



uOttawa

MEMORY-EFFICIENT HIGH-ACCURACY FOOD INTAKE ACTIVITY RECOGNITION WITH 3D MMWAVE RADARS

Hsin-Che Chiang¹, Yi-Hung Wu¹, Shervin Shirmohammadi², and Cheng-Hsin Hsu¹

¹ Department of Computer Science, National Tsing-Hua University, Taiwan

² School of Electrical Engineering and Computer Science, University of Ottawa, Canada

MADiMa 2023



FOOD INTAKE ACTIVITY RECOGNITION

- Motivation:
 - Rise of **lifestyle-related diseases**
 - Monitoring food intake gains importance
- Problems with food logging/food diaries:
 - Error-prone, inconvenient, and time-consuming
 - Need for an **automated** recognition system

My Food Diary

Date: _____

Monday	
Breakfast	
Snack	
Lunch	
Snack	
Dinner	
Snack	

Tuesday	
Breakfast	
Snack	
Lunch	
Snack	
Dinner	
Snack	

Wednesday	
Breakfast	
Snack	
Lunch	
Snack	
Dinner	
Snack	

Thursday	
Breakfast	
Snack	
Lunch	
Snack	
Dinner	
Snack	

Friday	
Breakfast	
Snack	
Lunch	
Snack	
Dinner	
Snack	

Saturday	
Breakfast	
Snack	
Lunch	
Snack	
Dinner	
Snack	

Sunday	
Breakfast	
Snack	
Lunch	
Snack	
Dinner	
Snack	

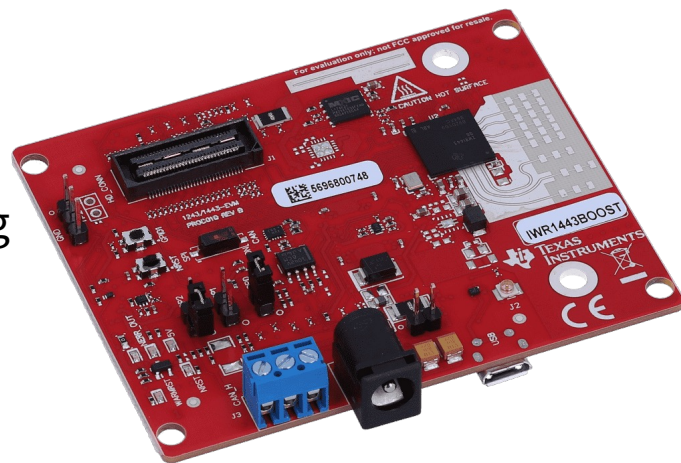
Notes:

Learn more at https://www.cdc.gov/healthyweight/losing_weight/eating_habits.html



FOOD INTAKE ACTIVITY RECOGNITION

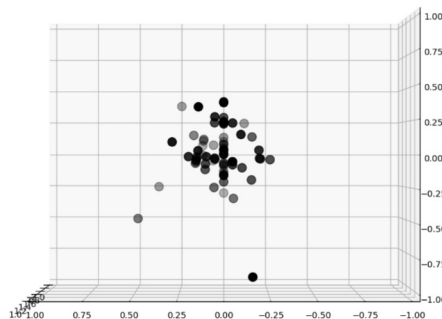
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 - Rise of **lifestyle-related diseases**
 - Monitoring food intake gains importance
- Problems with food logging/food diaries:
 - Error-prone, inconvenient, and time-consuming
 - Need for an **automated** recognition system
- Problems with RGB cameras:
 - Privacy concerns drive users away
 - Vulnerable to poor/fluctuating lighting
 - Explore alternative sensors, e.g., the **mmWave radar**



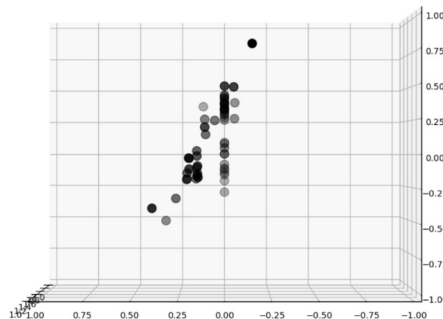


MMWAVE POINT CLOUD DATASET [MMSys '23]

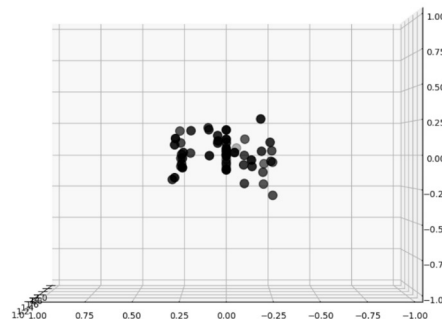
Sparse Dynamic
3D Point Cloud



(a)

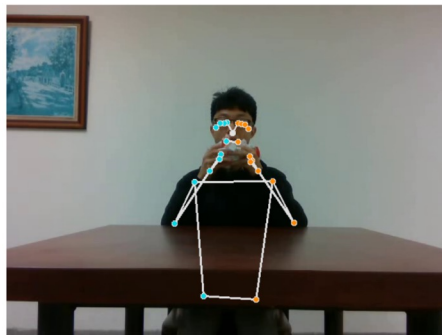


(c)

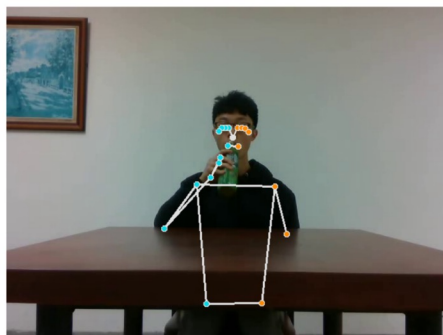


(e)

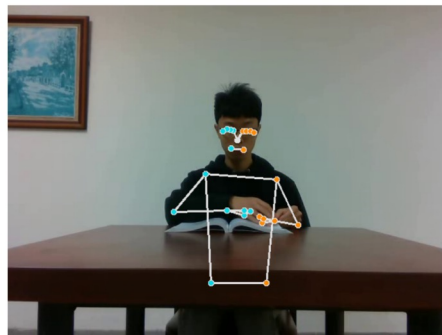
RGB videos
(w/ skeletons)



(b)



(d)



(f)

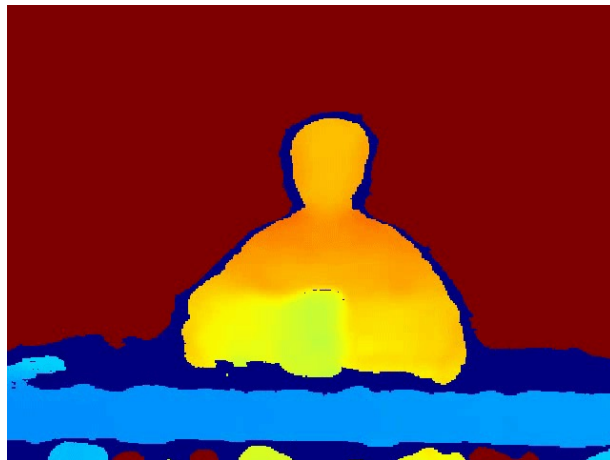
[MMSys '23] Y. Wu, H. Chiang, S. Shirmohammadi, and C. Hsu. 2023.

A Dataset of Food Intake Activities Using Sensors with Heterogeneous Privacy Sensitivity Levels. In Proc. of the ACM MMSys '23. 416–422. ³

