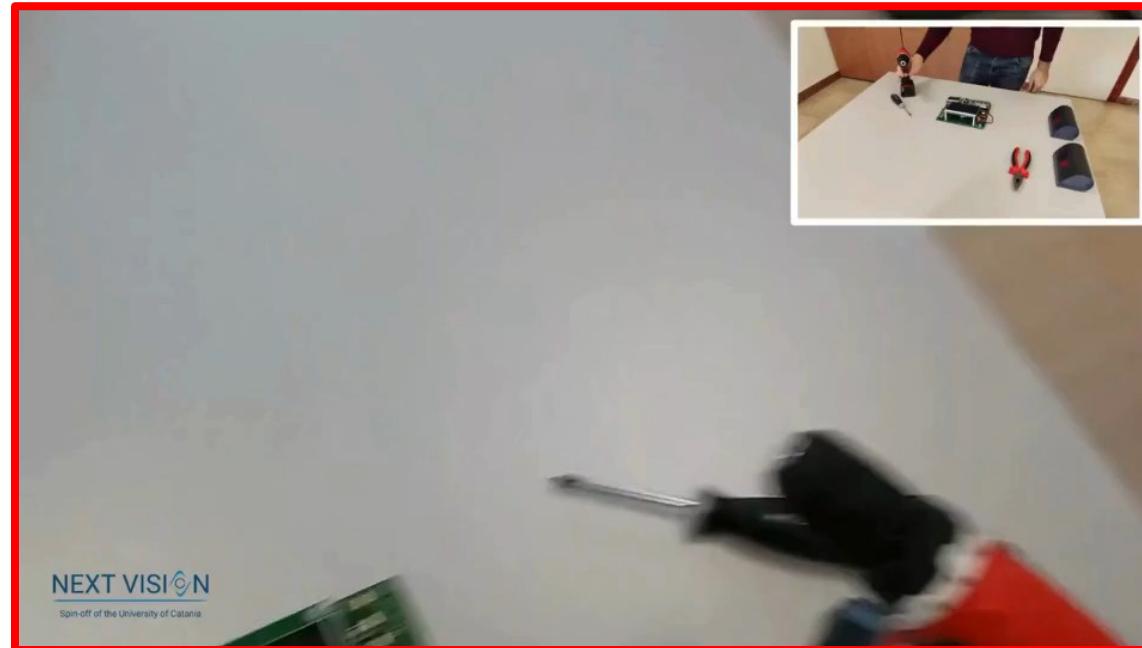
Hand-Object Interaction (HOI): **(hand, object, contact state)**

*Shan Dandan, et al. "Understanding human hands in contact at internet scale" (CVPR 2020)*

# Applications



# Applications



# 2. Datasets and Benchmarks for Hand-Object Interactions in Egocentric Vision

# Hand-Object Interactions Datasets



<https://fouheylab.eecs.umich.edu/~dandans/>



<https://epic-kitchens.github.io/VISOR/>



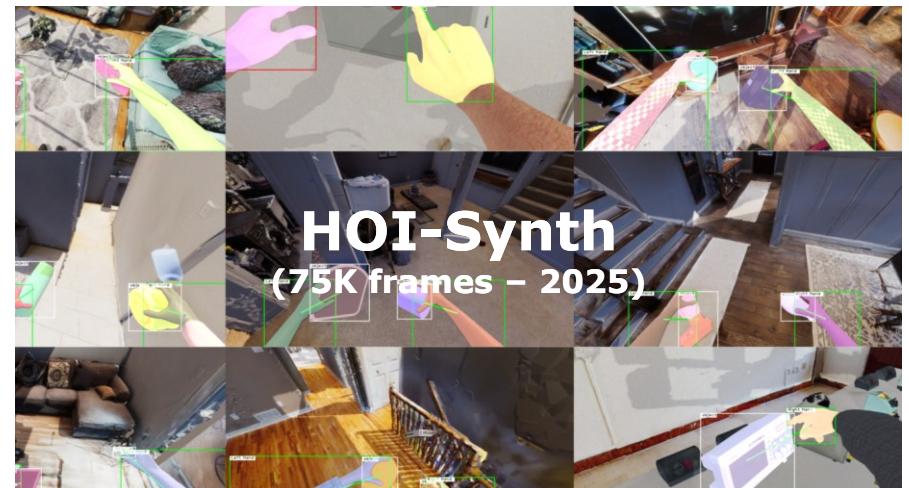
<https://github.com/owenzlz/EgoHOS>



<https://iplab.dmi.unict.it/MECCANO/>



<https://iplab.dmi.unict.it/ENIGMA-51/>



<https://fpv-iplab.github.io/HOI-Synth/>

# 100 Days of Hands



Shan Dandan, et al. "Understanding human hands in contact at internet scale" (CVPR 2020)

# 100 Days of Hands



**131 Days**

**12 Categories**

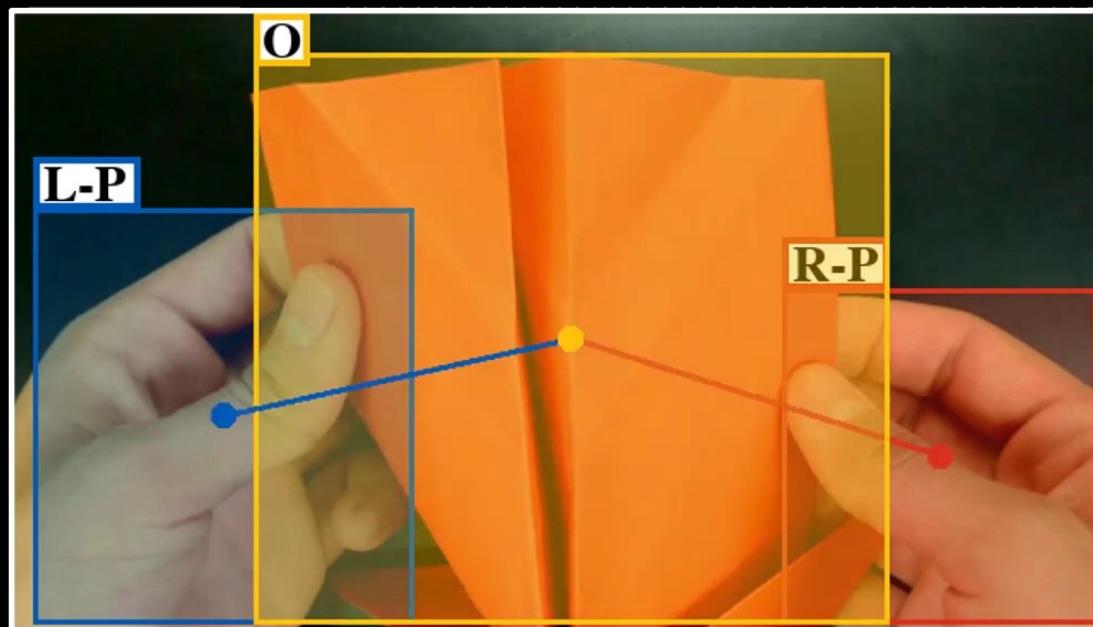
**27.3K Videos**

**19.2K  
Uploaders**

Category	Amount	Storage	Brief Description
Boardgame	2,654	179G	playing board games, e.g. checkers, chess, monopoly, etc.
DIY	2,902	198G	diy clothes, gifts, food, cards or experiments etc.
Drinks	2,739	155G	making drinks, e.g. coffee, tea, smoothie, hydromel, etc.
Food	2,737	203G	making food, e.g. pasta, yogurt, seafood, chocolate, etc.
Furniture	2,813	145G	assembling furniture, e.g. bookcases, bedstands, tables, etc.
Gardening	955	79G	making gardens, e.g. growing trees, flowers, vegetable etc.
Housework	2,809	323G	doing housework or cleaning, decorating rooms, etc.
Packing	2,809	234G	packing or unpacking boxes, clothes, bags, gifts, etc.
Puzzle	2,825	176G	solving puzzles or magic cubes, building legos, etc.
Repair	2,764	177G	repairing cars, trucks, engines, computers, smartphones, etc.
Study	1,299	106G	studying and explaining videos for finals, midterms, engineering, etc.
Vlog	---	---	<a href="#">VLOG Dataset</a> : videos documenting lives
<b>Total</b>	<b>27306</b>	<b>2.0T</b>	

# 100 Days of Hands: 100K Frames

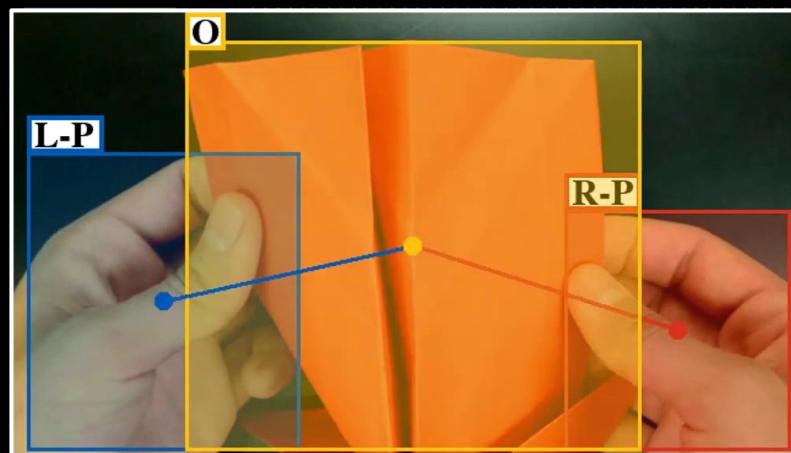
## 100K Frame-level Annotations



- Box around hand
- Side (left / right)
- Contact (no / self / other / portable / furniture)
- Box around object in contact
- Association

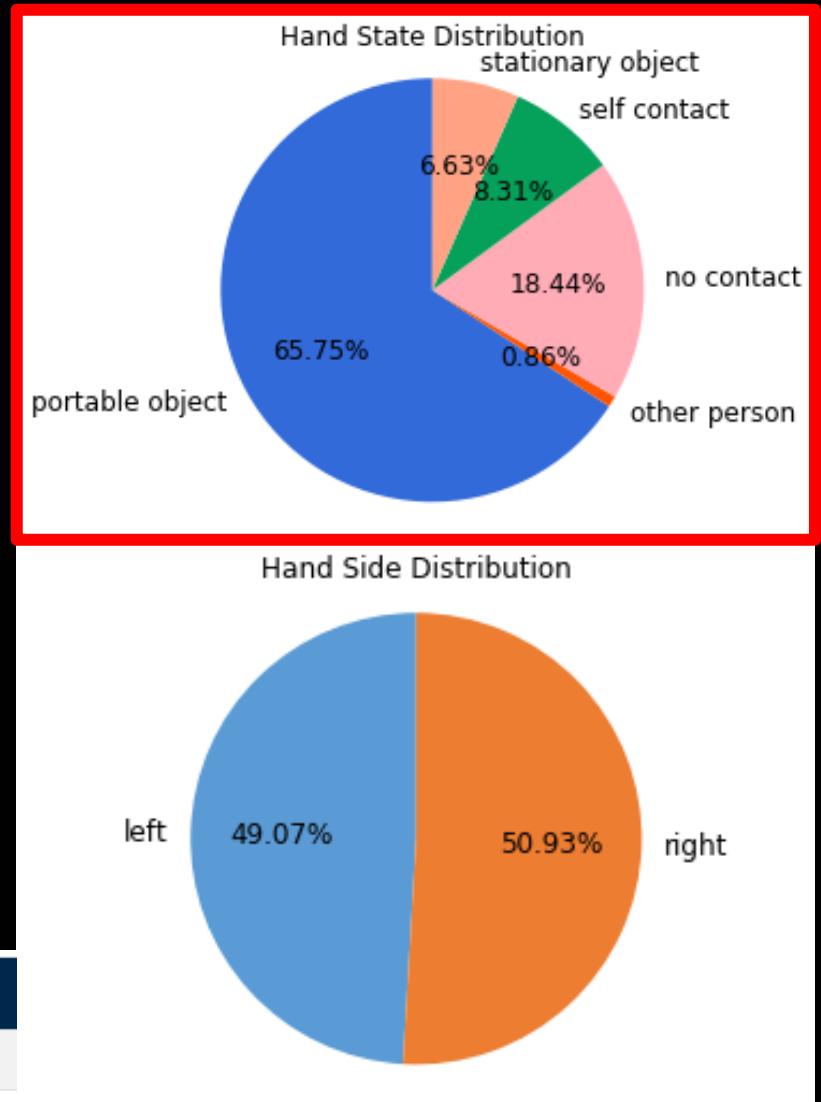
# 100 Days of Hands: 100K Frames

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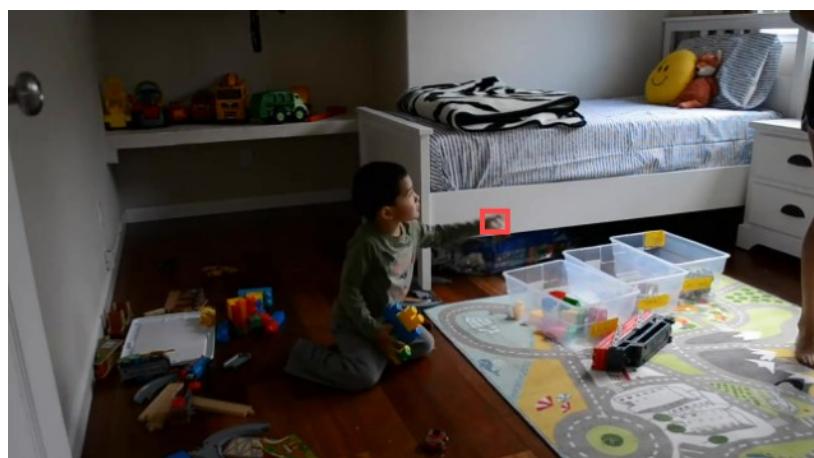


- Box around hand
- Side (left / right)
- Contact (no / self / other / portable / furniture)
- Box around object in contact
- Association

	#Frames	#Hand Box	#Hand Side	#Contact State	#Object Box
Total	99,899	189,426	189,426	189,426	140,431



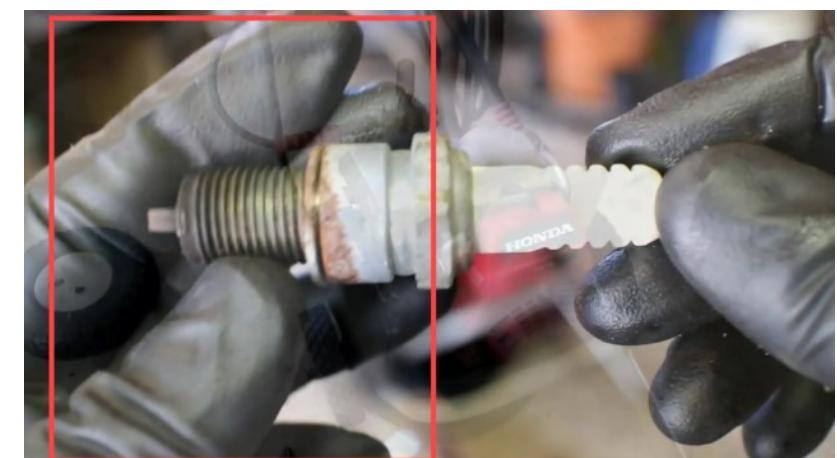
# 100 Days of Hands: Hand Size



Small

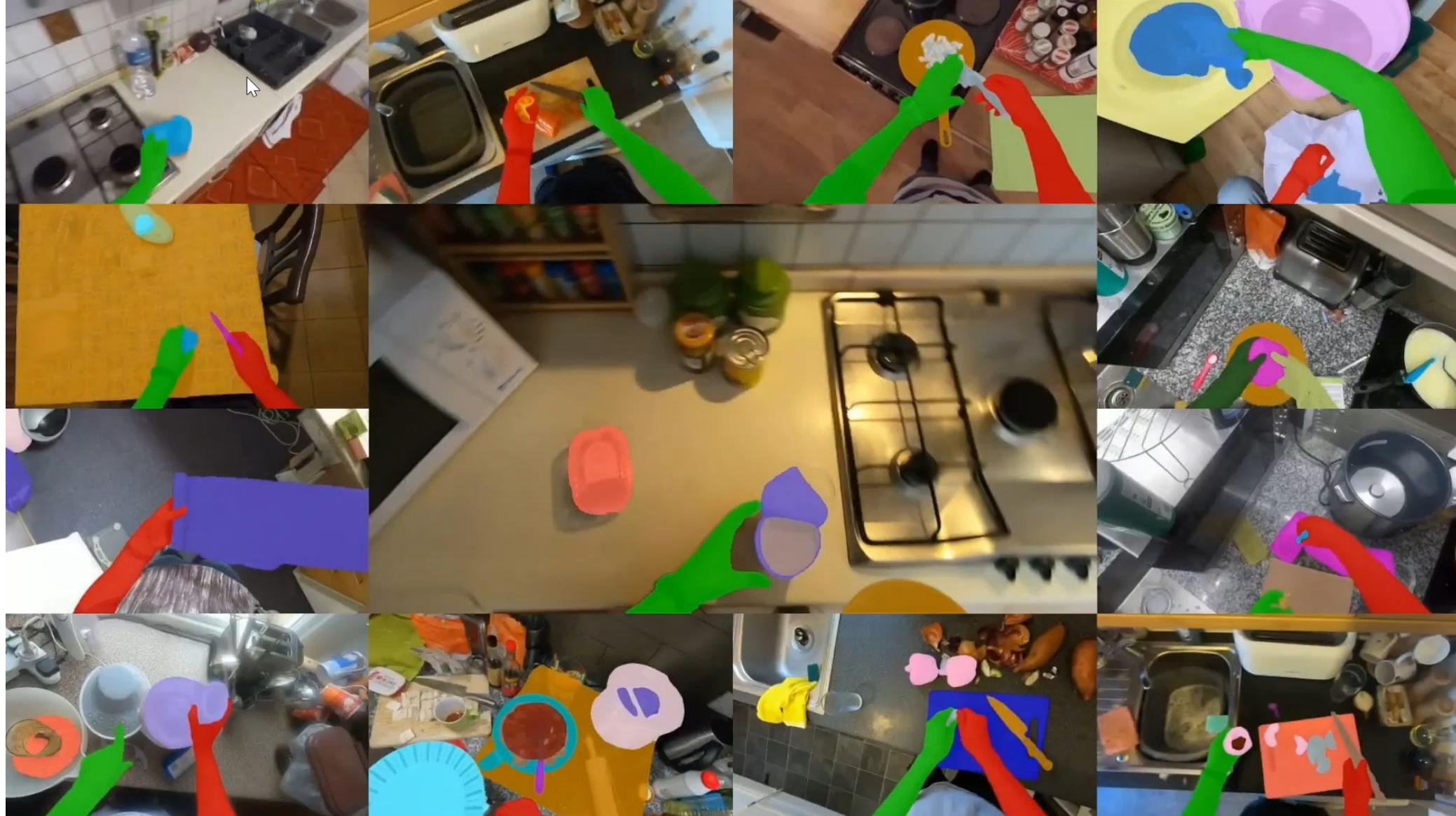


Medium



Large

# EPIC-Kitchens VISOR



# EPIC-Kitchens VISOR: Annotations

**Sparse Annotations**



271K masks covering 36 hours of untrimmed video

**Dense Annotations**



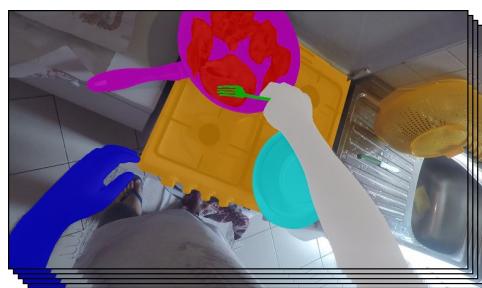
14.9M high quality automatic interpolations