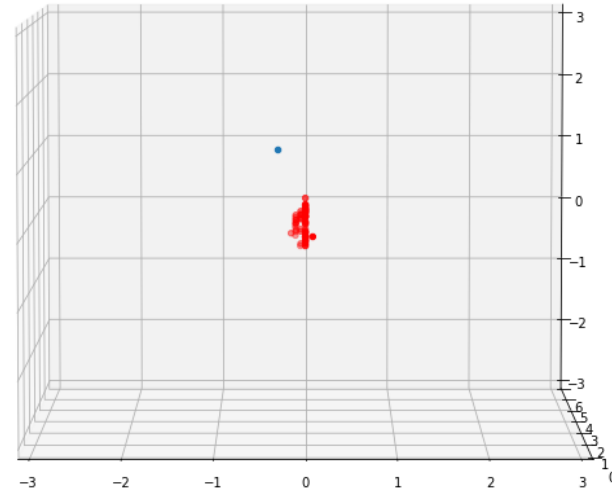
SAMPLE SENSOR DATA



RGB Video



Depth Video

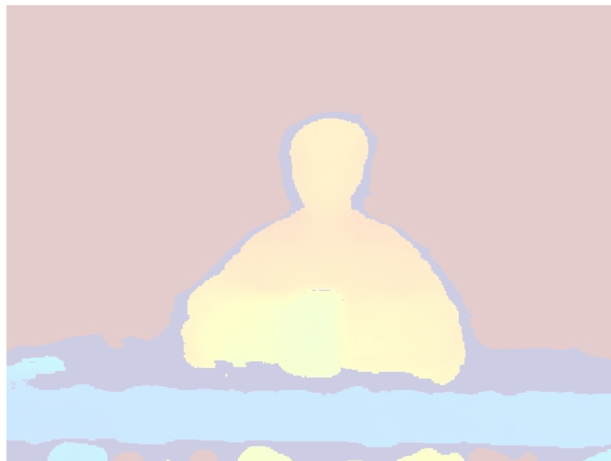


Sparse Dynamic
3D Point Cloud

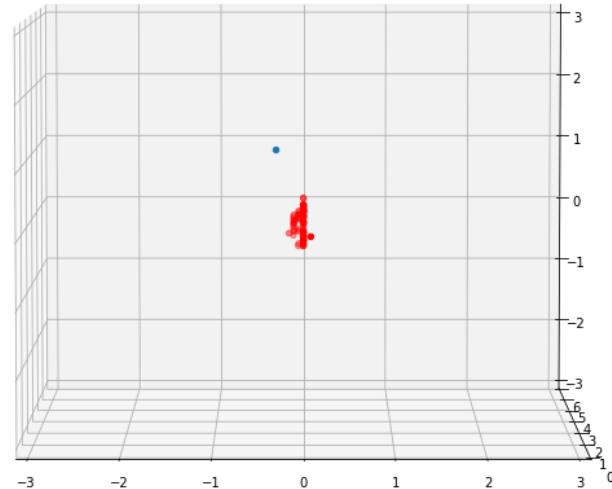
SAMPLE SENSOR DATA



RGB Video



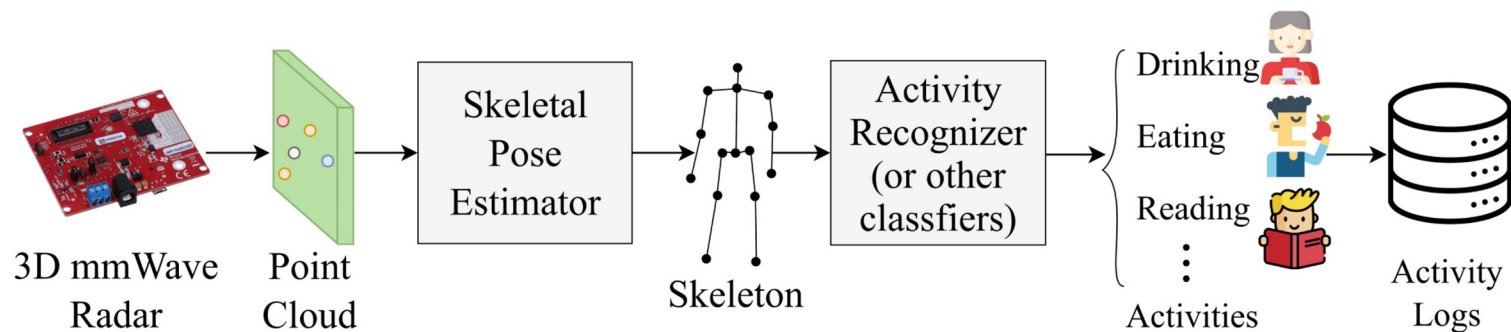
Depth Video



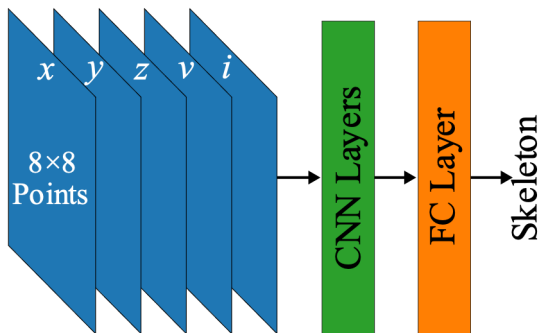
Sparse Dynamic
3D Point Cloud

SKELETAL POSE ESTIMATION

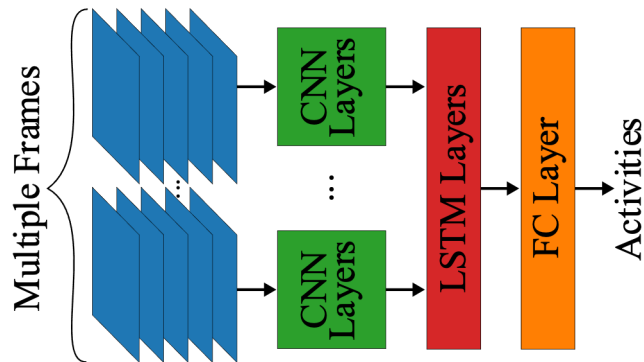
- Challenges:
 - Food intake activities involve **smaller movements**
 - Differentiating them requires higher precision
- Solution:
 - Skeletal Pose Estimation (a.k.a. Human Joint Estimation)
 - **Leverage the human body structure** to capture subtle nuances



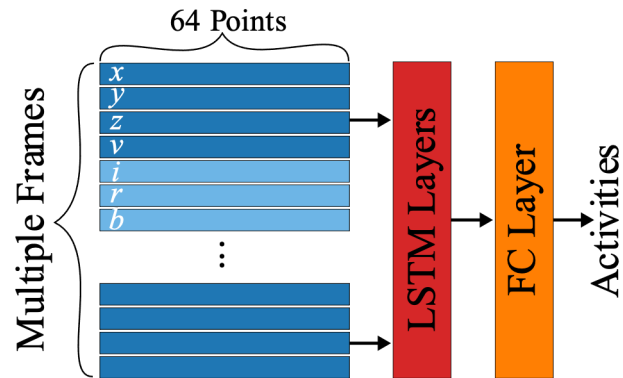
PROPOSED SOLUTIONS



① **Skeletal Pose Estimator (SPE)**

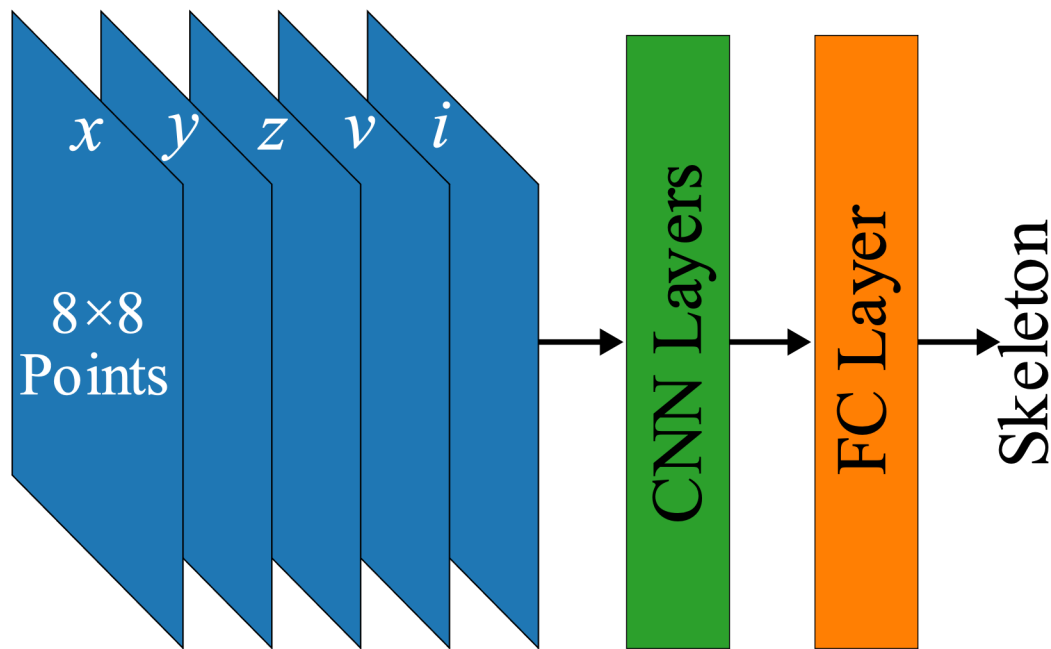


② **Dynamic Point Cloud Recognizer (DPR)**



③ **Lightweight Dynamic Point Cloud Recognizer (LDPR)**

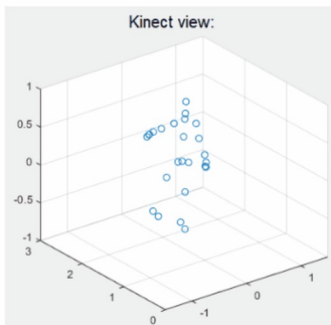
PROPOSED SOLUTIONS



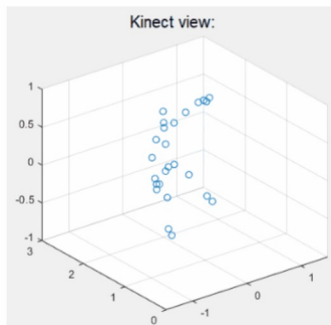
① **Skeletal Pose Estimator (SPE)**

MARS [1]