# EPIC-Kitchens VISOR: Annotations

Sparse Annotations



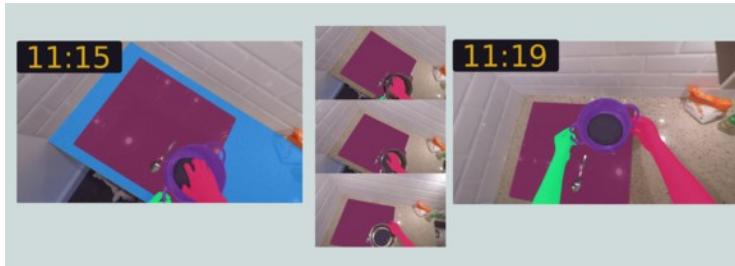
Dense Annotations



# EPIC-Kitchens VISOR: Challenges

## Video Object Segmentation

Goal: Track segments through video and occlusion



## Where Did This Come From?

Goal: Name and point to where things came from



## Hand Object Segmentation

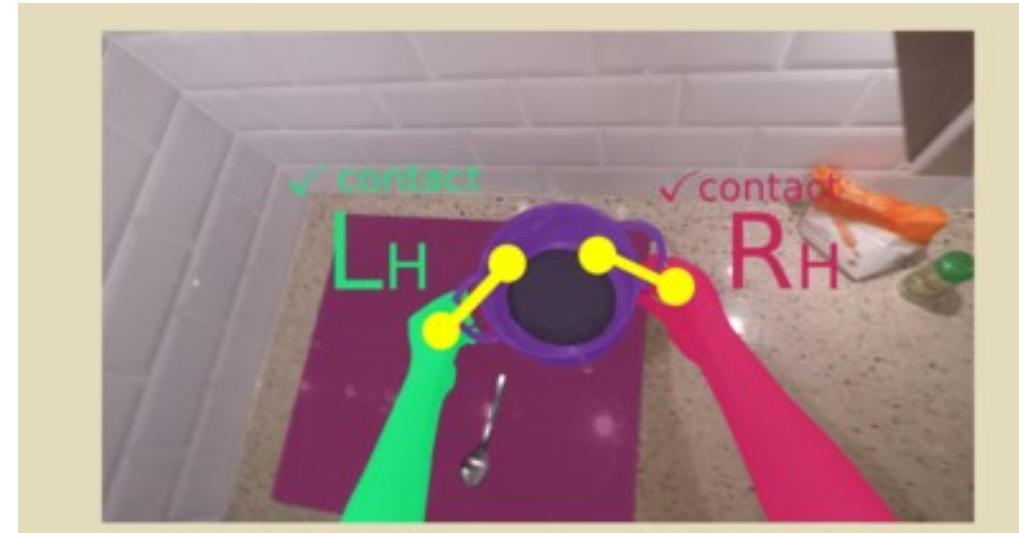
Goal: Identify contact with 67K in-hand object masks



# EPIC-Kitchens VISOR: Annotation Stats

## Hand Object Segmentation

Goal: Identify contact with 67K in-hand object masks

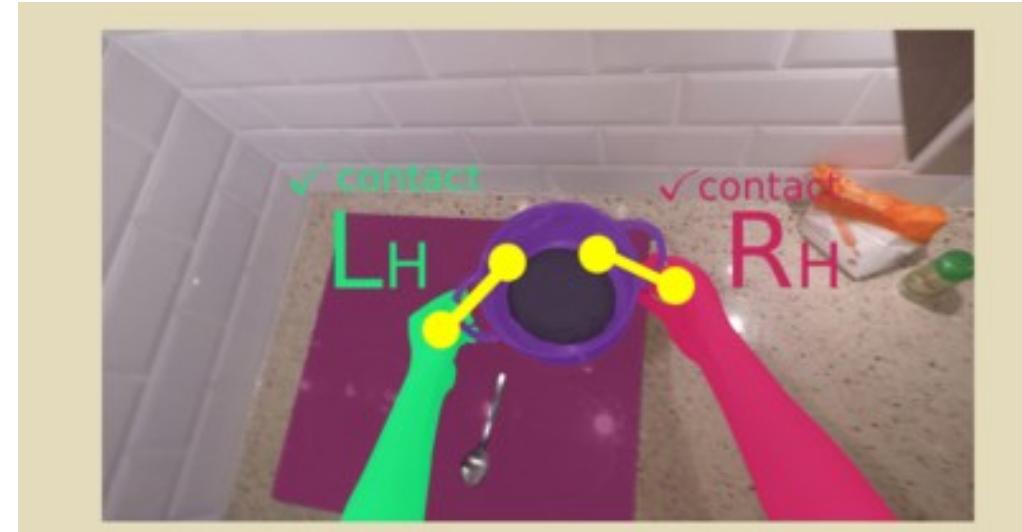


	Train+Val	Test
In Contact	52,685	14,233
Not-in-contact	4,144	1,341
Inconclusive	4,943	1,104

# EPIC-Kitchens VISOR: Annotation Stats

## Hand Object Segmentation

Goal: Identify contact with 67K in-hand object masks



	Train+Val	Test
In Contact	52,685	14,233
Not-in-contact	4,144	1,341
Inconclusive	4,943	1,104



# EgoHOS: Data Source

70%

Epic Kitchen



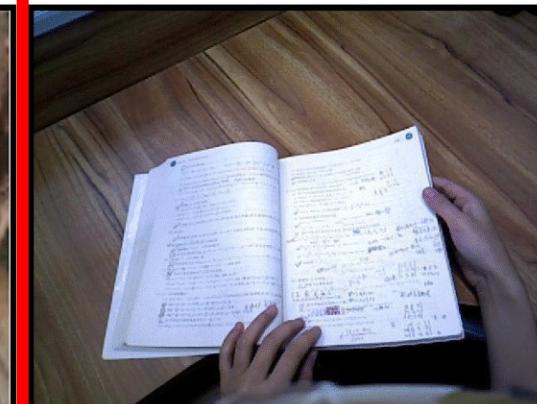
Ego4d



THU-Read

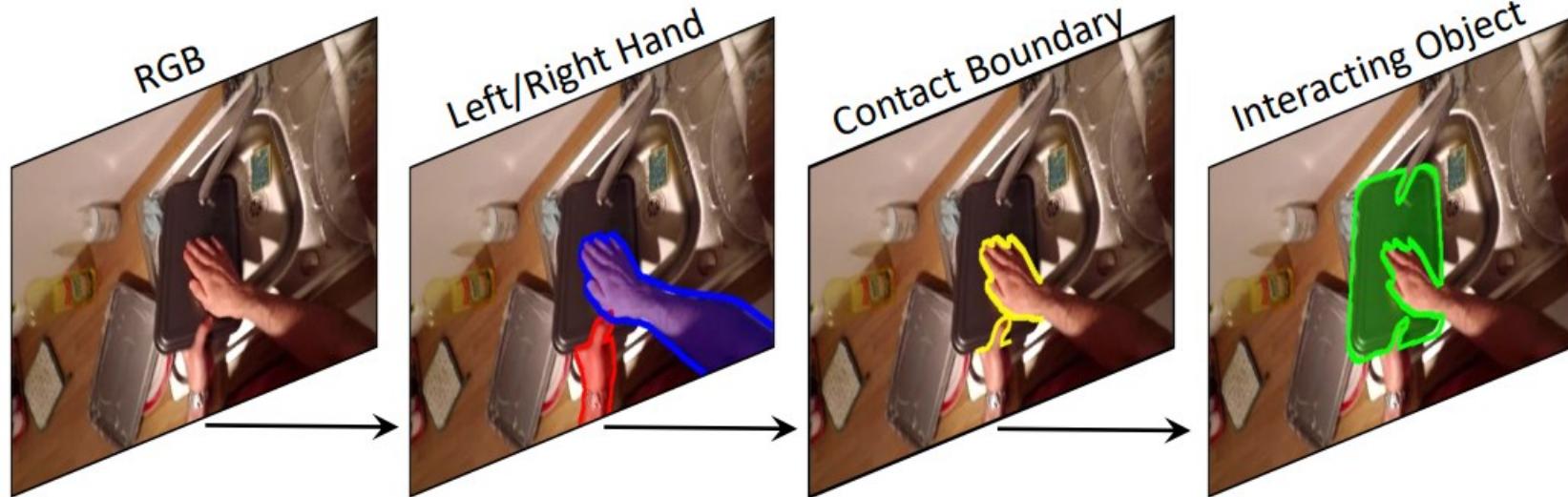


Escape Room

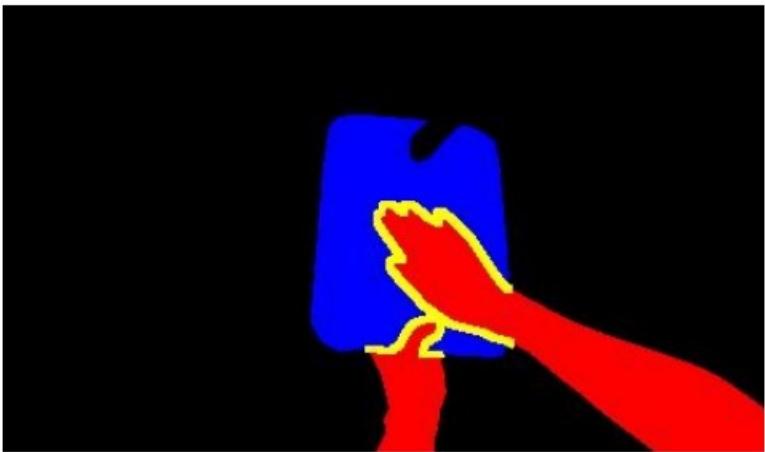


# EgoHOS: Annotations

A Causal Hand-Object Segmentation Pipeline



Dense Contact Boundary Generation

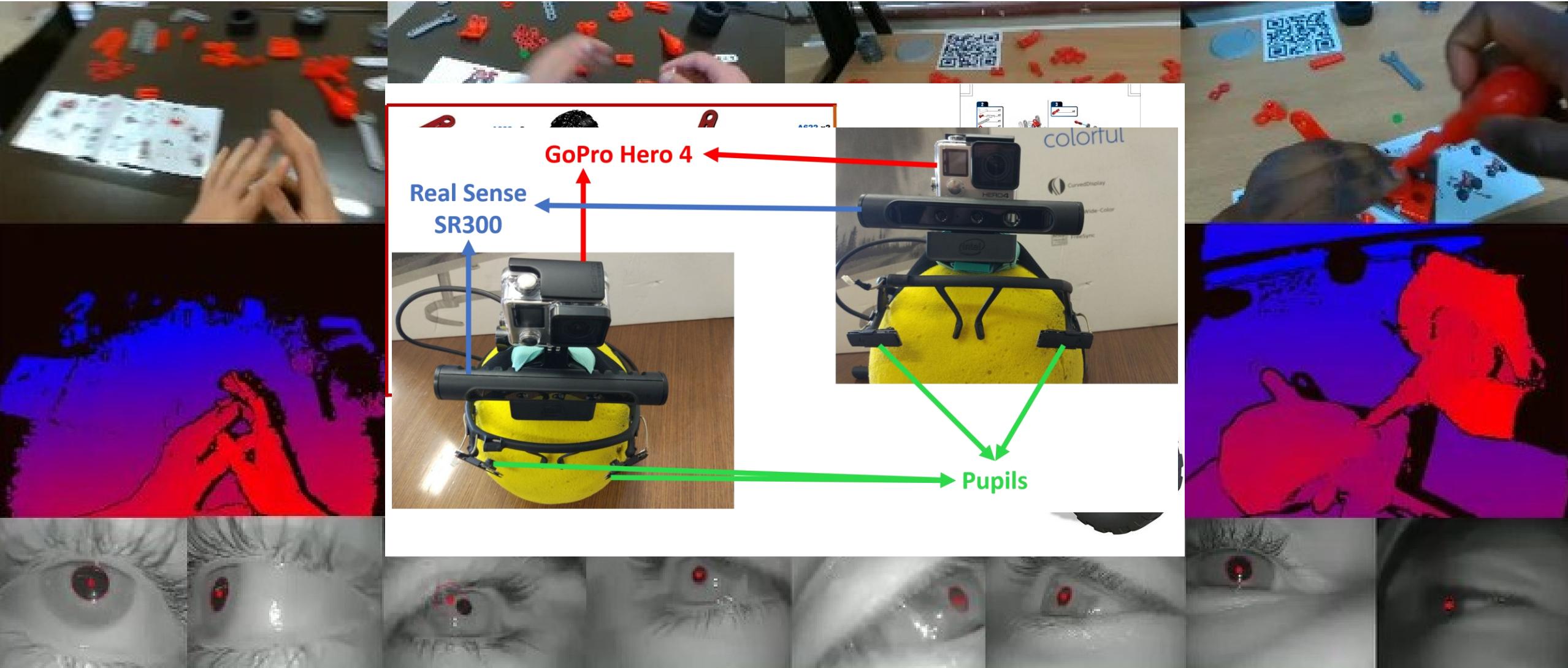


# EgoHOS: Hand and Interacting Object Segmentations



	<b>Label</b>	<b>#Frames</b>	<b>#Hands</b>	<b>#Objects</b>
EgoHOS	Mask	11,243	20,701	17,568

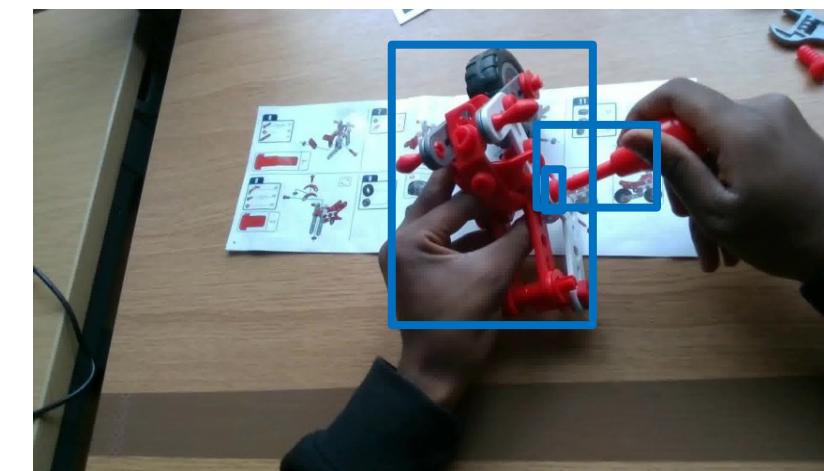
# The MECCANO Dataset



1. Action Recognition
2. Active Object Detection and Recognition
3. EHOI Detection
4. Action Anticipation
5. Next-Active Object (NAO) Detection