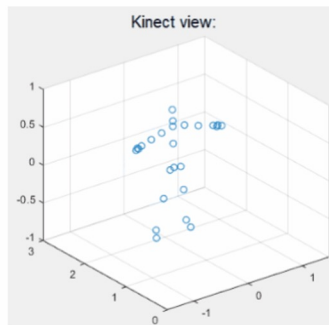
mmWave-Based Assistive Rehabilitation System for Smart Healthcare



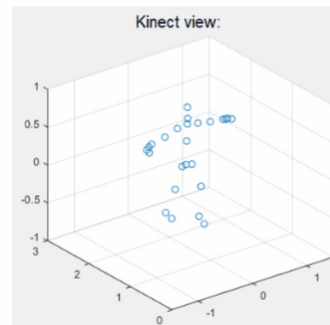
10) Right limb extension



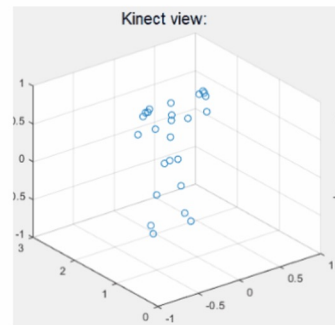
9) Left limb extension



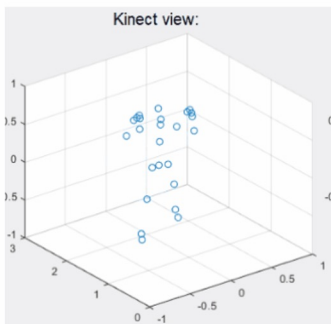
8) Right side lunge



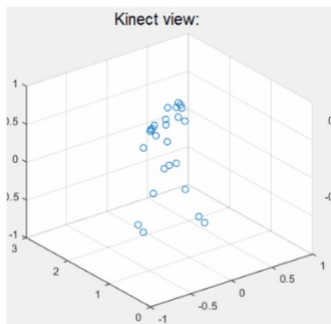
7) Left side lunge



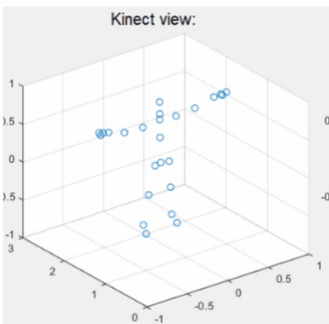
6) Squad



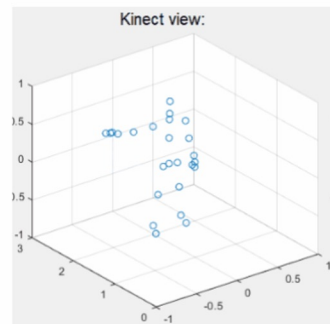
5) Right front lunge



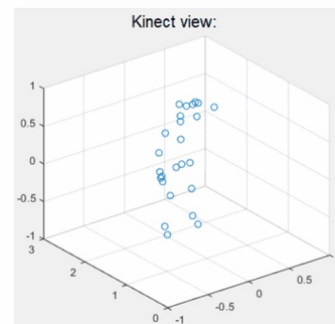
4) Left front lunge



3) Both upper limb extension



2) Right upper limb extension



1) Left upper limb extension

ERRORS OF THE ESTIMATED JOINTS IN SPE^①

	MARS	AlexNet	GoogLeNet	ResNet-18	ResNet-34	ResNet-50
Nose	8.28 (± 0.17)	6.91 (± 0.06)	4.73 (± 0.05)	4.41 (± 0.05)	4.22 (± 0.05)	4.75 (± 0.08)
L. Shldr	6.66 (± 0.10)	5.65 (± 0.05)	3.91 (± 0.04)	3.74 (± 0.04)	3.58 (± 0.04)	3.93 (± 0.05)
R. Shldr	6.58 (± 0.11)	5.54 (± 0.05)	3.86 (± 0.04)	3.67 (± 0.04)	3.52 (± 0.04)	3.91 (± 0.06)
L. Elbow	8.68 (± 0.15)	7.13 (± 0.05)	4.84 (± 0.04)	4.59 (± 0.04)	4.39 (± 0.04)	4.83 (± 0.05)
R. Elbow	8.38 (± 0.16)	7.05 (± 0.05)	4.97 (± 0.04)	4.76 (± 0.04)	4.57 (± 0.04)	4.94 (± 0.04)
L. Wrist	11.52 (± 0.13)	9.60 (± 0.06)	6.53 (± 0.05)	6.36 (± 0.05)	6.06 (± 0.05)	6.55 (± 0.06)
R. Wrist	11.78 (± 0.10)	10.19 (± 0.06)	7.29 (± 0.05)	7.15 (± 0.05)	6.85 (± 0.05)	7.33 (± 0.06)
L. Pinky	12.51 (± 0.13)	10.44 (± 0.07)	7.14 (± 0.05)	6.96 (± 0.05)	6.62 (± 0.05)	7.13 (± 0.06)
R. Pinky	13.27 (± 0.15)	11.47 (± 0.07)	8.24 (± 0.06)	8.08 (± 0.06)	7.74 (± 0.06)	8.28 (± 0.06)
L. Index	12.54 (± 0.13)	10.50 (± 0.07)	7.20 (± 0.06)	7.00 (± 0.05)	6.67 (± 0.05)	7.21 (± 0.06)
R. Index	13.16 (± 0.11)	11.41 (± 0.07)	8.23 (± 0.06)	8.06 (± 0.06)	7.73 (± 0.06)	8.26 (± 0.06)
L. Thumb	11.63 (± 0.13)	9.70 (± 0.06)	6.62 (± 0.05)	6.46 (± 0.05)	6.15 (± 0.05)	6.63 (± 0.05)
R. Thumb	11.96 (± 0.09)	10.36 (± 0.06)	7.42 (± 0.05)	7.29 (± 0.05)	6.99 (± 0.05)	7.47 (± 0.06)
Average	10.54 (± 1.33)	8.92 (± 1.16)	6.23 (± 0.85)	6.04 (± 0.86)	5.78 (± 0.83)	6.25 (± 0.85)

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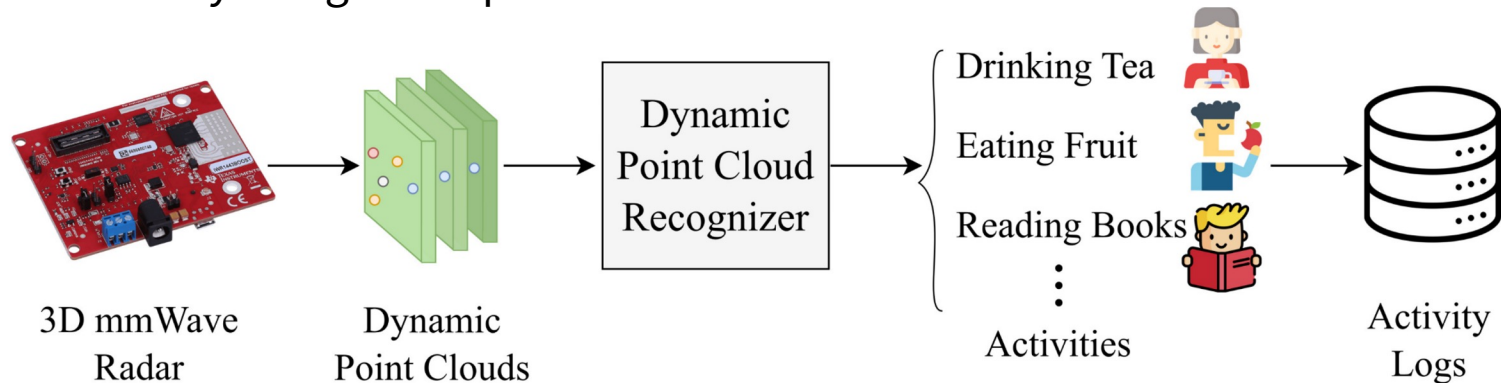
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END-TO-END SOLUTION

- End-to-end learning
 - An ML technique where we train a **single neural network** for complex tasks
 - Directly using raw input data without manual feature extraction

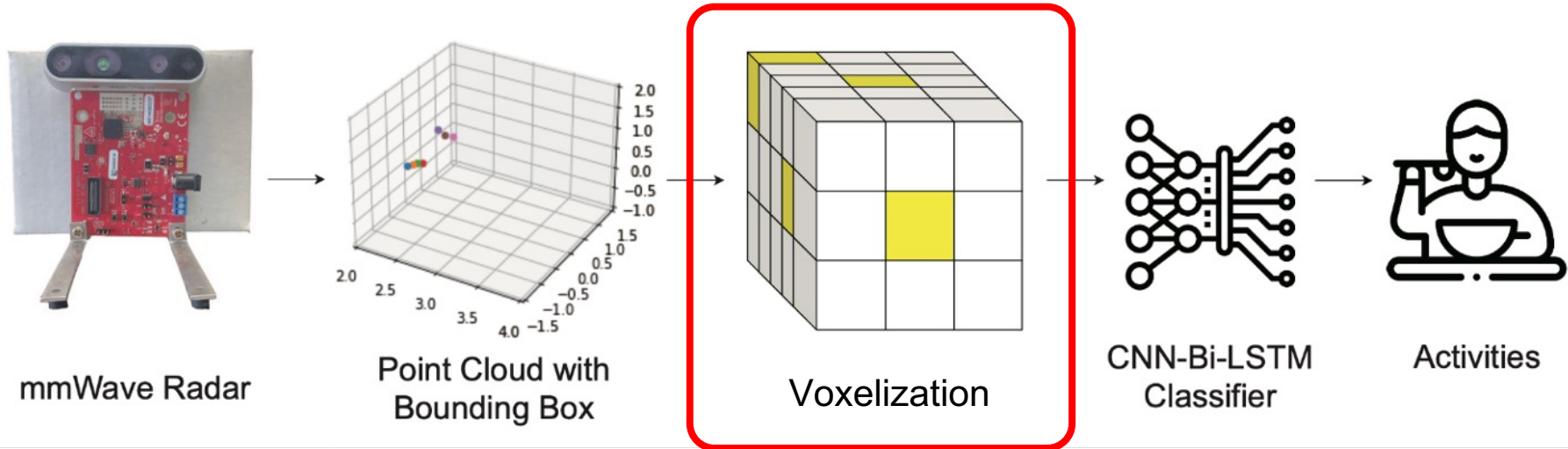


- Food Intake Activity (FIA) [MADiMa '22]
 - Uses **voxelization**, which is quite memory inefficient for sparse point clouds

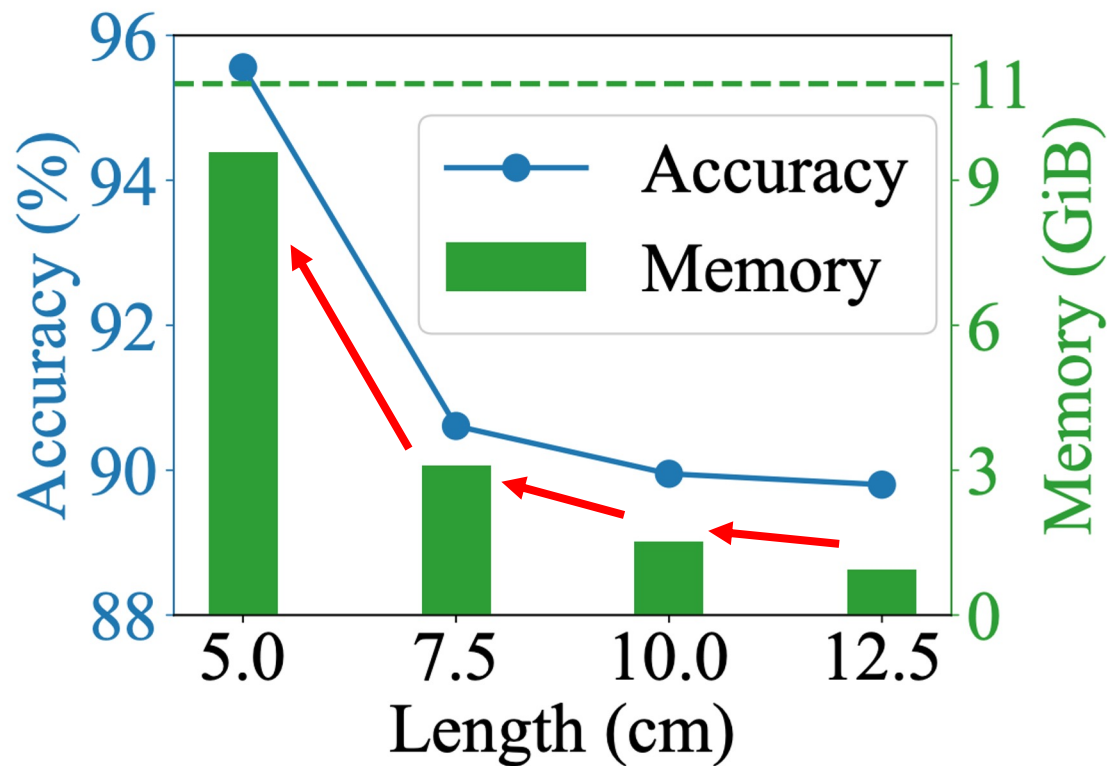
[MADiMa '22] Y. Wu, Y. Chen, S. Shirmohammadi, and C. Hsu. 2022.

AI-Assisted Food Intake Activity Recognition Using 3D mmWave Radars. In Proc. of the ACM MADiMa '22. 81–89.

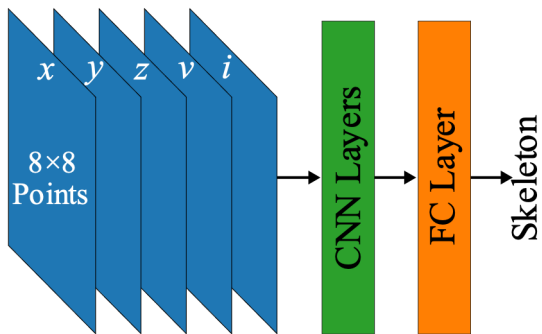
FIA PIPELINE



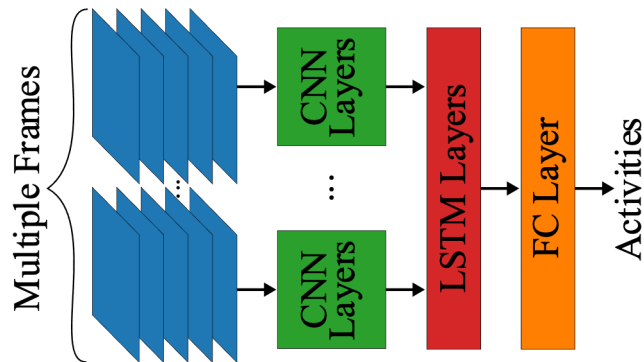
FIA VOXEL SIZE ↓ ACCURACY ↑ MEMORY ↑



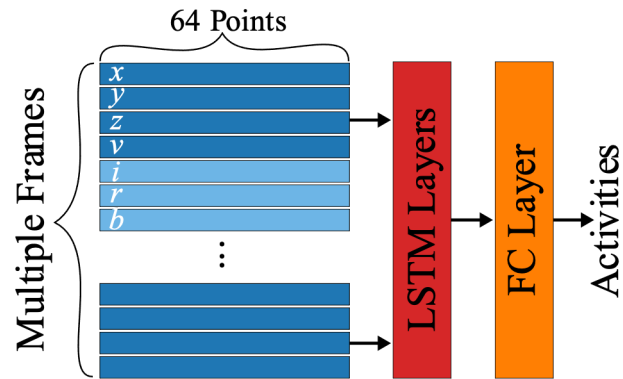
PROPOSED SOLUTIONS



① Skeletal Pose Estimator (SPE)