<take, screwdriver>



<screw, {screwdriver, screw, partial\_model}>

# Egocentric Human-Object Interactions

## Egocentric Human-Object Interaction

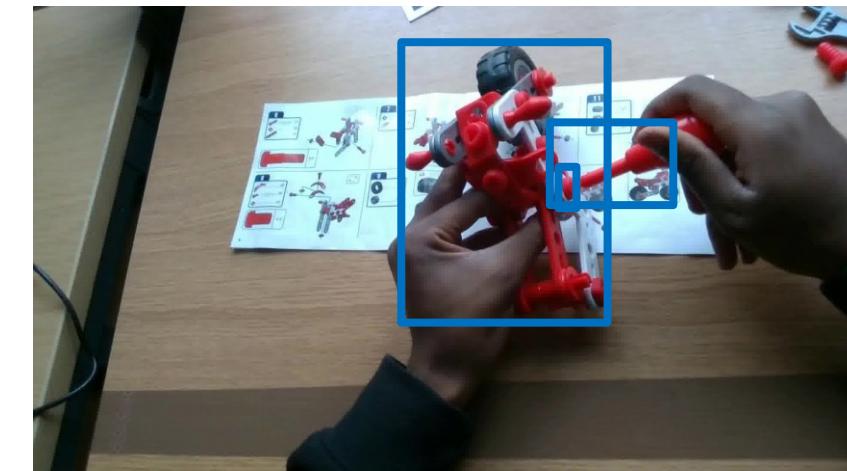
$$O = \{o_1, o_2, \dots, o_n\}$$

$$V = \{v_1, v_2, \dots, v_m\}$$

$$e = (v_h, \{o_1, o_2, \dots, o_i\})$$

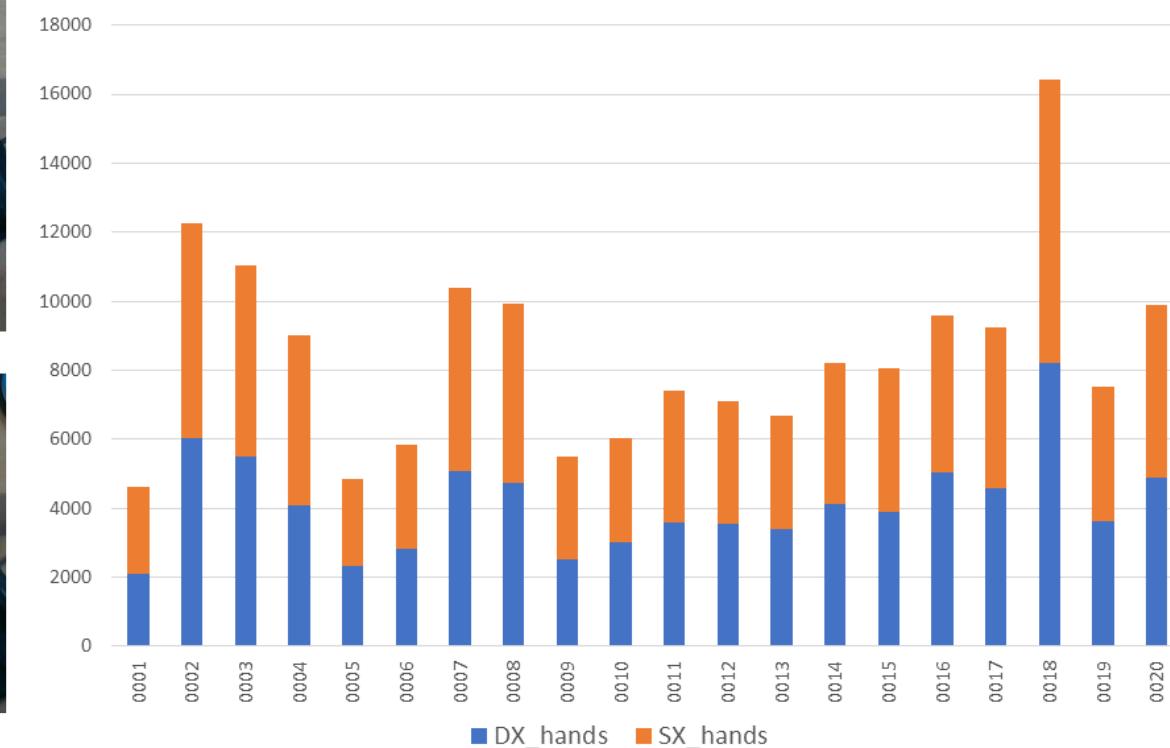
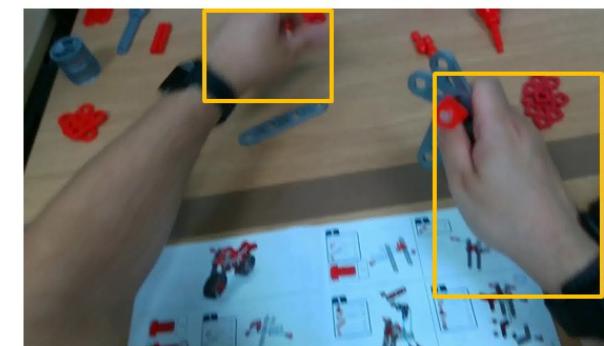
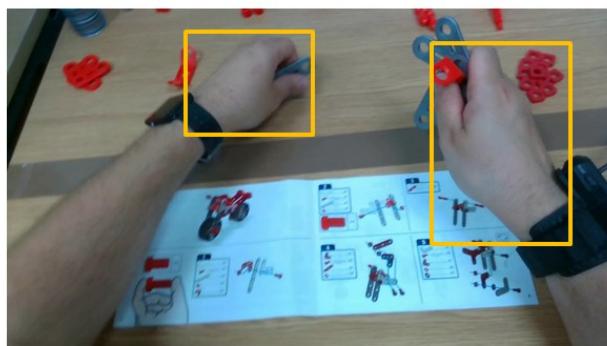
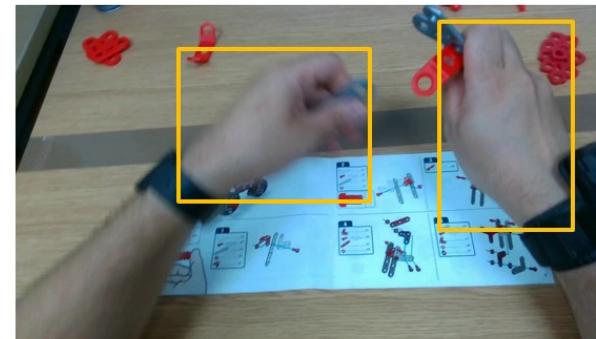
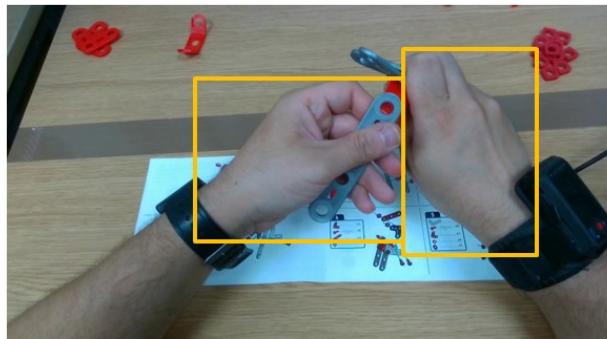


<take, screwdriver>

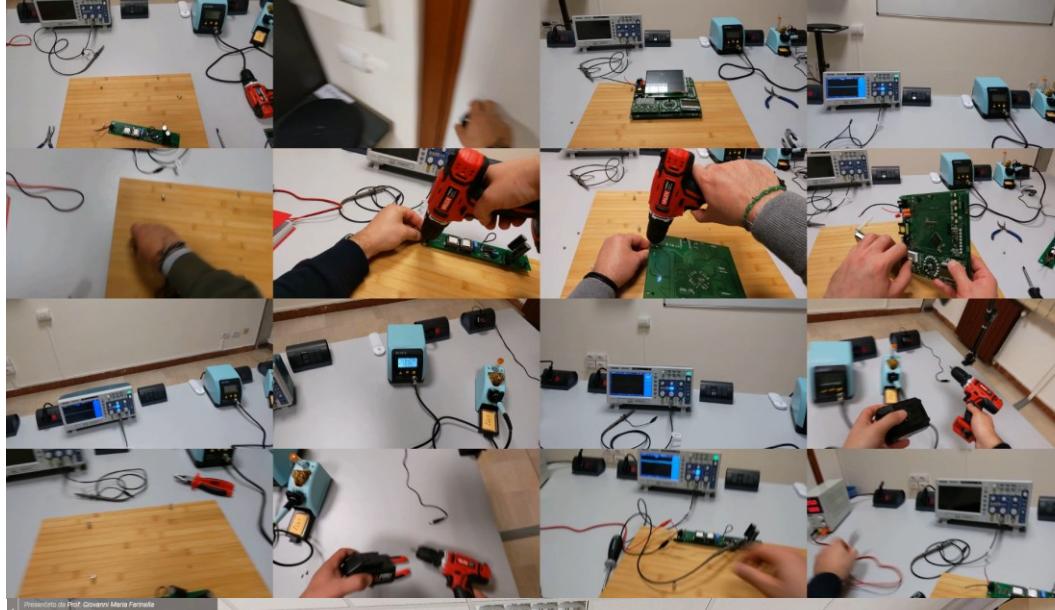


<screw, {screwdriver, screw, partial\_model}>

# Data Annotation: Hands Annotations

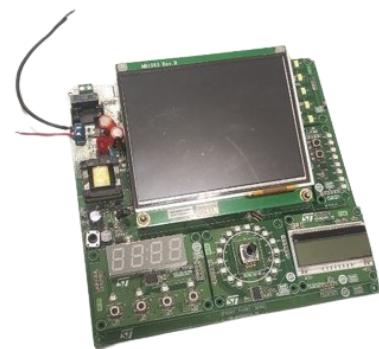


# ENIGMA-51 Dataset

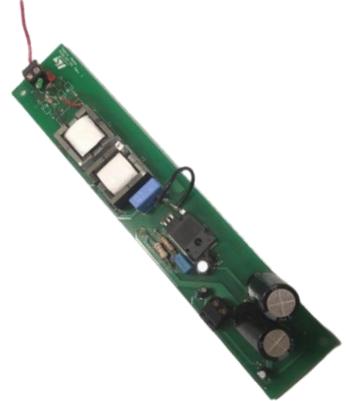


We designed two procedures consisting of instructions that involve humans interacting with the objects present in the laboratory to achieve the goal of repairing two electrical boards

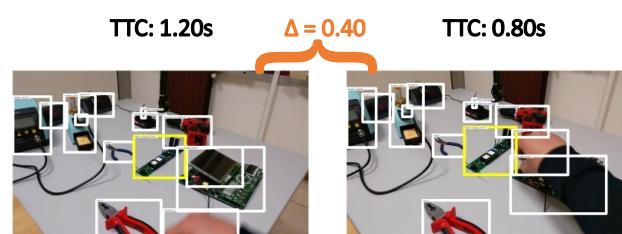
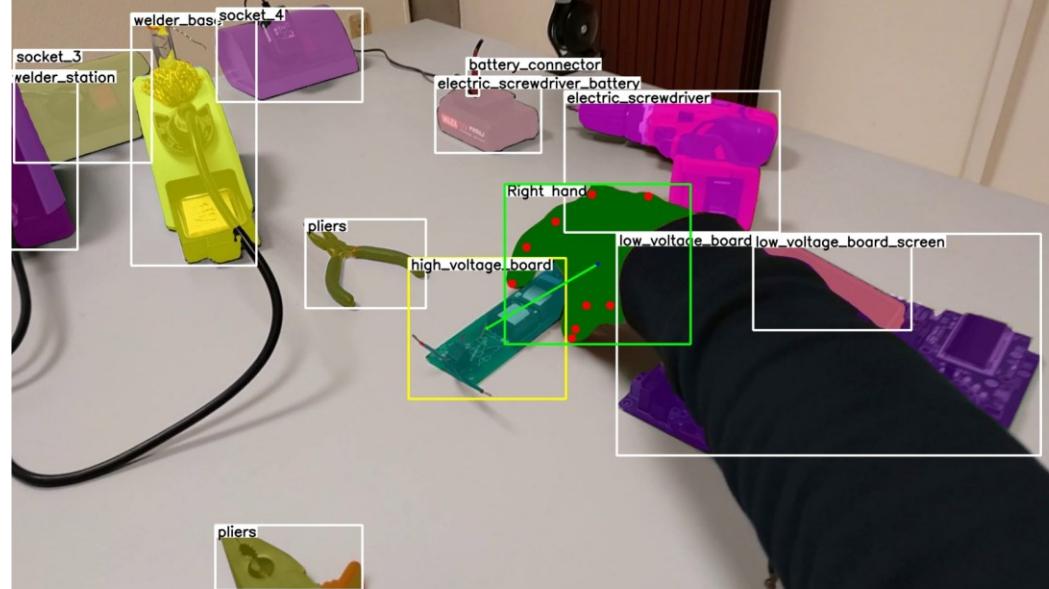
Low-Voltage



Hight-Voltage



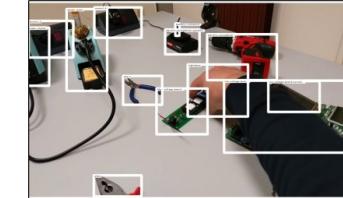
# ENIGMA-51: Annotations



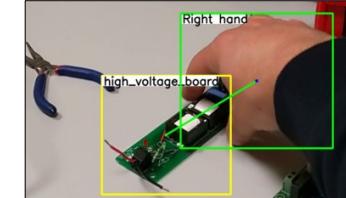
Past Frames



Interaction Frame



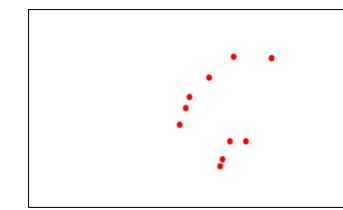
Hand-Object boxes



Human-Object Interactions



Hand-Object Masks



Hand Keypoints



Environment 3D Model



Object 3D Models

## Procedure :

.....

**4. Take the high voltage board and put it on the working area**

5. Take the screwdriver

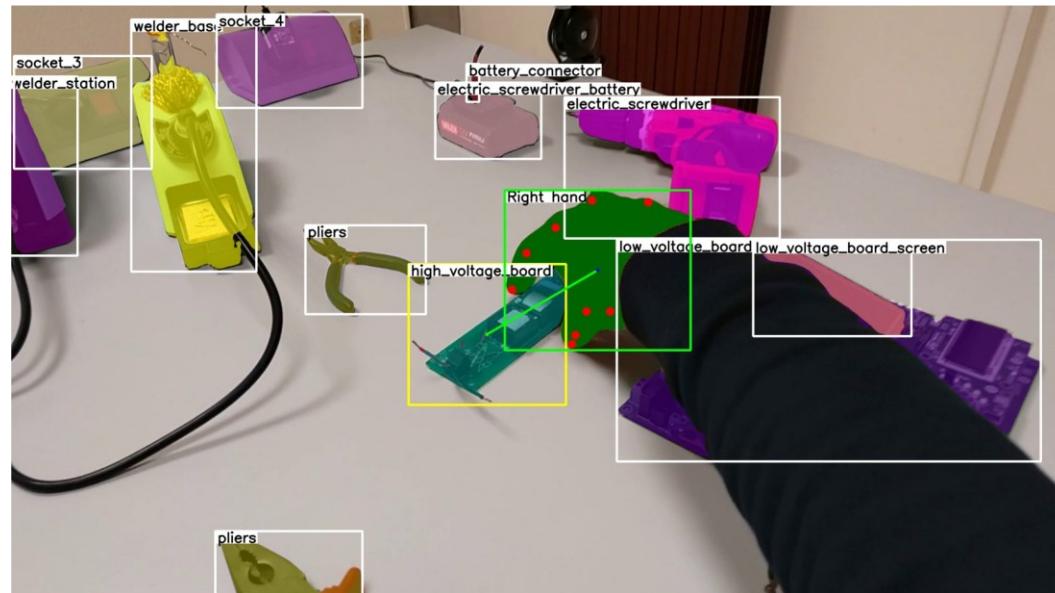
.....