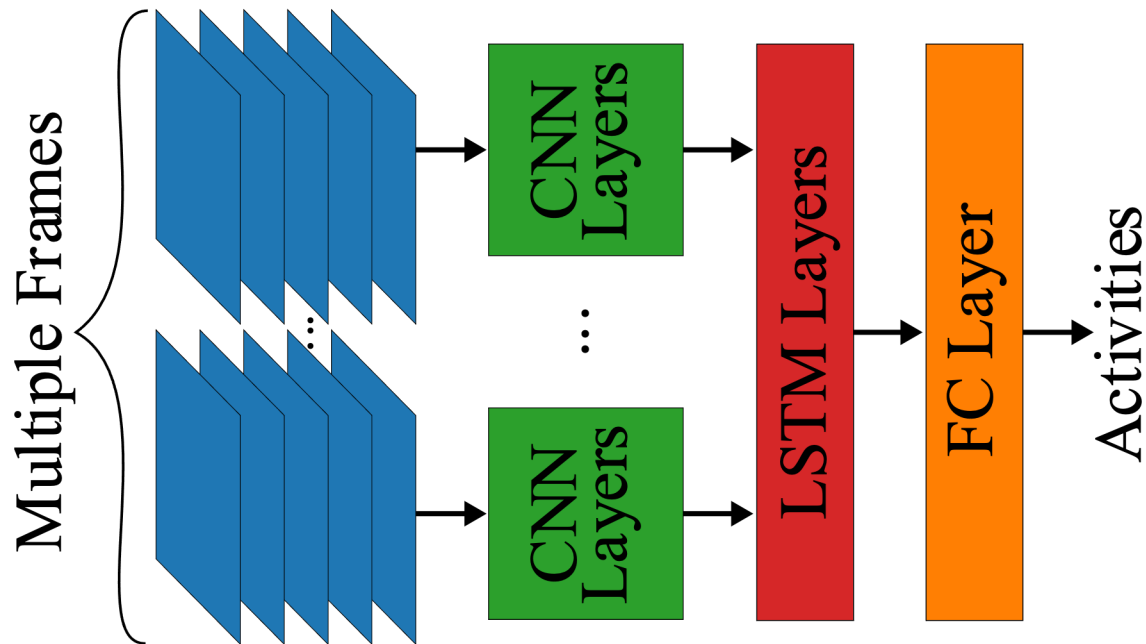


② Dynamic Point Cloud Recognizer (DPR)



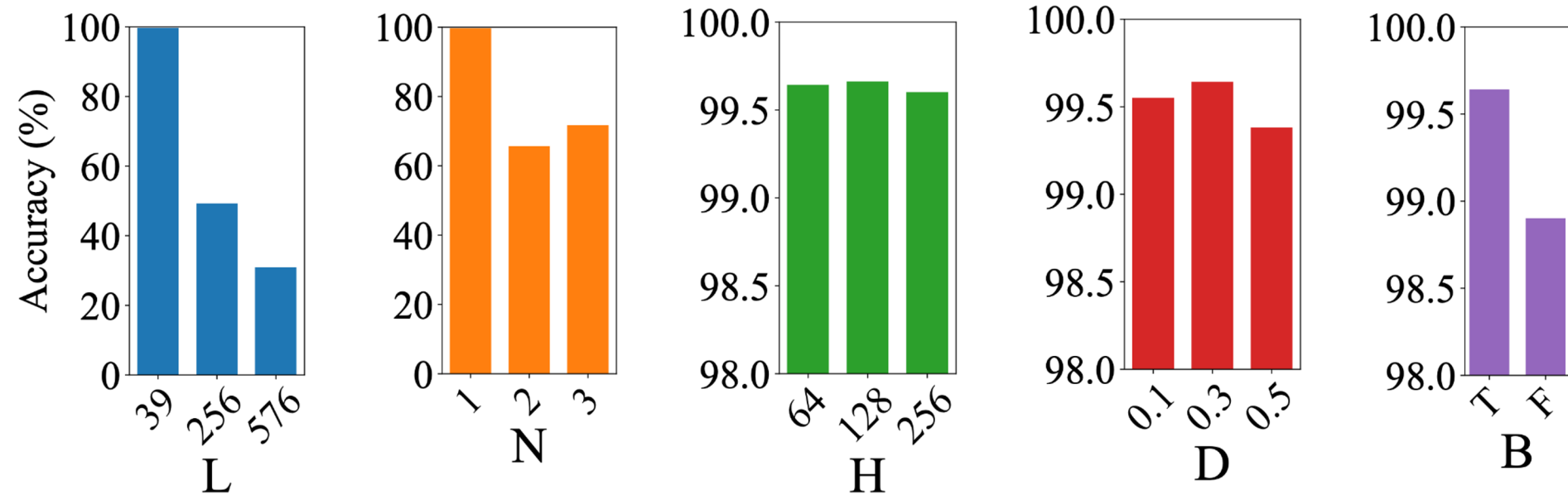
③ Lightweight Dynamic Point Cloud Recognizer (LDPR)

PROPOSED SOLUTIONS



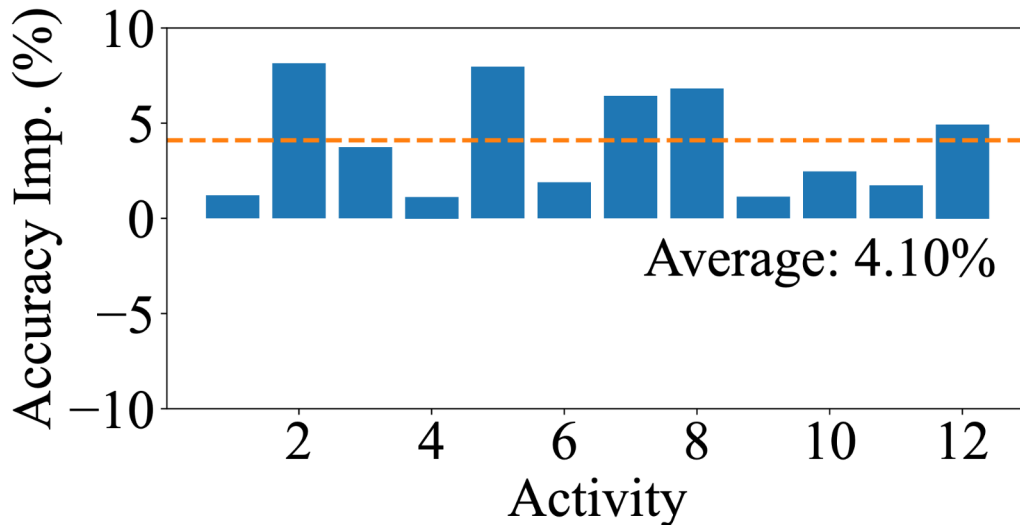
② **Dynamic Point Cloud
Recognizer (DPR)**

FINDING THE OPTIMAL PARAMETERS

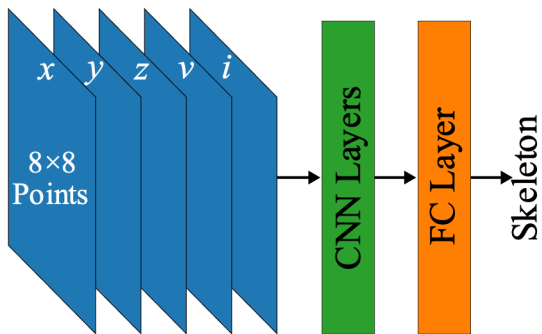


IMPROVEMENT OF DPR^② OVER FIA

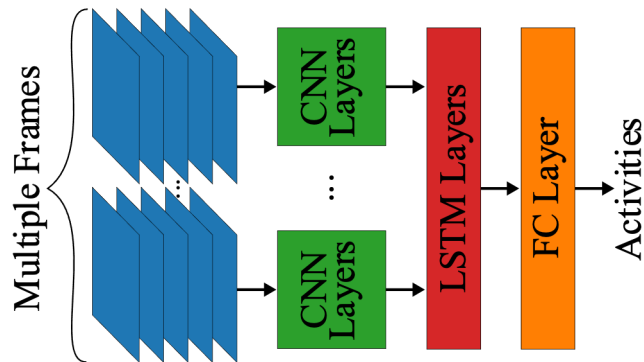
- Activity Recognition Accuracy
 - 95.56% → 99.66% (4.10% improvement)
- GPU Memory Consumption
 - 9817 MiB → 2131 MiB (**78.29% reduction**)