22. Turn on the welder using the switch on the corresponding socket (second from right)

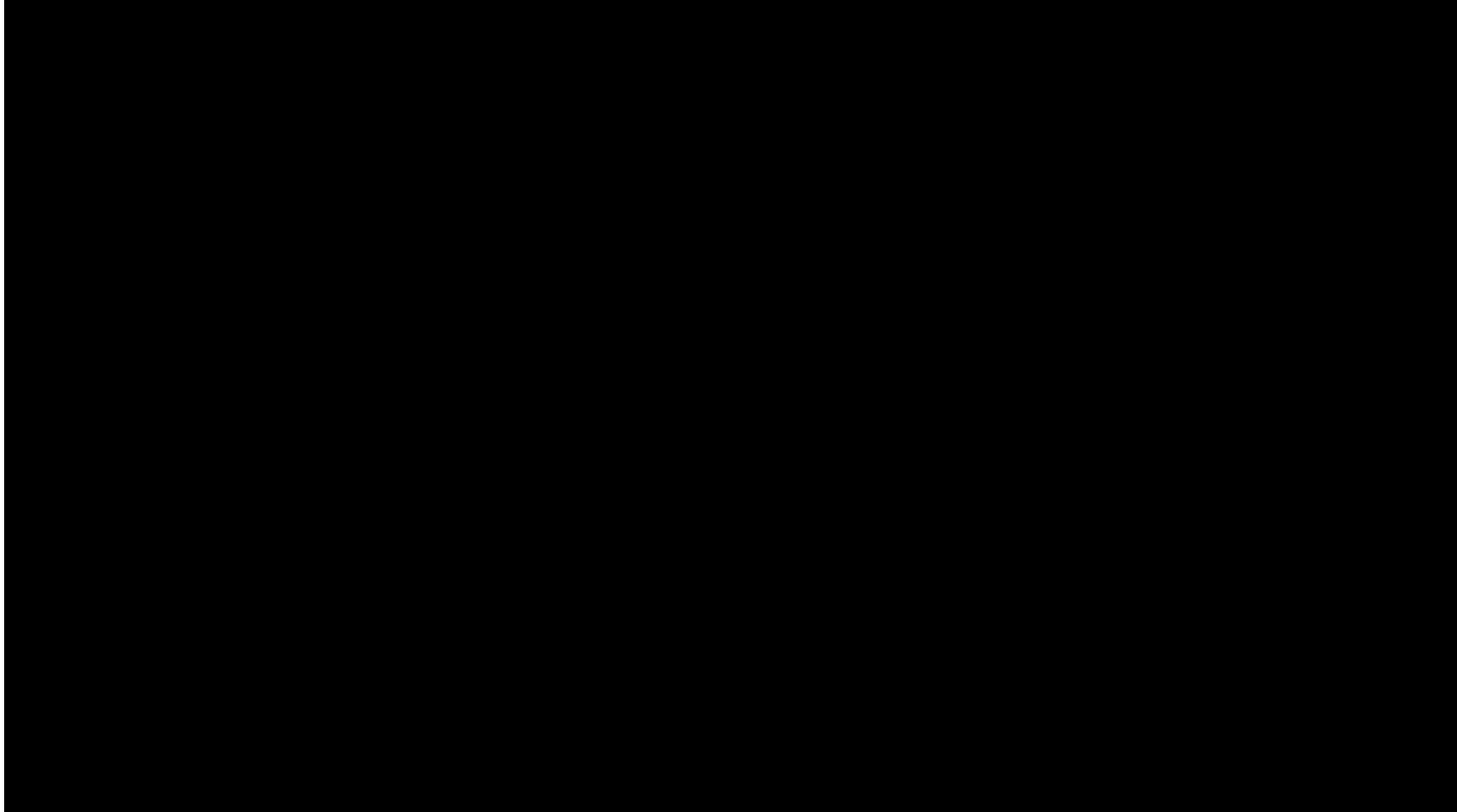
23. Set the temperature of the welder to 480 °C using the yellow "UP" button

.....

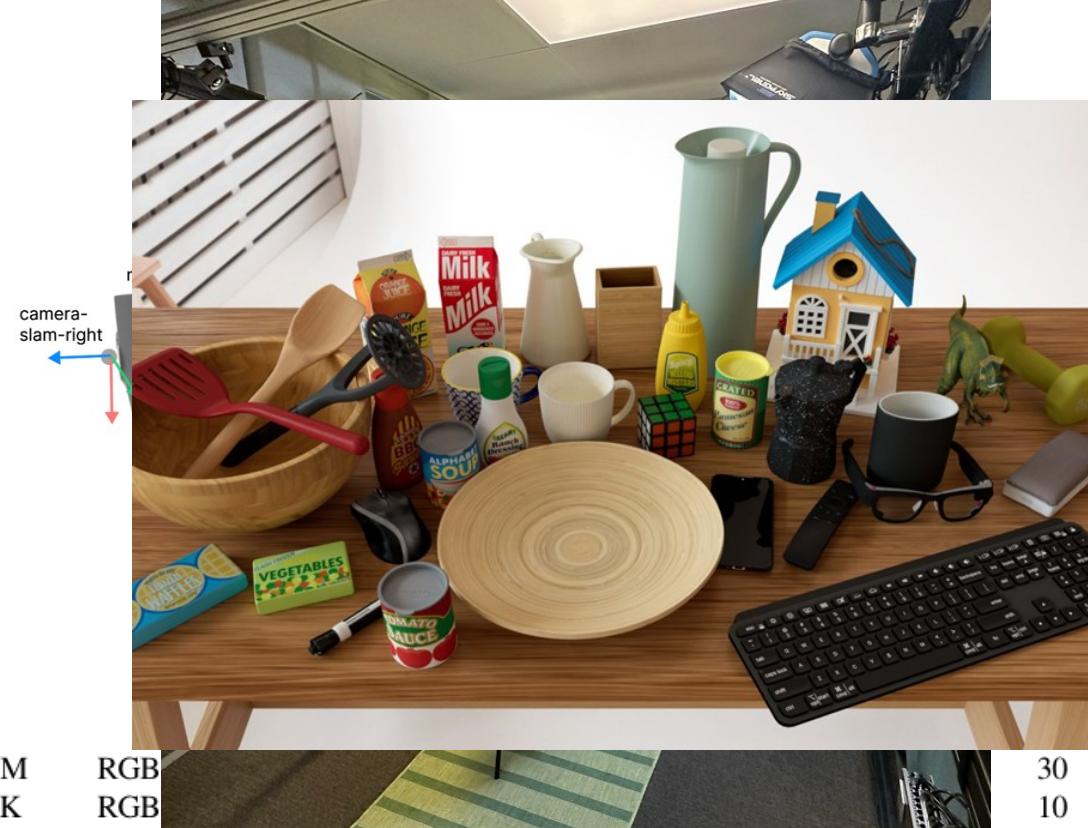
# ENIGMA-51 Dataset



Splits	Train	Val	Test	Total
# Videos	27	8	16	51
# Videos Length	≈11h	≈4h	≈7h	≈22h
# Images	25,311	8,528	11,666	45,505
# Objects	152,865	53,486	68,784	275,135
# Active Objects	4,709	1,700	2,933	9,342
# Hands	31,249	11,322	13,902	56,473
# Hands in contact	5,039	1,833	3,171	10,043
# Interactions frames	6,386	2,150	4,061	12,597
# Interactions	7,133	2,406	4,497	14,036
# Past frames	19,090	6,437	7,683	33,210
# Next Object Interactions	21,535	7,280	8,499	37,314



# HOT3D

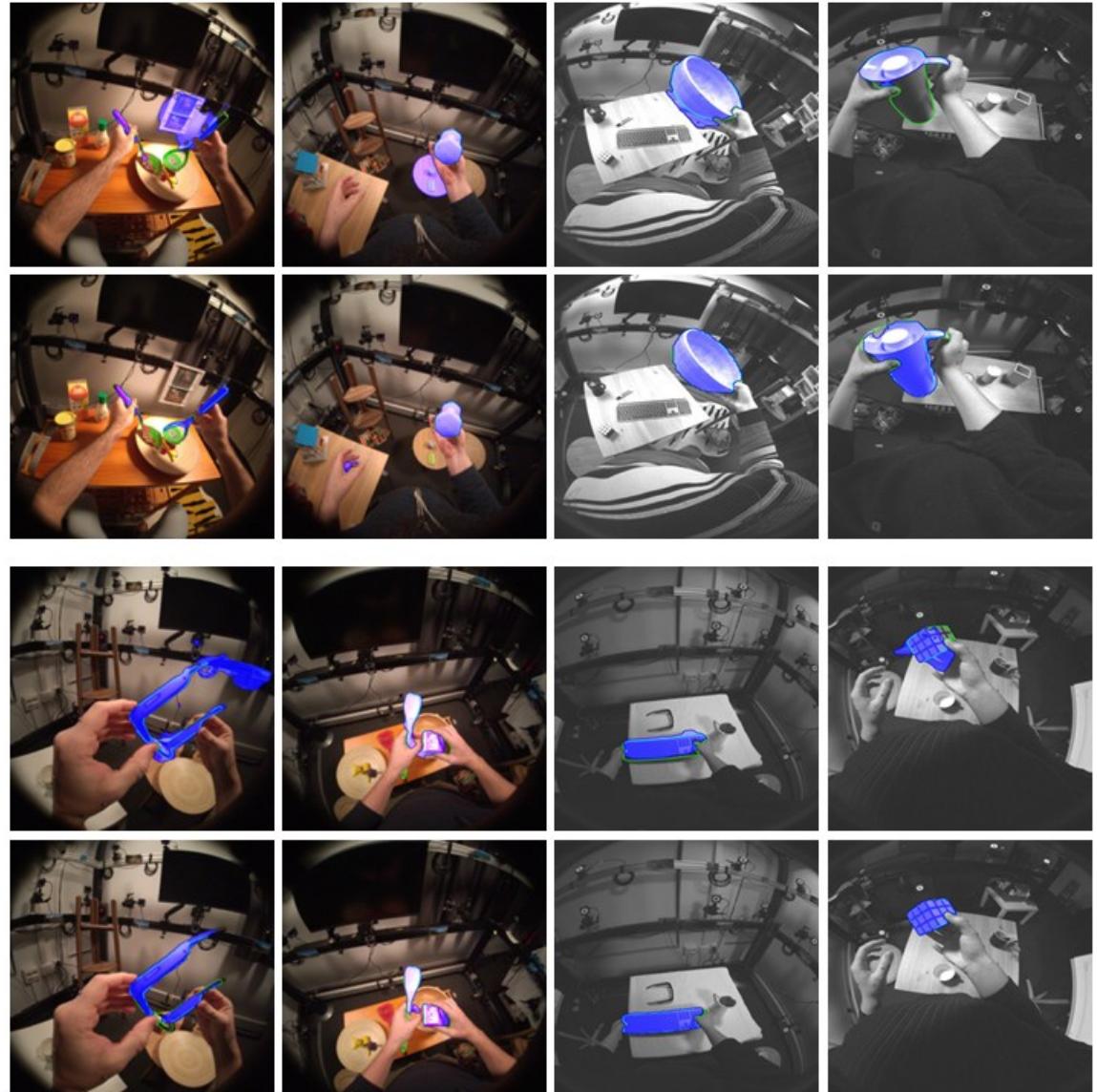


Dataset	Im							
HOT3D (ours)	3.							
ARTIC [15]	2.							
HOI4D [39]	2.							
HO-Cap [69]	6.							
DexYCB [8]	58							
HOGrapNet [9]	1.5M	RGB						
H2O-3D [24]	75K	RGB						
HO-3D [23]	78K	RGB	0 / 1	—	—	10	Single	10
H2O [38]	572K	RGB-D	1 / 4	✓	Helmet	4	Both	8
ContactPose [5]	2.9M	RGB-D	0 / 3	✗	—	50	Both	25
ObMan [27]	147K	Synth. RGB	0 / 1	—	—	20	Single	2772

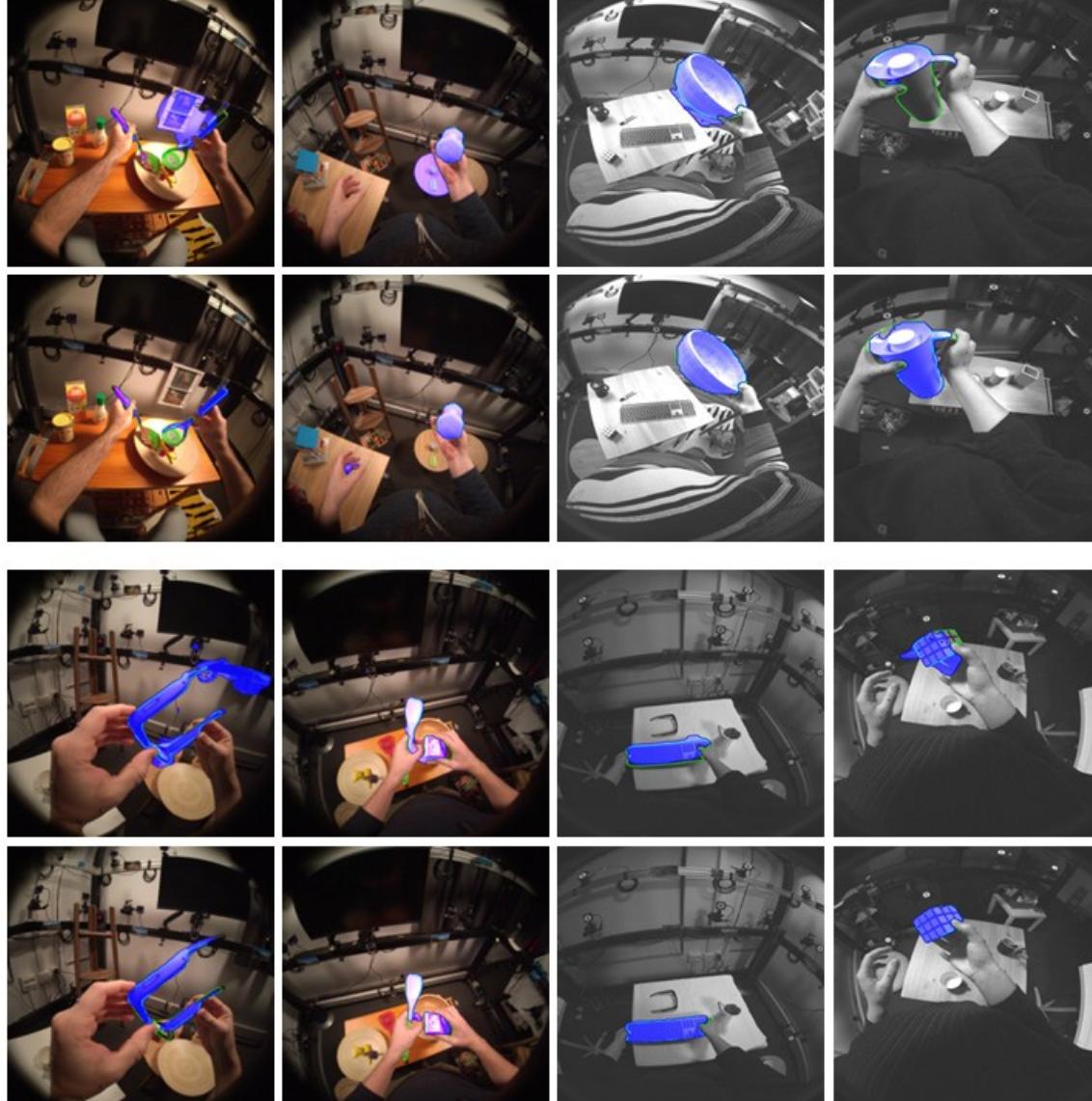
per scene	Gaze	Annotation
~6	✓	Mocap
1	✗	Mocap
1–12	✗	RGB-D + man.
4	✗	RGB-D + optim.
2–4	✗	Manual
1	✗	RGB-D + optim.
1	✗	RGB-D + optim.
1	✗	RGB-D + optim.
1	✗	RGB-D + optim.
1	✗	RGB-D + mocap
1	✗	Synthetic

# HOT3D: Tasks

1. 3D hand pose tracking
2. 6DoF object pose estimation
3. **2D segmentation of in-hand objects**
4. 3D lifting of in-hand objects