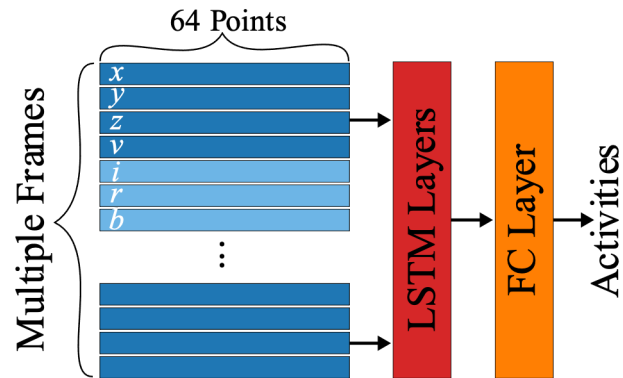
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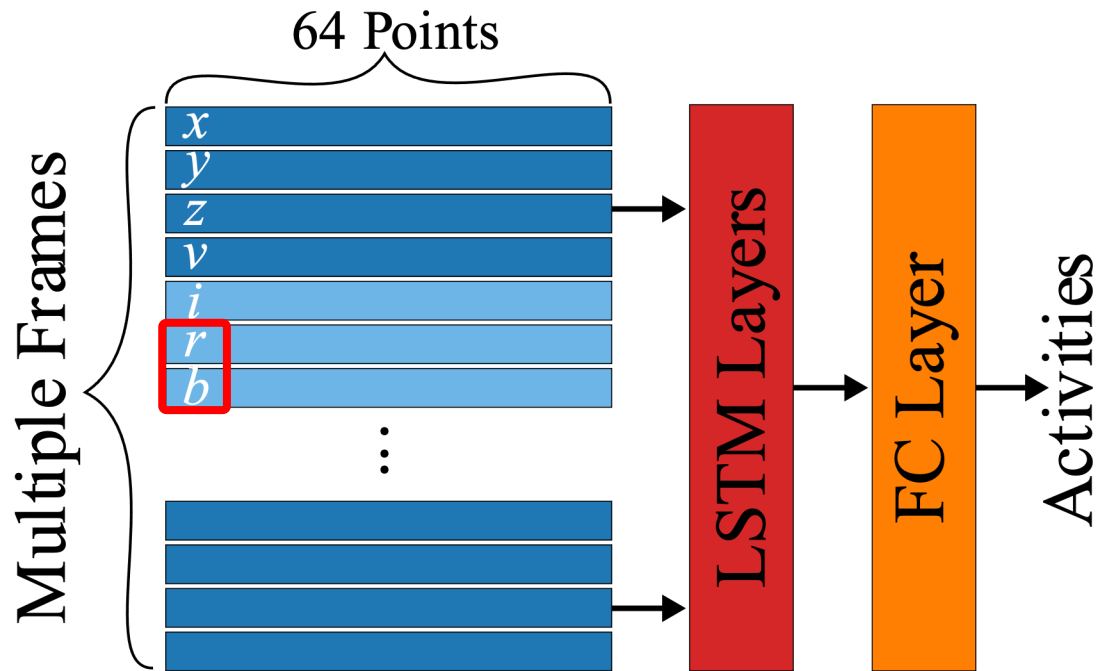


② Dynamic Point Cloud Recognizer (DPR)



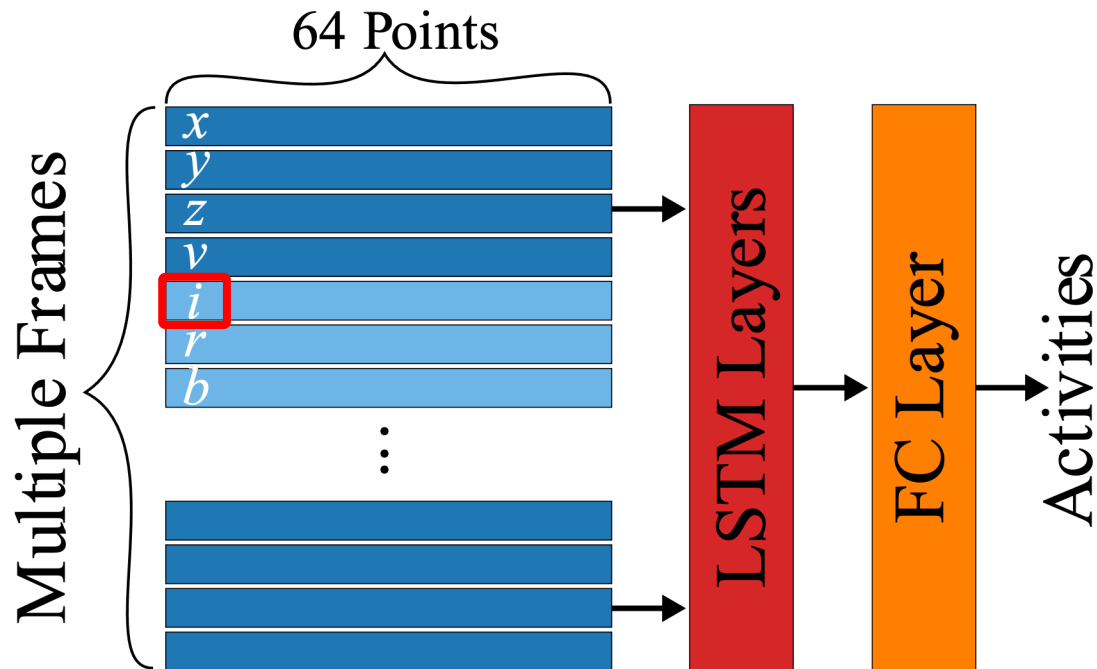
③ Lightweight Dynamic Point Cloud Recognizer (LDPR)

PROPOSED SOLUTIONS



③ **Lightweight Dynamic Point
Cloud Recognizer (LDPR)**

PROPOSED SOLUTIONS



③ **Lightweight Dynamic Point Cloud Recognizer (LDPR)**

LDPR^③ ACCURACY USING DIFFERENT FEATURES

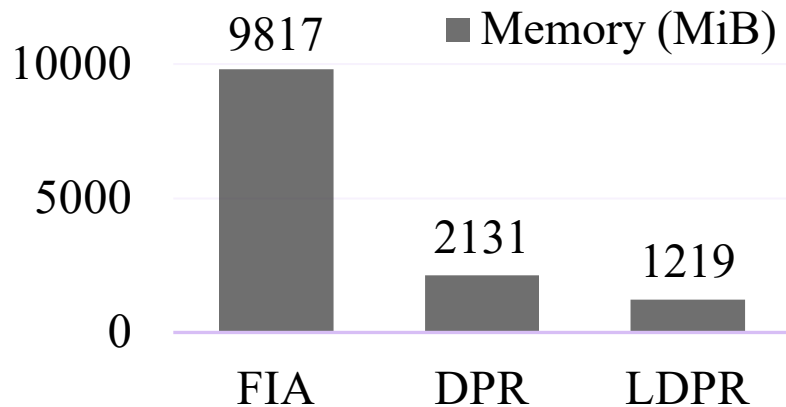
Accuracy	$\{x, y, z\}$	$\{r, b\}$	$\{x, y, z, r, b\}$
With i	98.51%	99.74%	99.78%
Without i	99.81%	99.74%	99.81%

LDPR^③ ACCURACY USING DIFFERENT FEATURES

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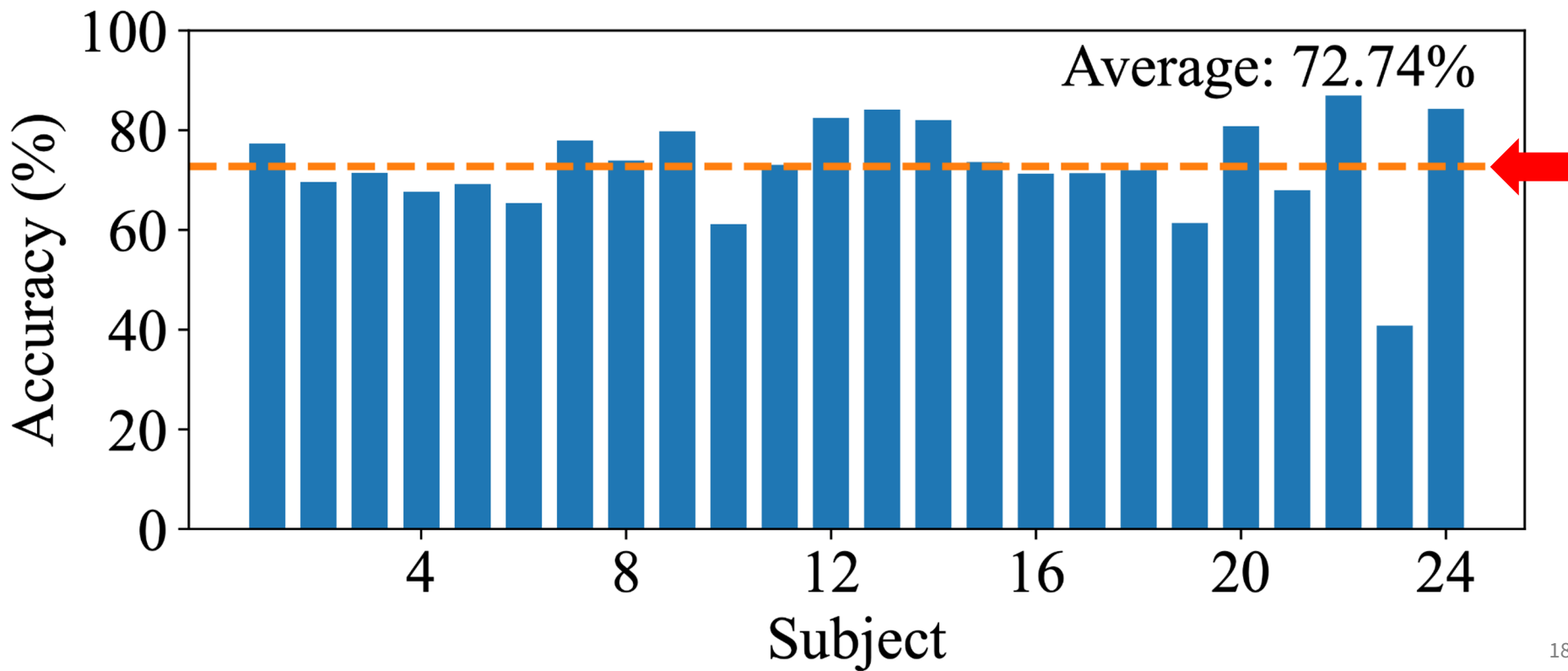
IMPROVEMENT OF LDPR^③ OVER DPR^②