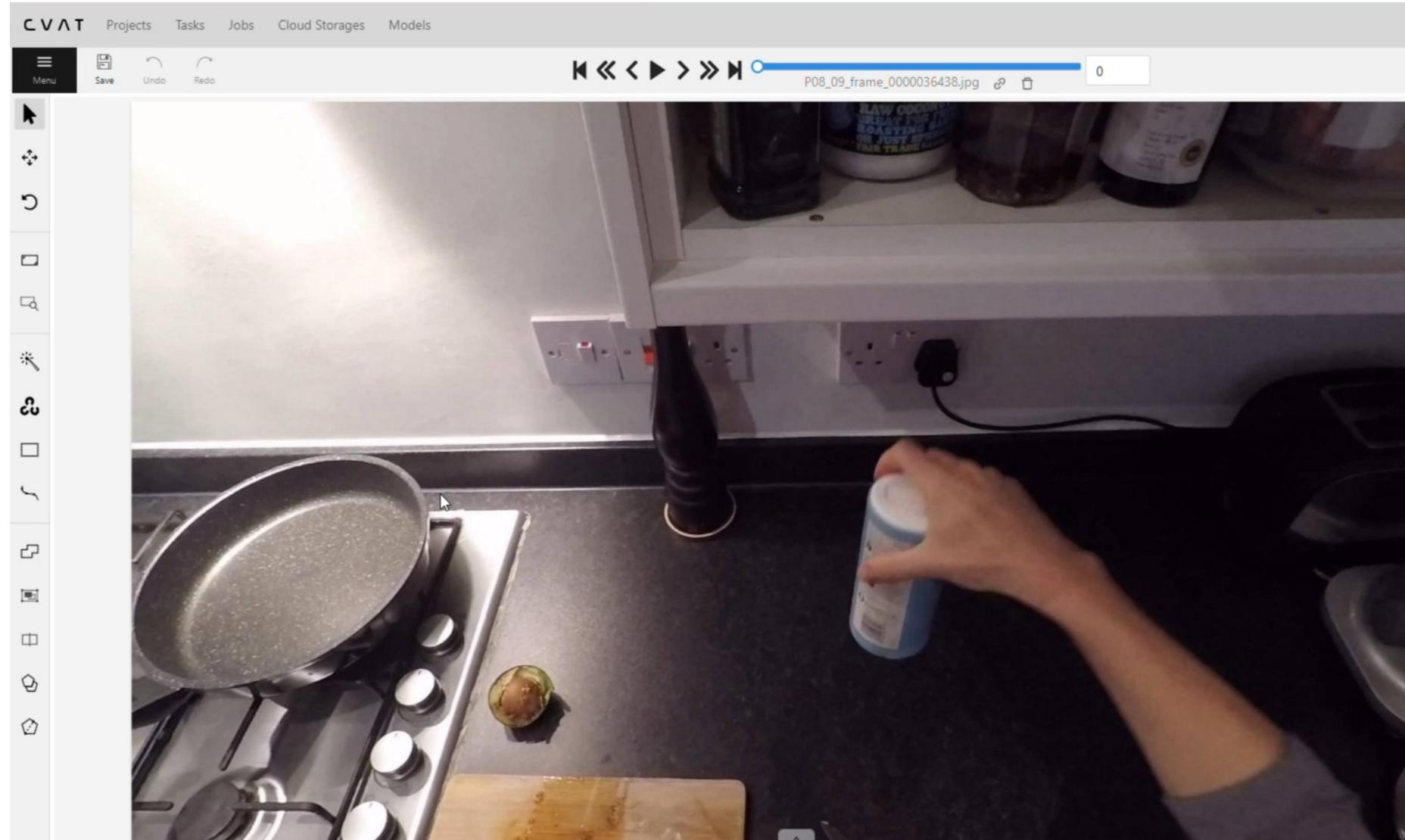
# HOT3D: Tasks



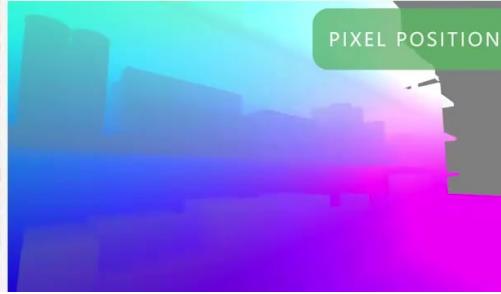
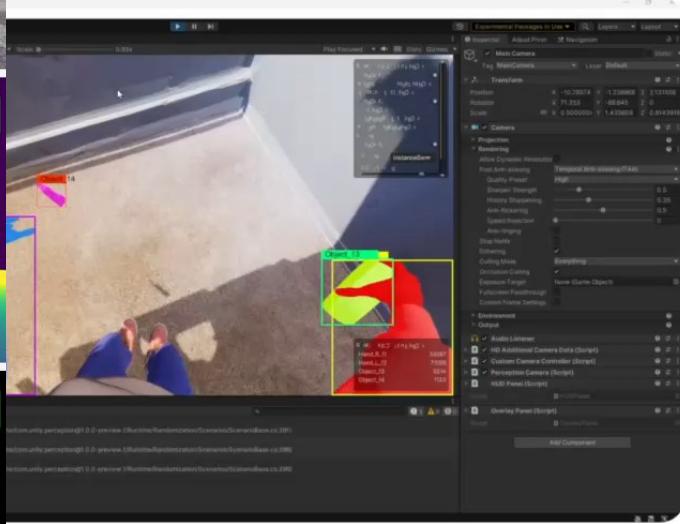
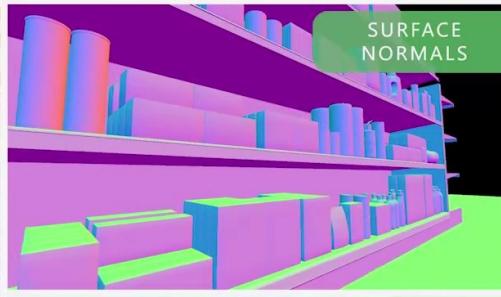
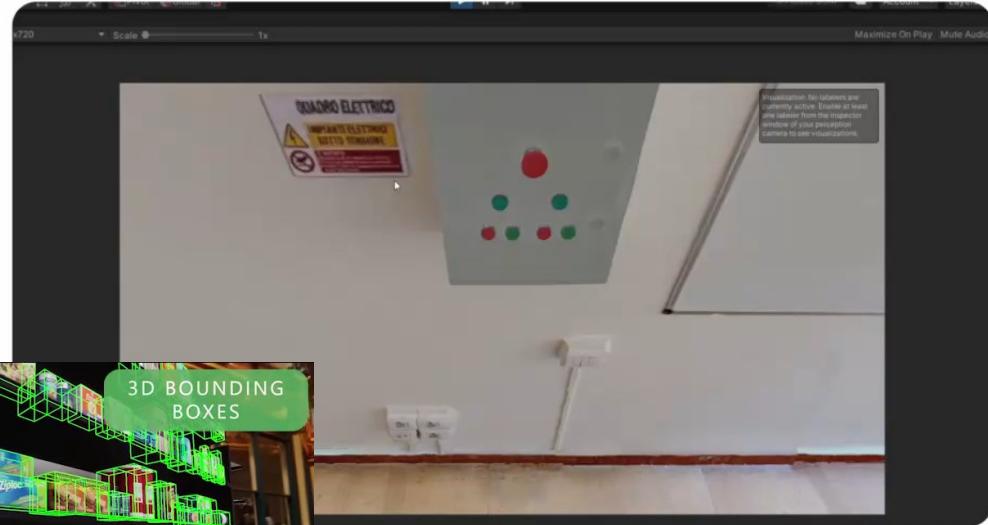
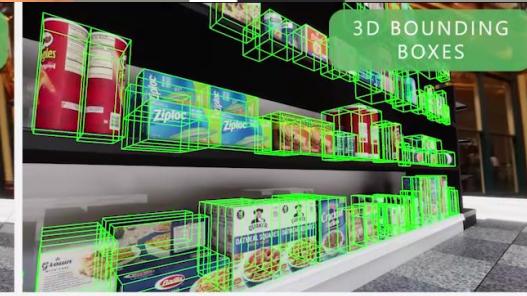
Method	Test dataset	Object in hand (mIoU ↑):			
		Either	Left	Right	Both
EgoHOS [75]	EgoHOS	–	62.2	44.4	52.8
EgoHOS [75]	HOT3D-Aria	42.6	21.0	26.3	32.5
MRCNN	HOT3D-Aria	47.1	–	–	–
MRCNN-DA	HOT3D-Aria	<b>55.2</b>	–	–	–
EgoHOS [75]	HOT3D-Quest3	33.1	13.5	14.4	24.8
MRCNN	HOT3D-Quest3	37.8	–	–	–
MRCNN-DA	HOT3D-Quest3	<b>54.7</b>	–	–	–

Table 4. **2D segmentation of in-hand objects.** EgoHOS [75] trained on the EgoHOS dataset is compared with our baselines based on Mask R-CNN [28] and trained on our in-house dataset of images from Aria. We observe a large accuracy drop of the EgoHOS model on HOT3D.

# Challenges in dataset collection and annotation



# Synthetic Data: Automatic Labeling



# Data Generation Pipeline



Gibson



Carla



ObMan



AI2THOR

# Generic vs In-Domain Data



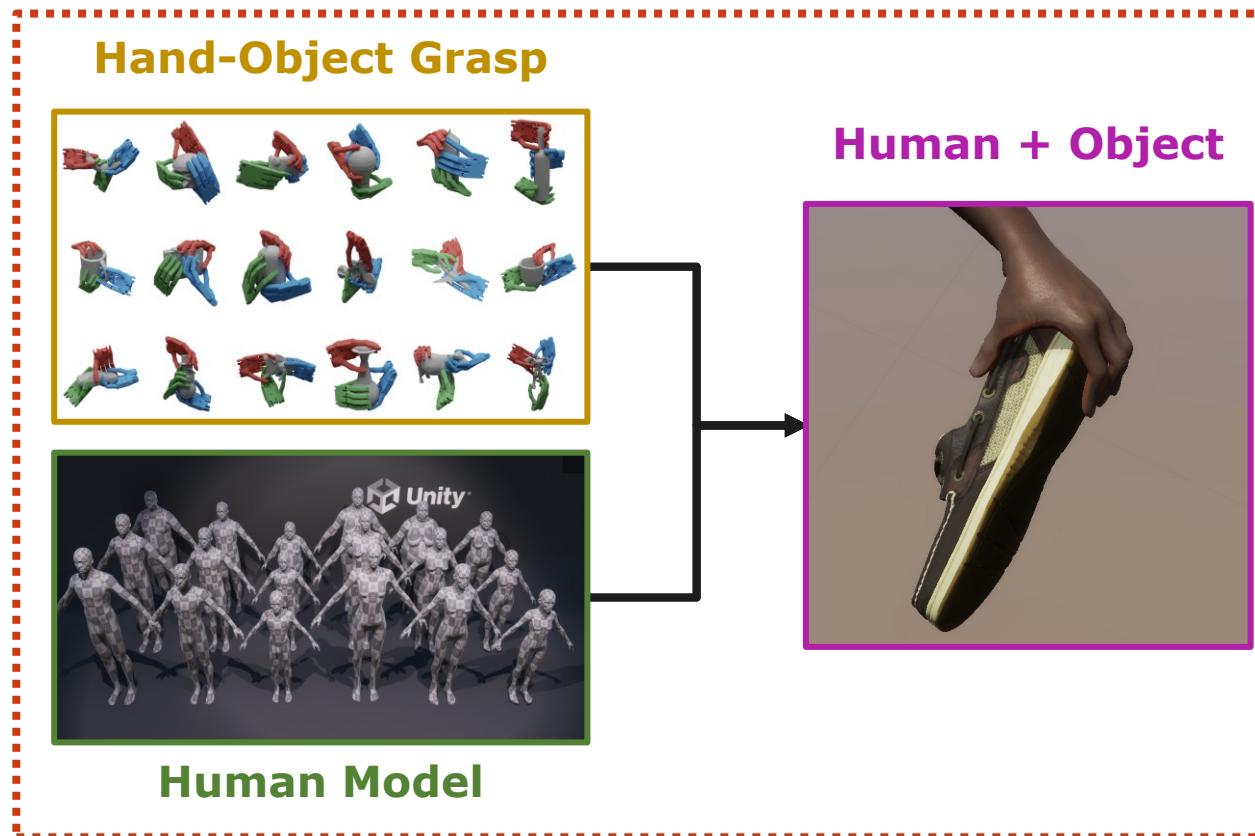
**“Ideal” Synthetic Data should cover a wide range of scenarios and conditions, accurately representing the variability and complexity present in real-world data.**

# HOI-Synth: Data Generation Pipeline



# HOI-Synth: Data Generation Pipeline

## (a) Hand-Object Interaction Generation



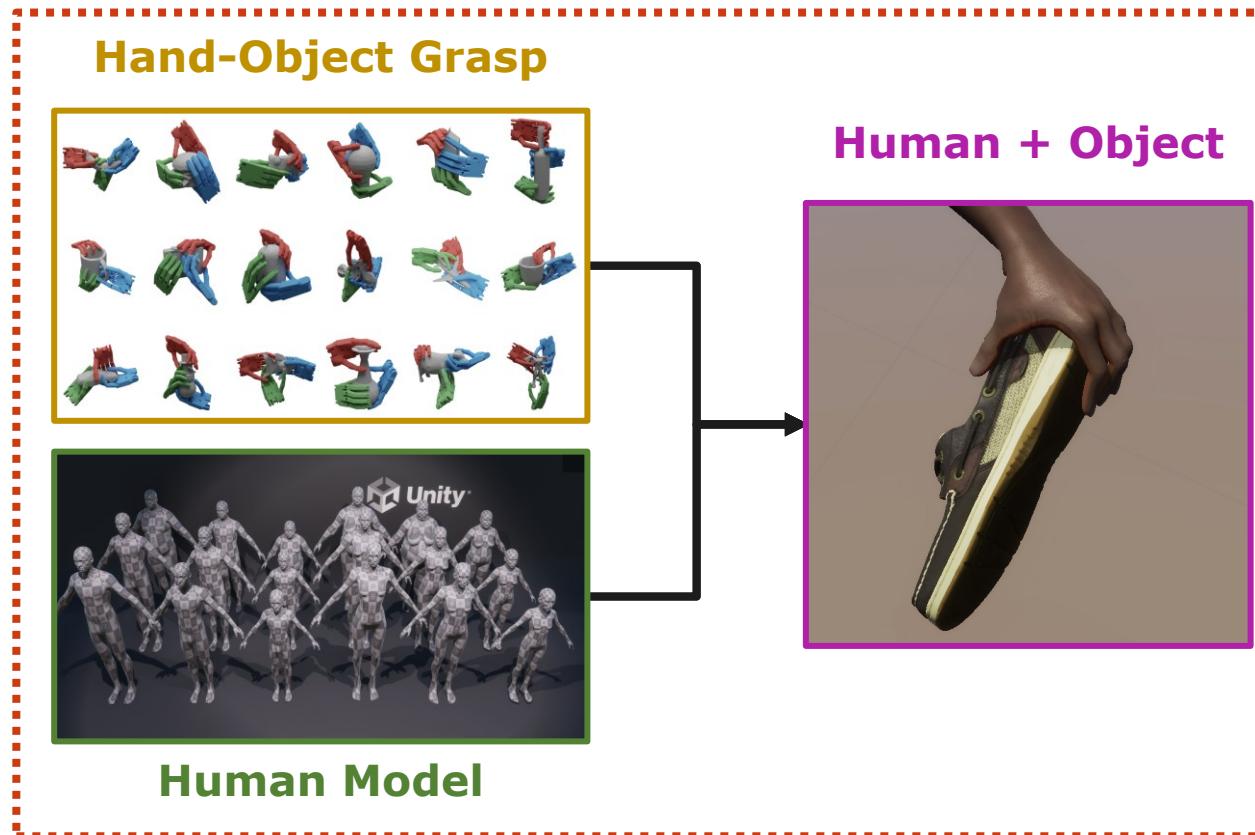
DexGraspNet



- 1.32 million grasps
- 5355 objects

# HOI-Synth: Data Generation Pipeline

## (a) Hand-Object Interaction Generation



## Synthetic Humans



# HOI-Synth: Data Generation Pipeline



# HOI-Synth: Data Generation Pipeline

## (b) Environment Selection and Human Placement



Habitat - Matterport 3D Research Dataset (HM3D)