- Activity Recognition Accuracy
 - 99.66% → 99.81 (0.15% improvement)
- GPU Memory Consumption
 - 2131 MiB → 1219 MiB (**42.80% reduction**)

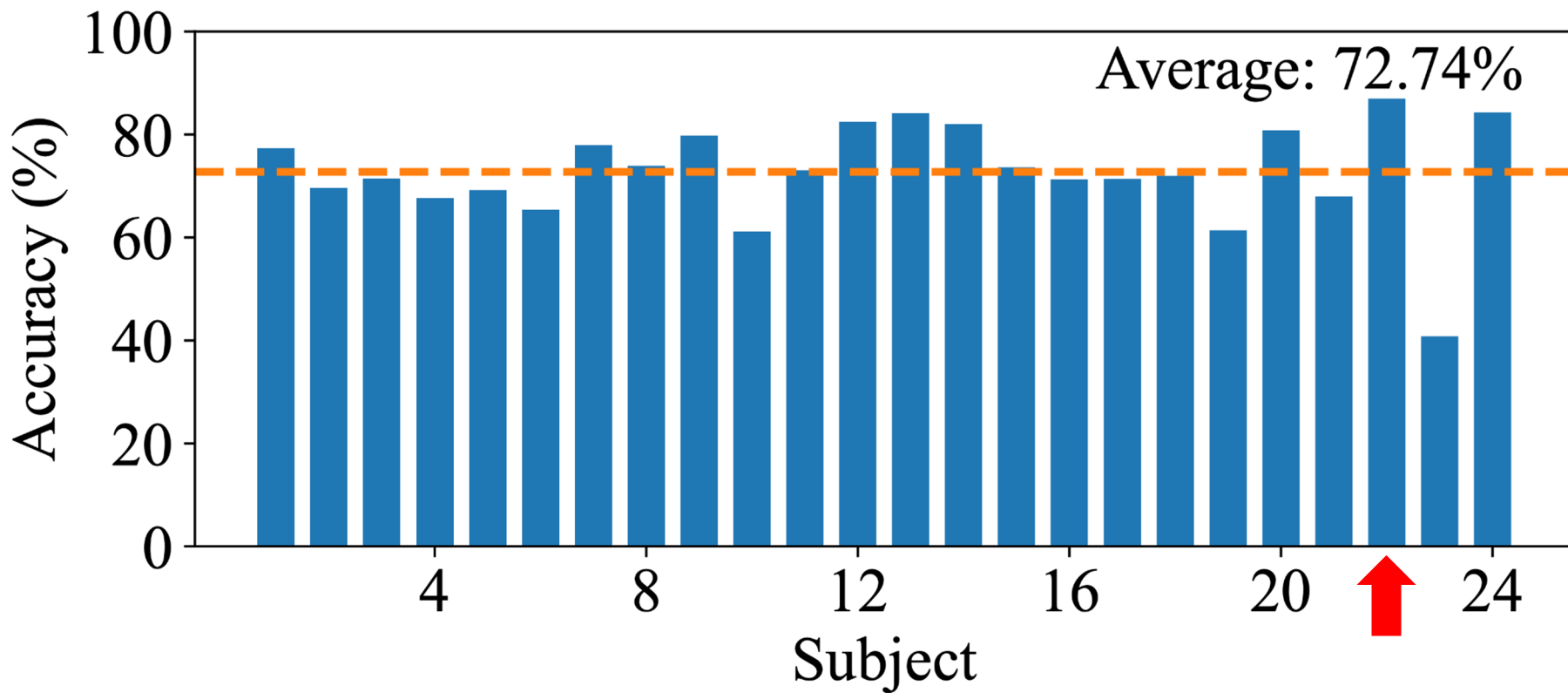


- Besides the standard 80-20 split, we also experimented with the **leave-one-out test**
 - Each subject is selected for testing
 - Remaining 23 subjects for training
 - Replicates the situation of **recognizing a new subject**

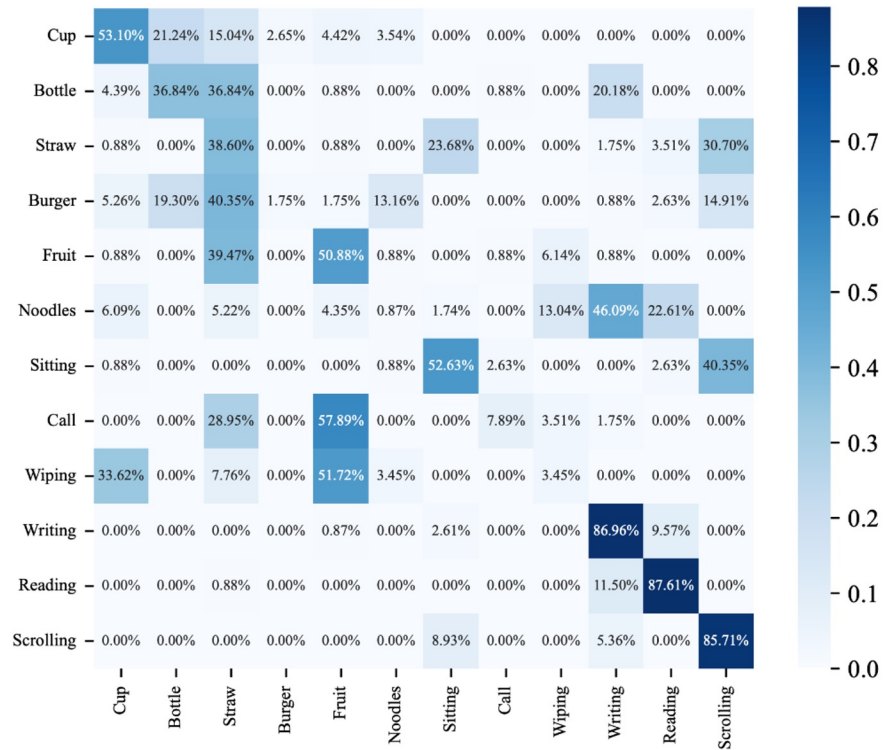
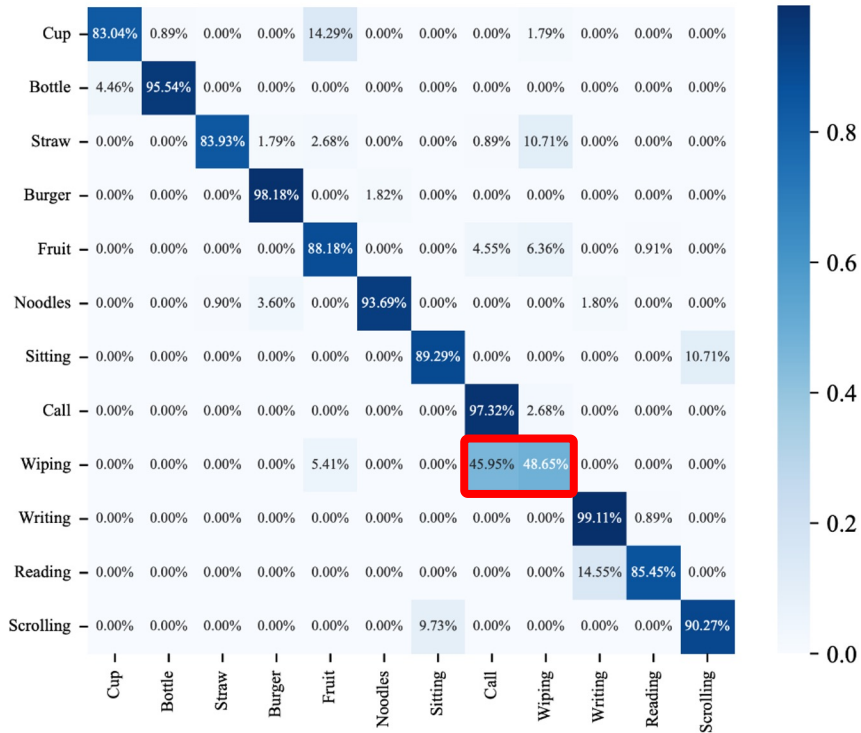
LDPR^③ ACCURACY: LEAVE-ONE-OUT TEST



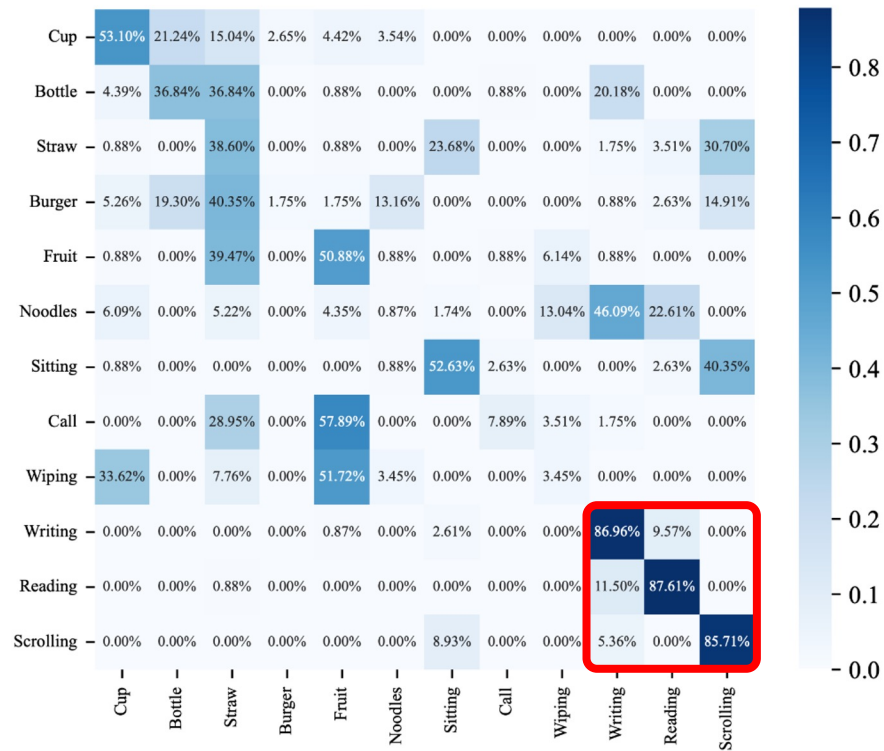
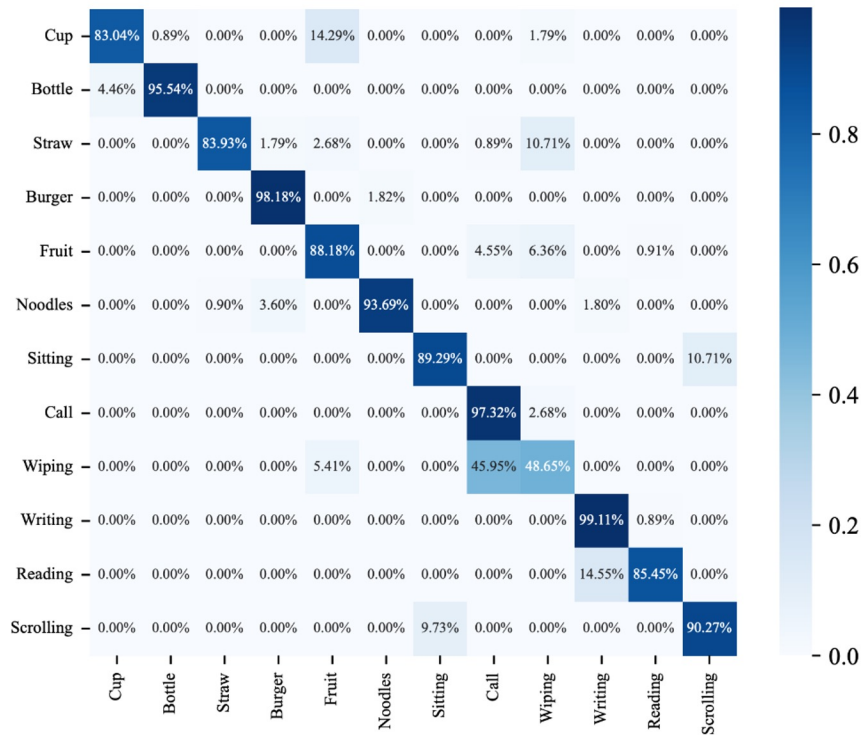
LDPR^③ ACCURACY: LEAVE-ONE-OUT TEST



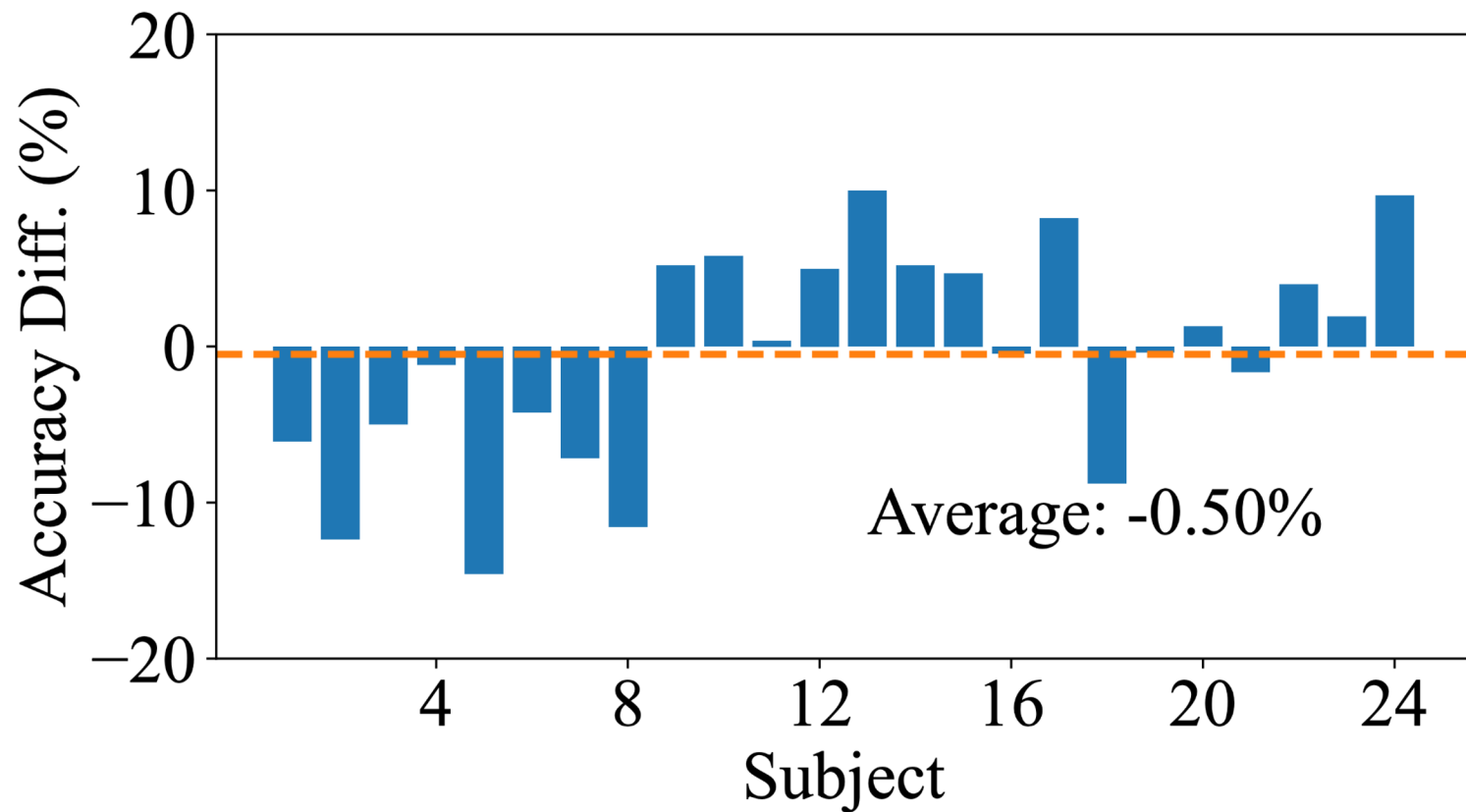
CONFUSION MATRIX: BEST/WORST SUBJECT



CONFUSION MATRIX: BEST/WORST SUBJECT



ACCURACY DIFF. BETWEEN LDPR^③ AND DPR^②



SUMMARY

Task:

- Food intake activity recognition using mmWave point clouds

Proposed solutions:

- Skeletal Pose Estimator (SPE)
- Dynamic Point Cloud Recognizer (DPR)
- Lightweight Dynamic Point Cloud Recognizer (LDPR)

Ongoing works:

- Further enhancing the **precision of the estimated skeletons**
- Enhance the model's **generalization capability**
- Apply these solutions to other scenarios, e.g., **Driver Monitoring System** (DMS)

ANY QUESTIONS?