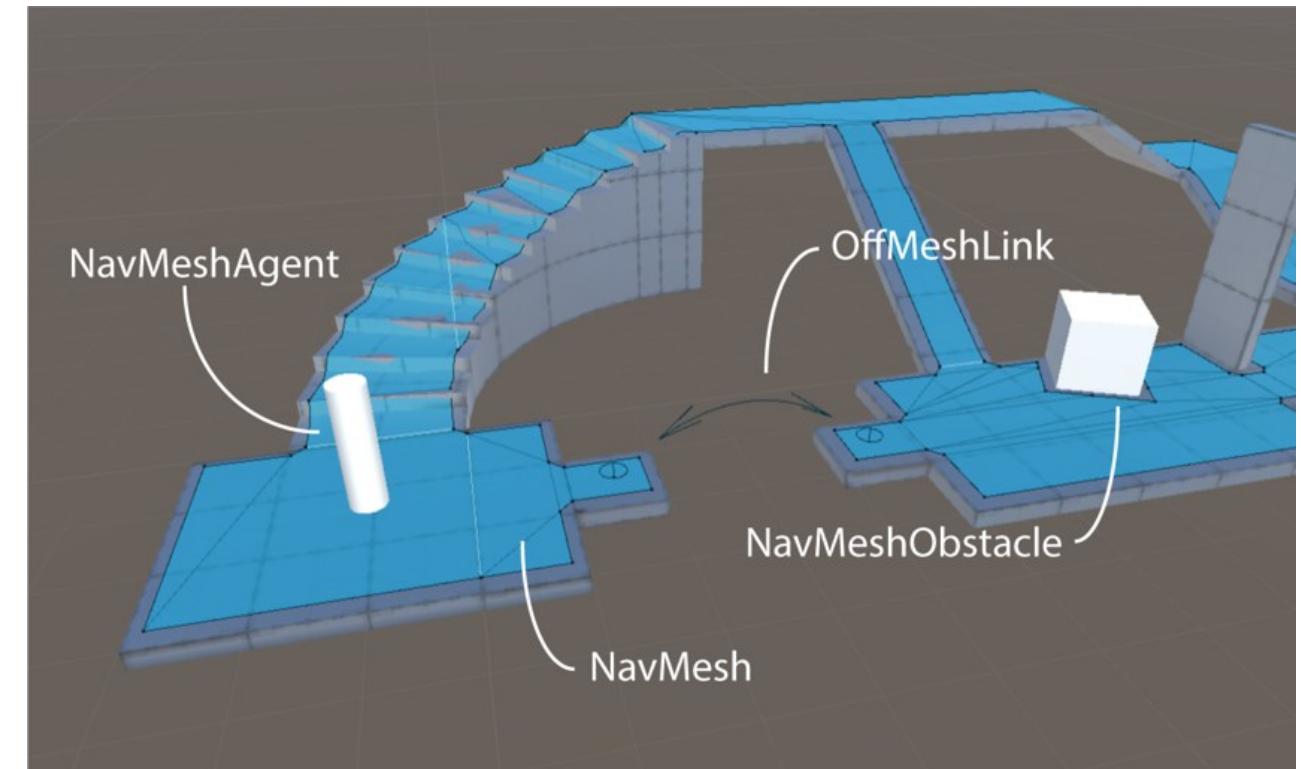


# HOI-Synth: Data Generation Pipeline

## (b) Environment Selection and Human Placement



## Navigation (NavMesh) System (Unity)

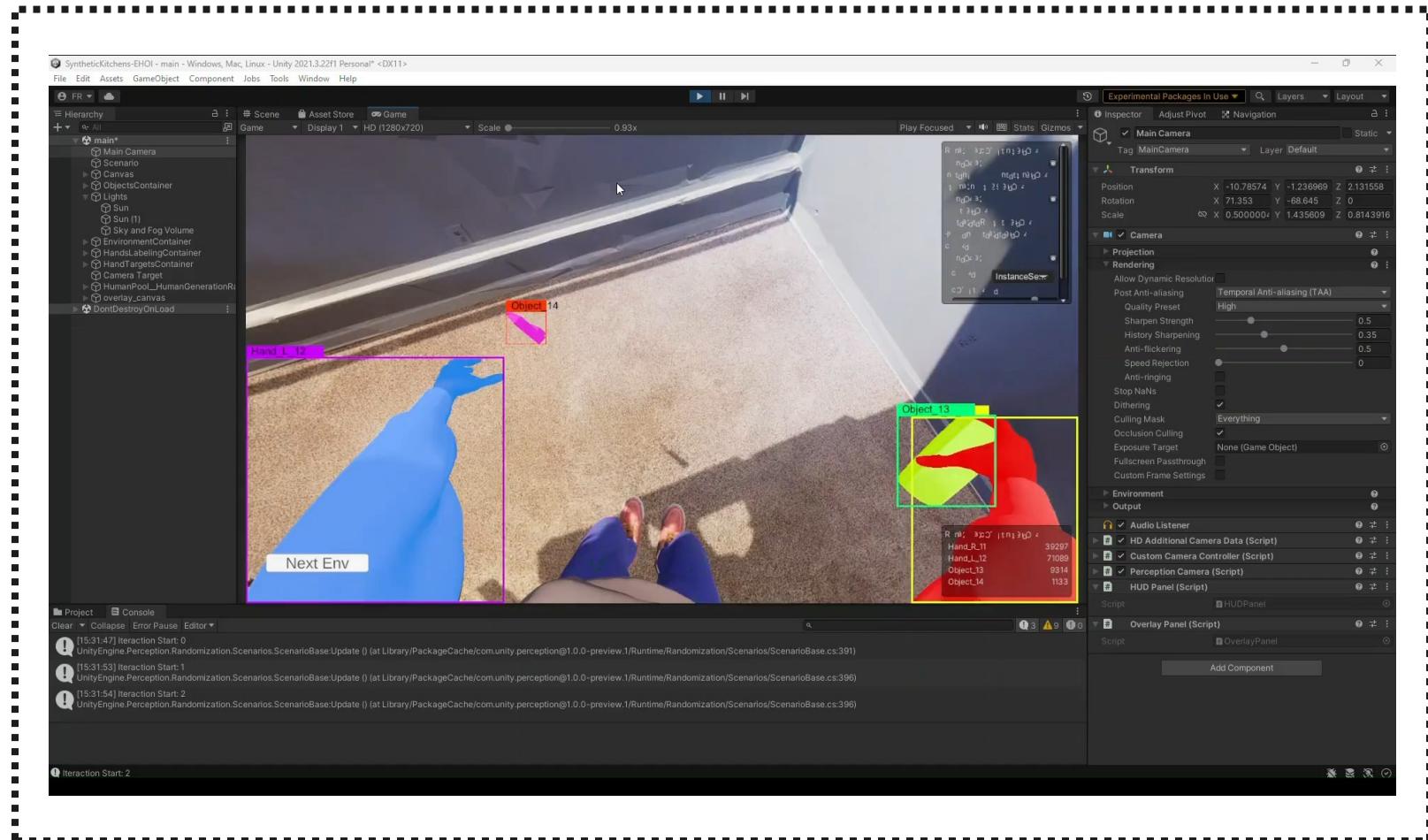


# HOI-Synth: Data Generation Pipeline

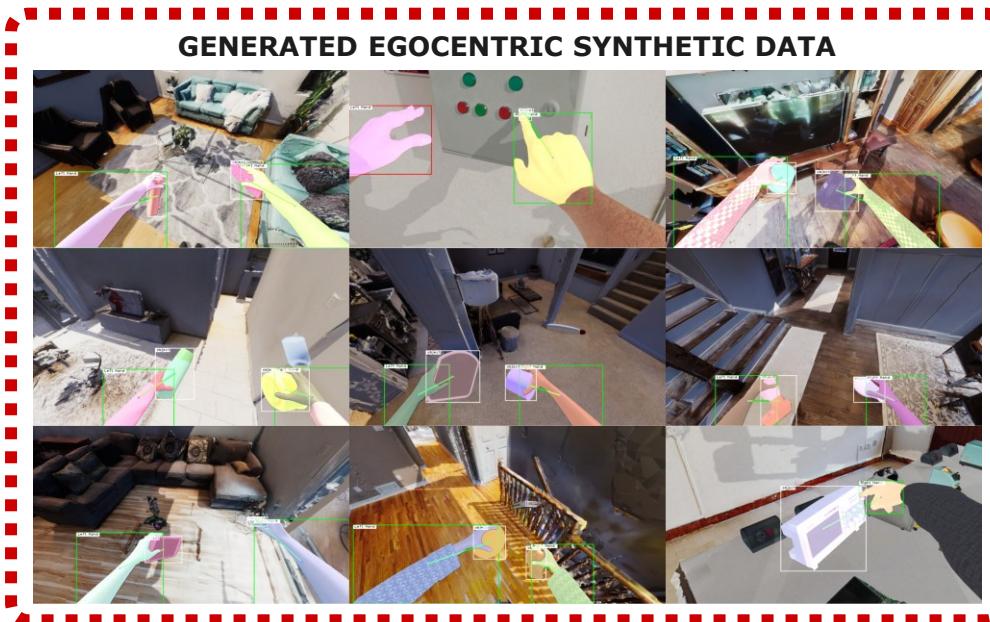


# HOI-Synth: Data Generation Pipeline

## (c) Generated Labeled Egocentric Data



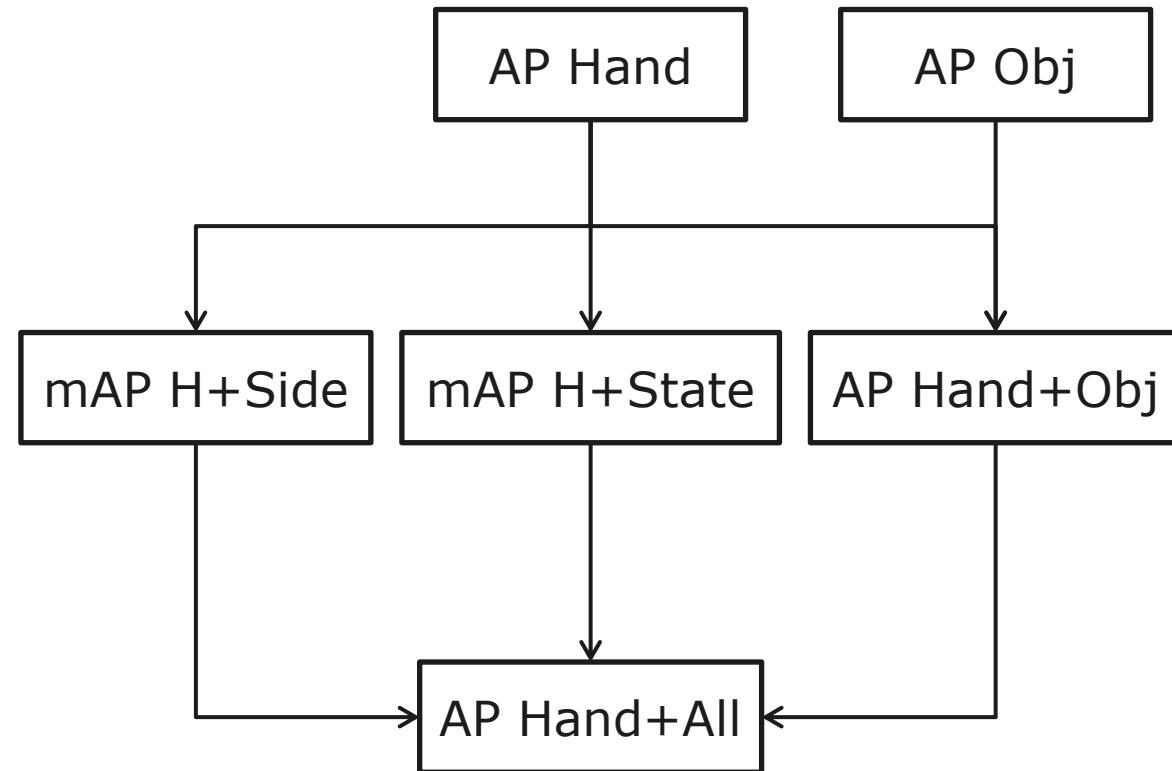
# HOI-Synth Benchmark



- **Epic-Kitchens VISOR**
  - 32,857 real + 30,259 synthetic images
- **EgoHOS**
  - 8,107 real + 8,107 synthetic images
- **ENIGMA-51**
  - 3,479 real images
  - In-Domain 16,773 + Out-domain 20,321 synthetic images

# 3. Models and Architectures for Hand-Object Interactions Detection

# Evaluation Protocols: mAP with criterion

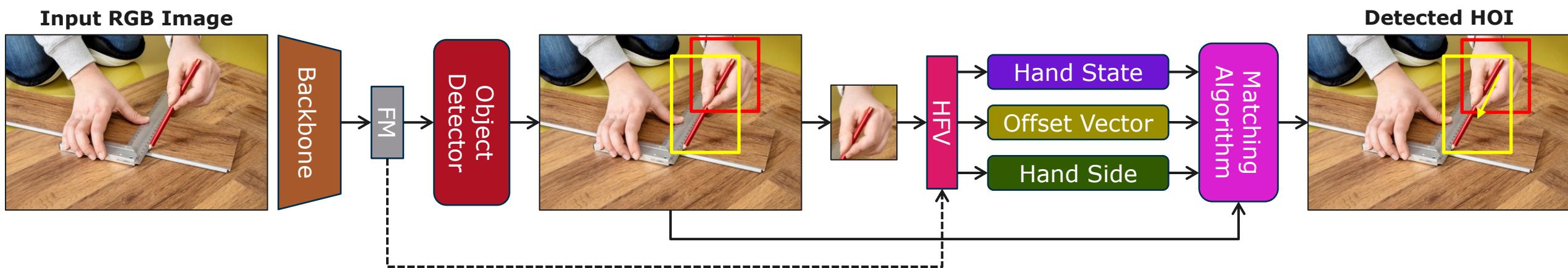


FM

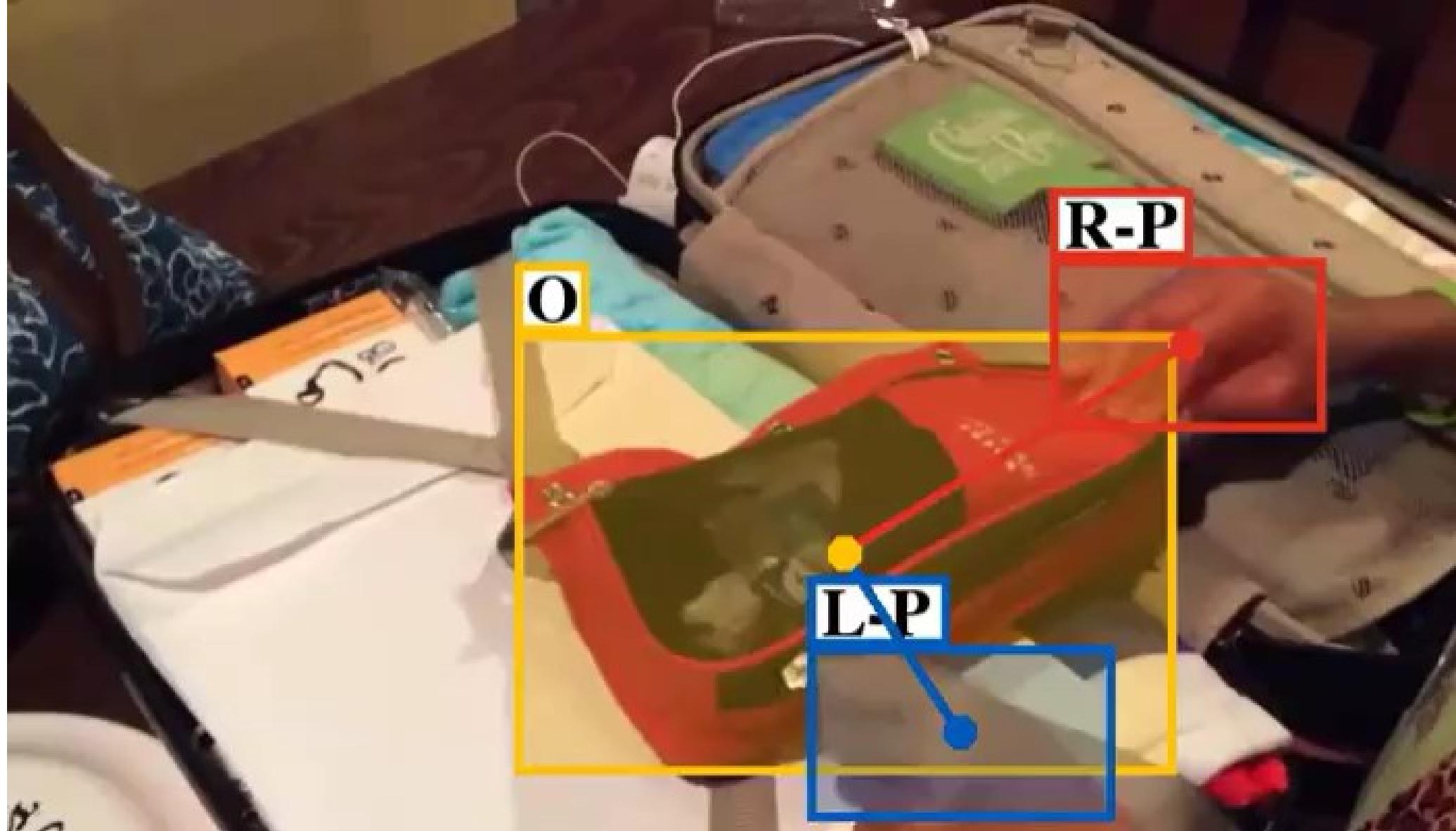
Features Map

HFV

Hand Features Map



# 100 Days of Hands: Qualitative Results



# 100 Days of Hands: Quantitative Results

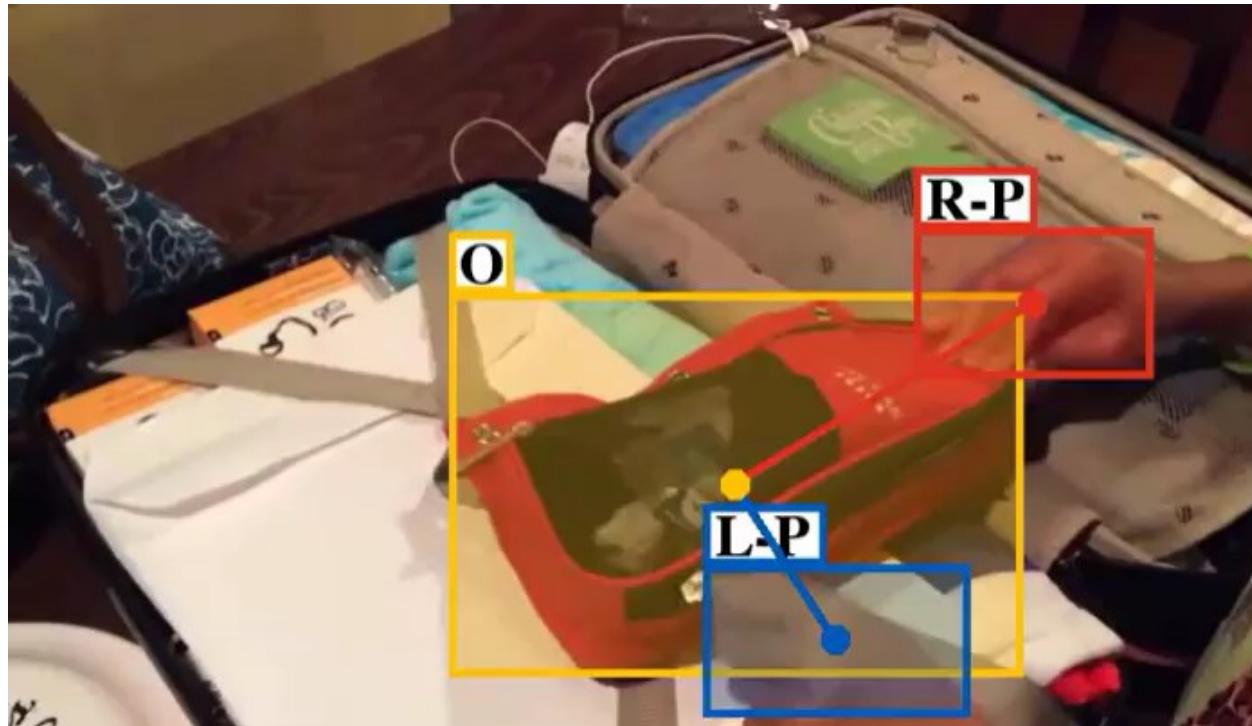
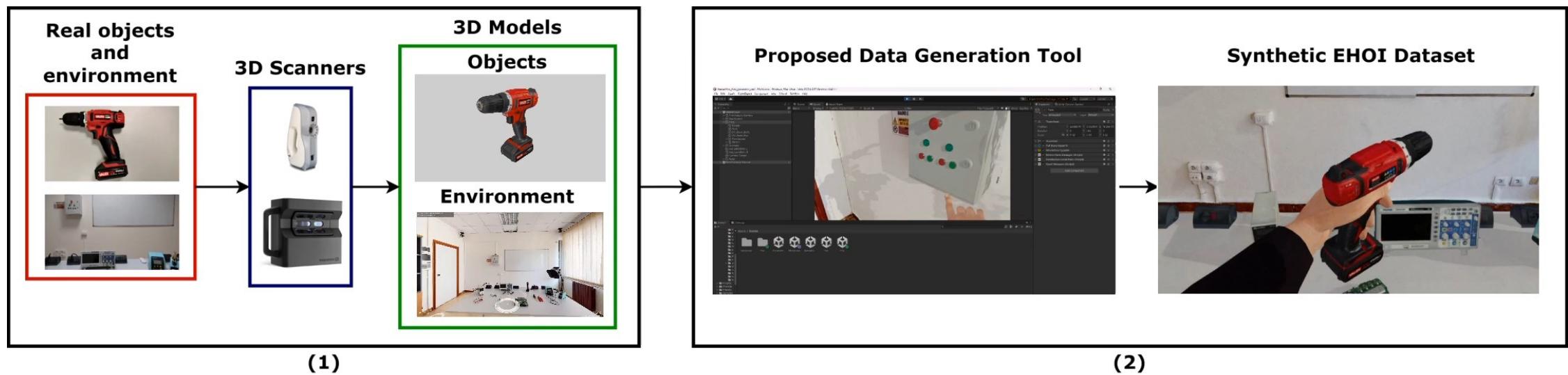


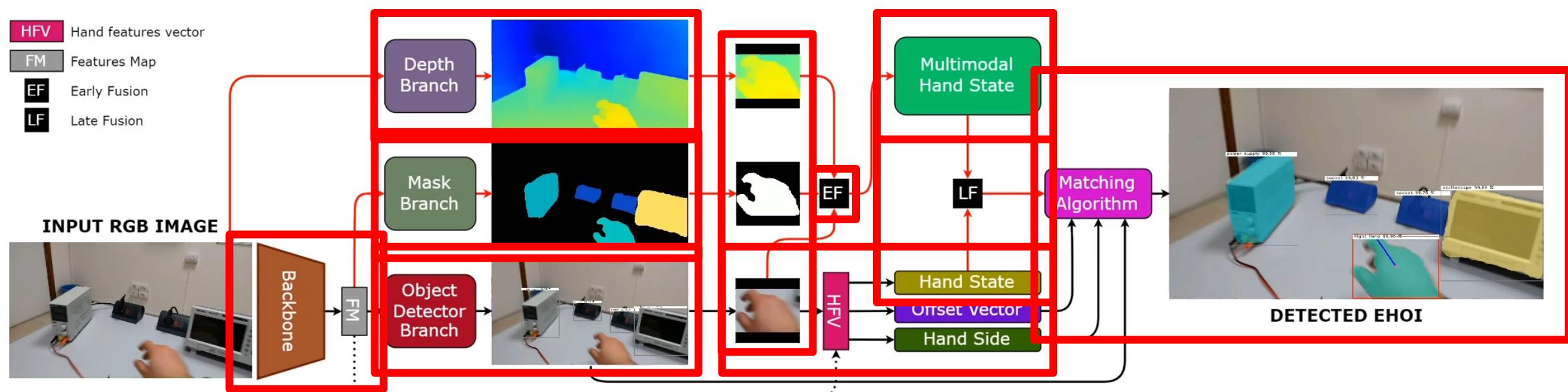
Table 4. Average Precision when we vary definitions of correct detection. Using 15K samples dramatically degrades performance on any category, and 45K samples produces a large drop on getting all outputs correct.

	Hand	Obj	H+Side	H+State	H+O	All
Full	89.6	63.9	78.9	64.0	46.9	38.5
45K	88.4	61.0	77.3	62.7	39.3	31.3
15K	80.9	54.2	66.8	53.3	27.3	19.7

# Proposed Synthetic Data Generation Pipeline

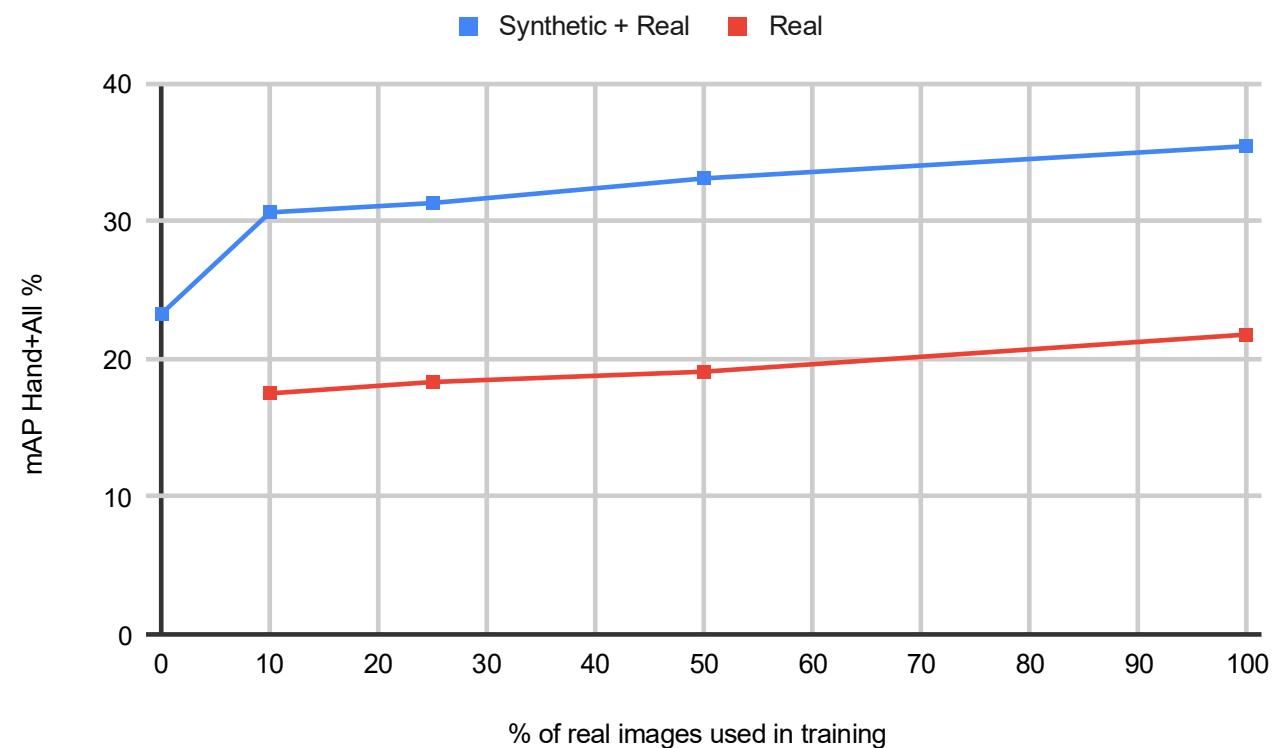


# Proposed Approach

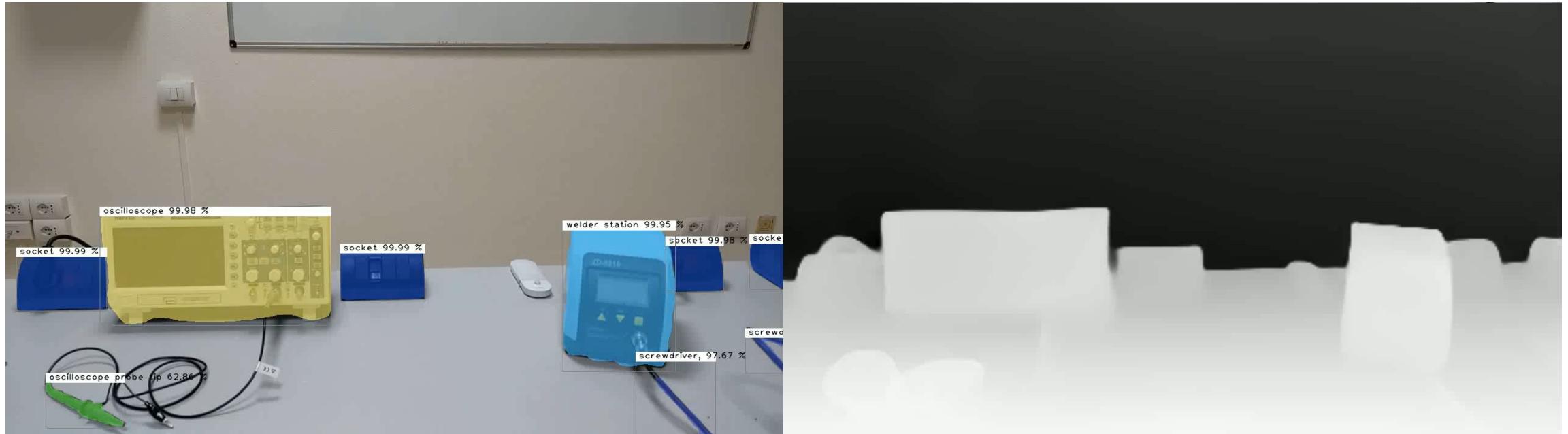


# Quantitative Results

Contact state	MHS Input Modalities	AP H+State	mAP H+All
HS	-	56.88	35.47
MHS	RGB+DEPTH+MASK	57.56	35.81
HS+MHS	RGB	58.29	35.71
HS+MHS	RGB+DEPTH	58.37	35.92
HS+MHS	RGB+MASK	58.30	35.34
FULL	RGB+DEPTH+MASK	<b>58.40</b>	<b>36.51</b>



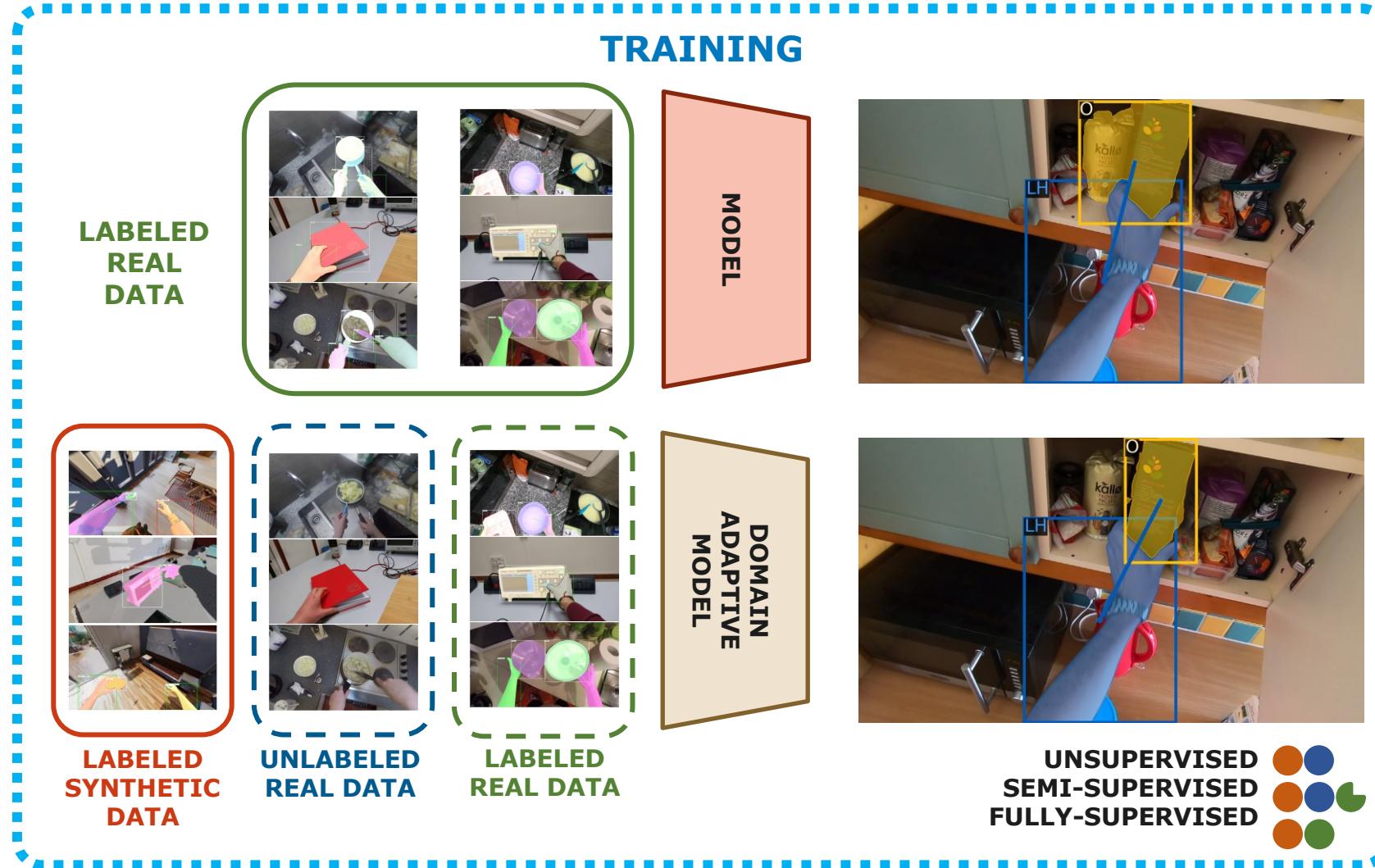
# Qualitative Results



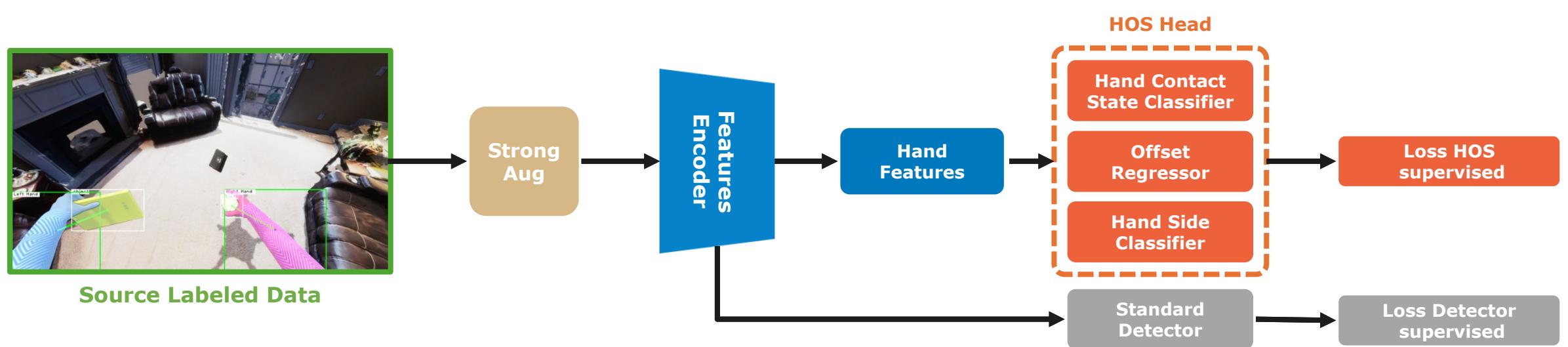
RGB

Estimated Monocular Depth Estimation

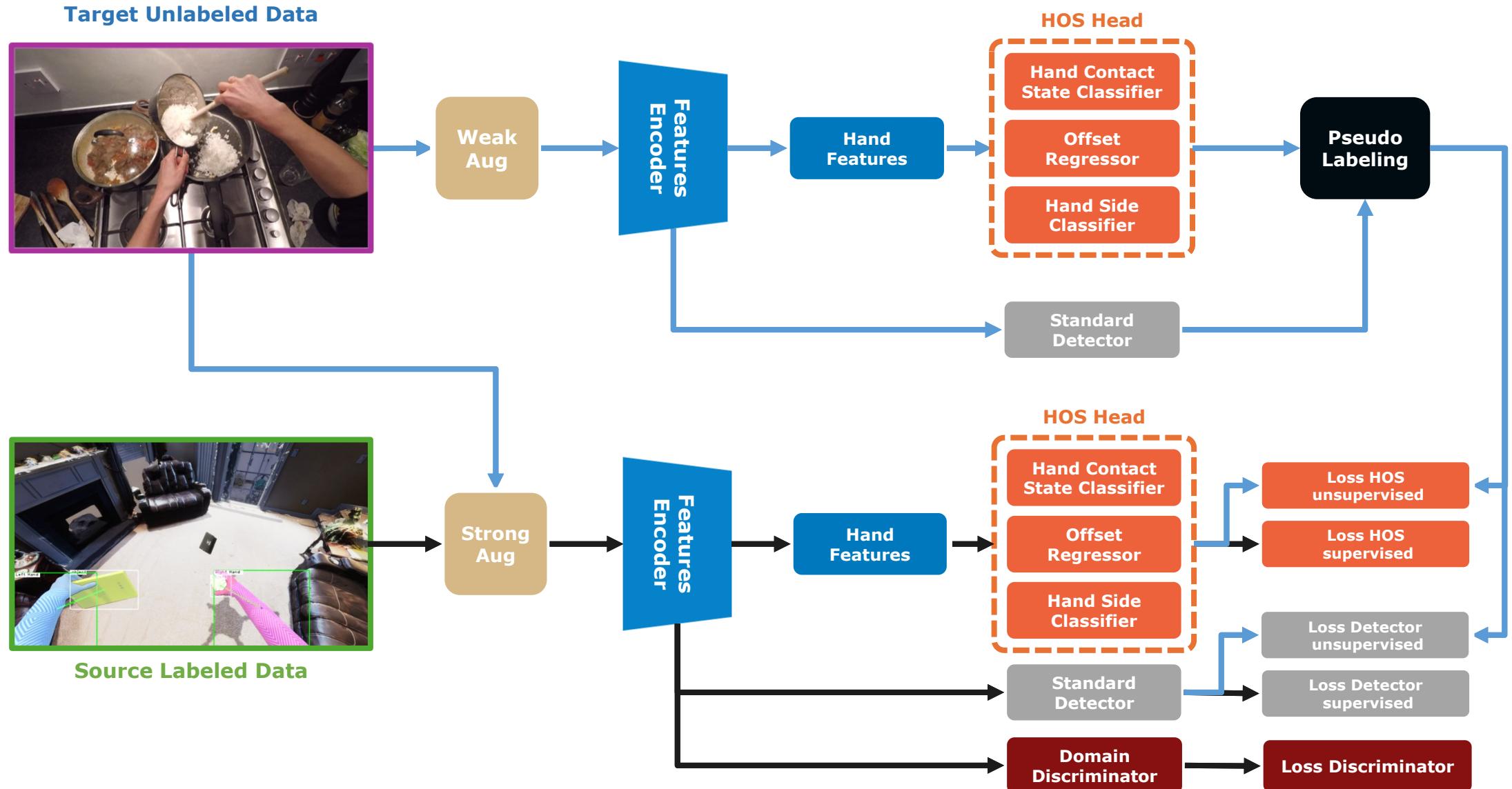
# Domain Adaptation



# Proposed Approach: Burn-in



# Proposed Approach: Teacher->Student



# Quantitative Results: Epic-Kitchens VISOR

## a) Unsupervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
0%	Synthetic-Only	09.88	28.41	24.89	08.64	01.23
	UDA	<b>33.33</b>	<b>80.16</b>	<b>65.98</b>	<b>33.47</b>	<b>08.35</b>
Absolute Improvement		<b>+23.45</b>	+51.75	+41.09	+24.83	+7.12

## b) Semi-supervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
25% (8,215 images)	Real-Only	37.90	90.14	<b>85.66</b>	53.99	17.85
	Synthetic+Real	38.19	89.98	84.67	<b>55.88</b>	18.49
	SSDA	<b>45.55</b>	<b>90.37</b>	84.42	52.59	<b>22.15</b>
Absolute Improvement		<b>+7.65</b>	+0.23	-0.99	+1.89	+4.30

## c) Fully-supervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
100% (32,857 images)	Real-Only	45.33	<b>92.25</b>	88.54	<b>59.24</b>	24.23
	Synthetic+Real	44.52	91.45	<b>88.94</b>	56.55	<b>27.77</b>
	FSDA	<b>46.48</b>	91.83	87.65	57.63	24.03
Absolute Improvement		<b>+1.15</b>	-0.42	+0.40	-1.61	+3.54

# Quantitative Results: Epic-Kitchens VISOR

a) Unsupervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
0%	Synthetic-Only	09.88	28.41	24.89	08.64	01.23
	UDA	<b>33.33</b>	<b>80.16</b>	<b>65.98</b>	<b>33.47</b>	<b>08.35</b>
Absolute Improvement	<b>+23.45</b>	+51.75	+41.09	+24.83	+7.12	

b) Semi-supervised Setting

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25% (8,215 images)	Real-Only	37.90	90.14	<b>85.66</b>	53.99	17.85
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Absolute Improvement	<b>+7.65</b>	+0.23	-0.99	+1.89	+4.30	

c) Fully-supervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
100% (32,857 images)	Real-Only	45.33	<b>92.25</b>	88.54	<b>59.24</b>	24.23
	Synthetic+Real	44.52	91.45	<b>88.94</b>	56.55	<b>27.77</b>
	FSDA	<b>46.48</b>	91.83	87.65	57.63	24.03
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# Quantitative Results: Epic-Kitchens VISOR

a) Unsupervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
0%	Synthetic-Only	09.88	28.41	24.89	08.64	01.23
	UDA	<b>33.33</b>	<b>80.16</b>	<b>65.98</b>	<b>33.47</b>	<b>08.35</b>
Absolute Improvement		<b>+23.45</b>	+51.75	+41.09	+24.83	+7.12

b) Semi-supervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
25% (8,215 images)	Real-Only	37.90	90.14	<b>85.66</b>	53.99	17.85
	Synthetic+Real SSDA	38.19 <b>45.55</b>	89.98 <b>90.37</b>	84.67 84.42	<b>55.88</b> 52.59	18.49 <b>22.15</b>
Absolute Improvement		<b>+7.65</b>	+0.23	-0.99	+1.89	+4.30

C) Fully-supervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
100% (32,857 images)	Real-Only	45.33	<b>92.25</b>	88.54	<b>59.24</b>	24.23
	Synthetic+Real	44.52	91.45	<b>88.94</b>	56.55	<b>27.77</b>
	FSDA	<b>46.48</b>	91.83	87.65	57.63	24.03
Absolute Improvement		<b>+1.15</b>	-0.42	+0.40	-1.61	+3.54

# Quantitative Results: EgoHOS

## a) Unsupervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
0%	Synthetic-Only	07.16	18.25	15.93	05.33	01.24
	UDA	<b>28.16</b>	<b>70.30</b>	<b>59.21</b>	<b>20.84</b>	<b>09.65</b>
Absolute Improvement		<b>+21.00</b>	+52.05	+43.28	+15.51	+8.41

## b) Semi-supervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
25% (2,026 images)	Real-Only	33.73	78.94	70.62	41.67	21.83
	Synthetic+Real	33.78	79.60	71.61	46.11	19.87
	SSDA	<b>37.16</b>	<b>83.79</b>	<b>74.28</b>	<b>49.00</b>	<b>23.82</b>
Absolute Improvement		<b>+3.43</b>	+4.85	+3.66	+7.33	+1.99

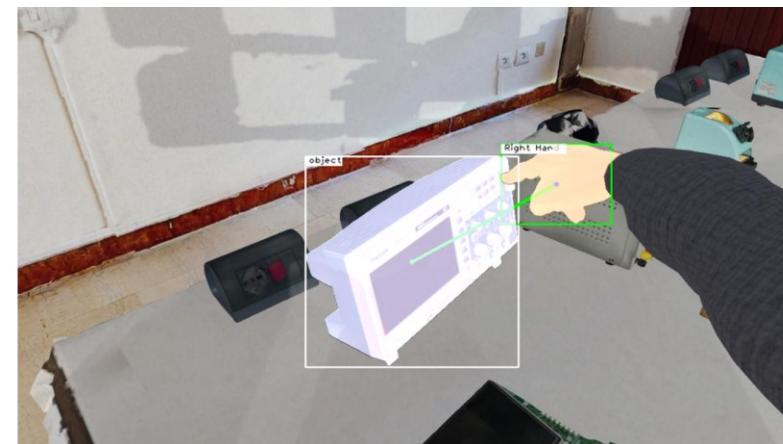
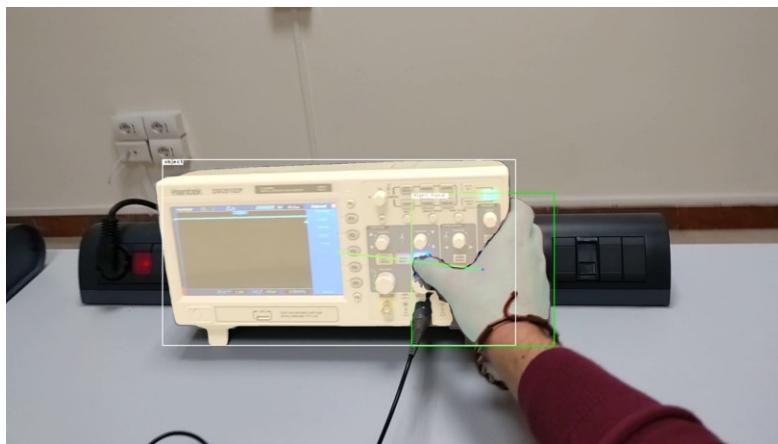
## c) Fully-supervised Setting

% Real Labeled Data	Approach	Overall	H	H+S	H+C	O
100% (8,758 images)	Real-Only	36.16	84.39	76.24	51.81	26.46
	Synthetic+Real	34.68	84.56	71.56	49.72	23.16
	FSDA	<b>39.61</b>	<b>85.58</b>	<b>76.80</b>	<b>51.99</b>	<b>27.05</b>
Absolute Improvement		<b>+3.45</b>	+1.19	+0.56	+0.18	+0.59

# Quantitative Results: ENIGMA-51

## a) Unsupervised Setting

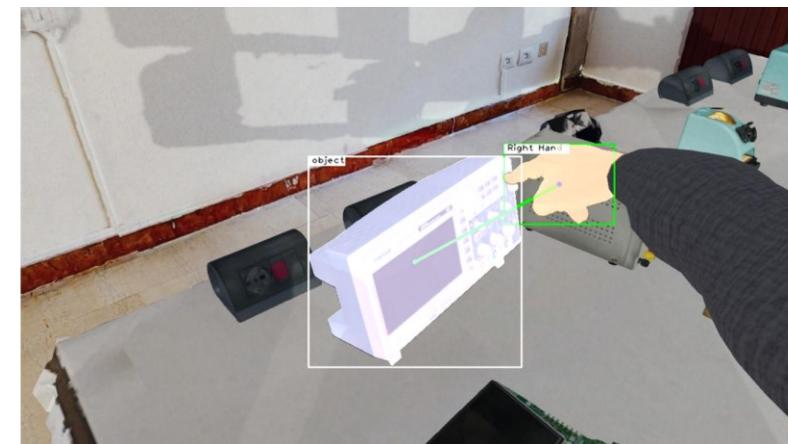
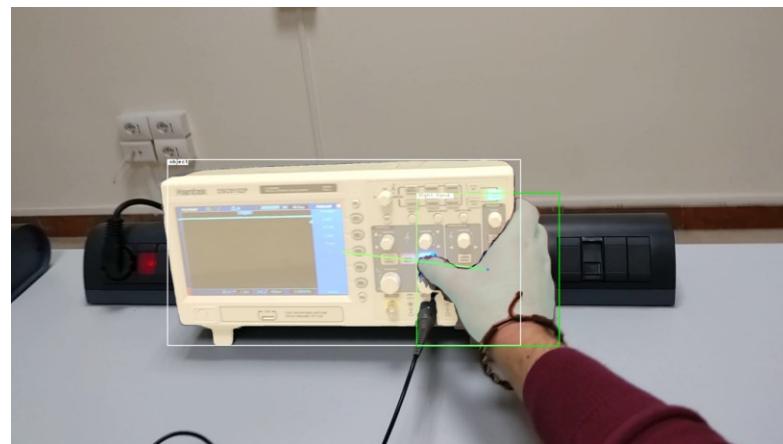
% Real Labeled Data	Approach	In-domain	Overall	H	H+C	O
0%	Synthetic-Only		5.67	15.78	2.66	2.31
	Synthetic-Only	✓	12.85	56.05	15.24	4.79
	UDA		18.57	58.17	17.74	13.15
	UDA	✓	<b>34.78</b>	<b>78.83</b>	<b>28.14</b>	<b>25.84</b>
Absolute Improvement			+16.21	+20.66	+10.40	+12.69



# Quantitative Results: ENIGMA-51

## a) Supervised Setting

% Real Labeled Data	Approach	In-domain	Overall	H	H+C	O
100%	Real-only	✓	63.84	85.01	52.32	51.35
	FSDA		<b>64.41</b>	<b>85.94</b>	<b>54.13</b>	52.50
	FSDA	✓	64.20	85.37	51.60	<b>53.30</b>
Absolute Improvement			+0.57	+0.93	+1.81	+1.95



# 4. Open Challenges

# Open Challenges

- Standardization of evaluation protocols and task definitions!!!!

***mIoU Hand & Object Mask***

***Hand Object Interaction Detection***

***Egocentric Hand Object Interaction Detection***

***mAP All***

***Egocentric Hand-Object Segmentation***

***Egocentric Human Object Interaction Detection***

***mAP Hand + All***

***Hand Object Segmentation***

- Updating and improving pre-existing architectures
- Handling occlusions and complex interactions
- Integration of multimodal and temporal data



# Open Challenges

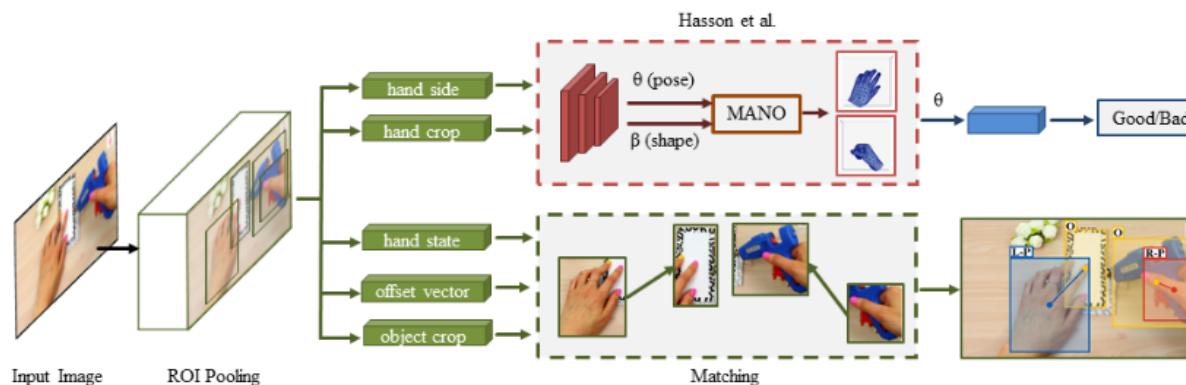
- Standardization of evaluation protocols and task definitions!!!!
- Updating and improving pre-existing architectures

## Hand Object Detector

This is the code for our paper *Understanding Human Hands in Contact at Internet Scale* (CVPR 2020, Oral).

Dandan Shan, Jiaqi Geng\*, Michelle Shu\*, David F. Fouhey

Watch 5 ▾ Fork 70 ▾ Star 274 ▾



2020

- Handling occlusions and complex interactions
- Integration of multimodal and temporal data

# Open Challenges

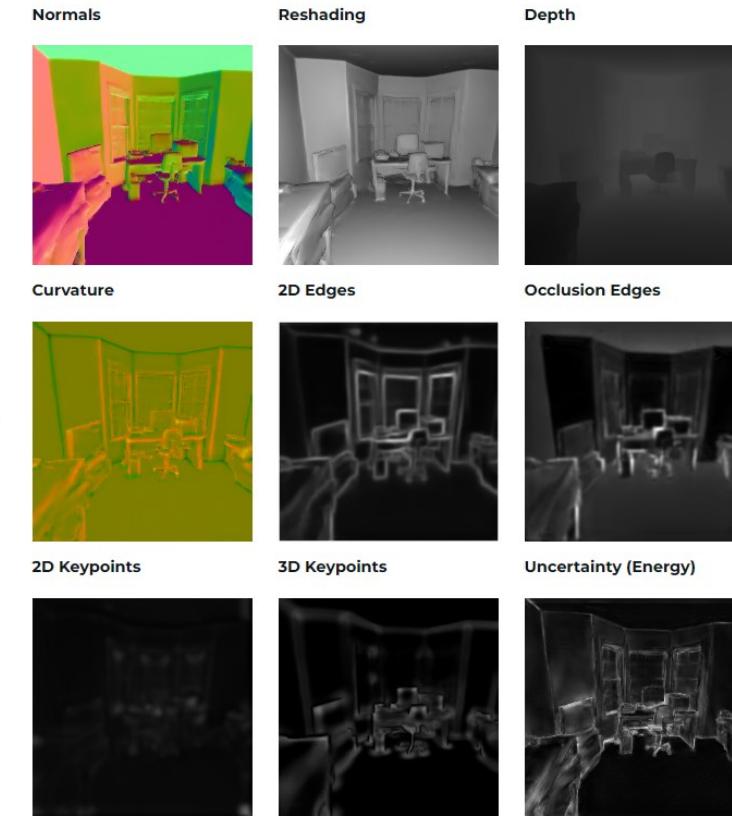
- Standardization of evaluation protocols and task definitions!!!!
  - Updating and improving pre-existing architectures
- Handling occlusions and complex interactions



- Integration of multimodal and temporal data

# Open Challenges

- Standardization of evaluation protocols and task definitions!!!!
  - Updating and improving pre-existing architectures
    - Handling occlusions and complex interactions
- Integration of multimodal and temporal data



# Open Challenges

- Standardization of evaluation protocols and task definitions!!!!
  - Updating and improving pre-existing architectures
    - Handling occlusions and complex interactions
- Integration of multimodal and temporal data



**Static Frame**

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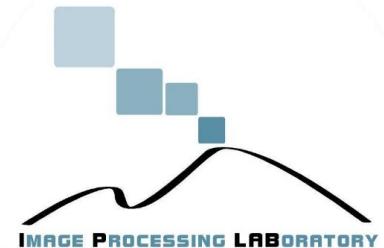
**Video Shot**



Università  
di Catania

NEXT VISION

Spin-off of the University of Catania



## Hand-Object Interactions in Egocentric Vision

# Thank you!

Rosario Leonardi

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Next Vision - <http://www.nextvisionlab.it/>

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