A Tiny Supervised ODL Core with Auto Data Pruning for Human Activity Recognition

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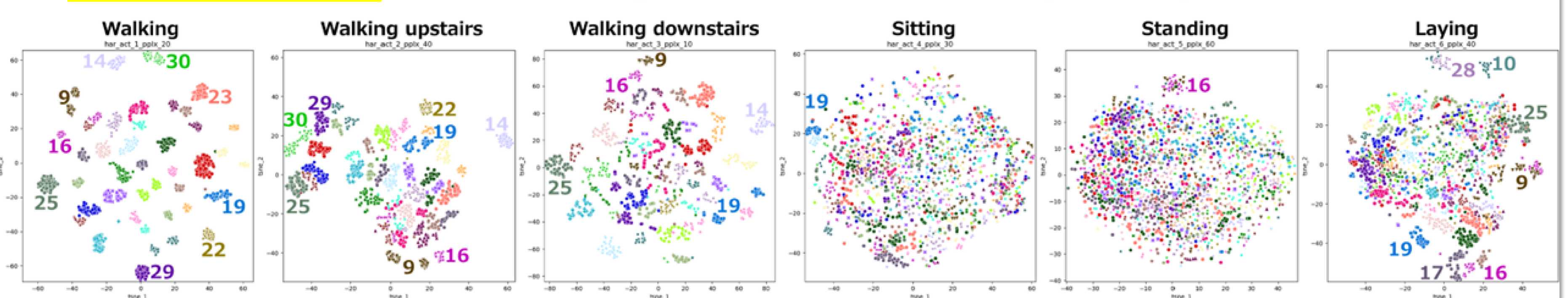
Human activity recognition: Data drifts

- 2-D visualization results of 6-class human activity recognition dataset (30 human subjects) [1]



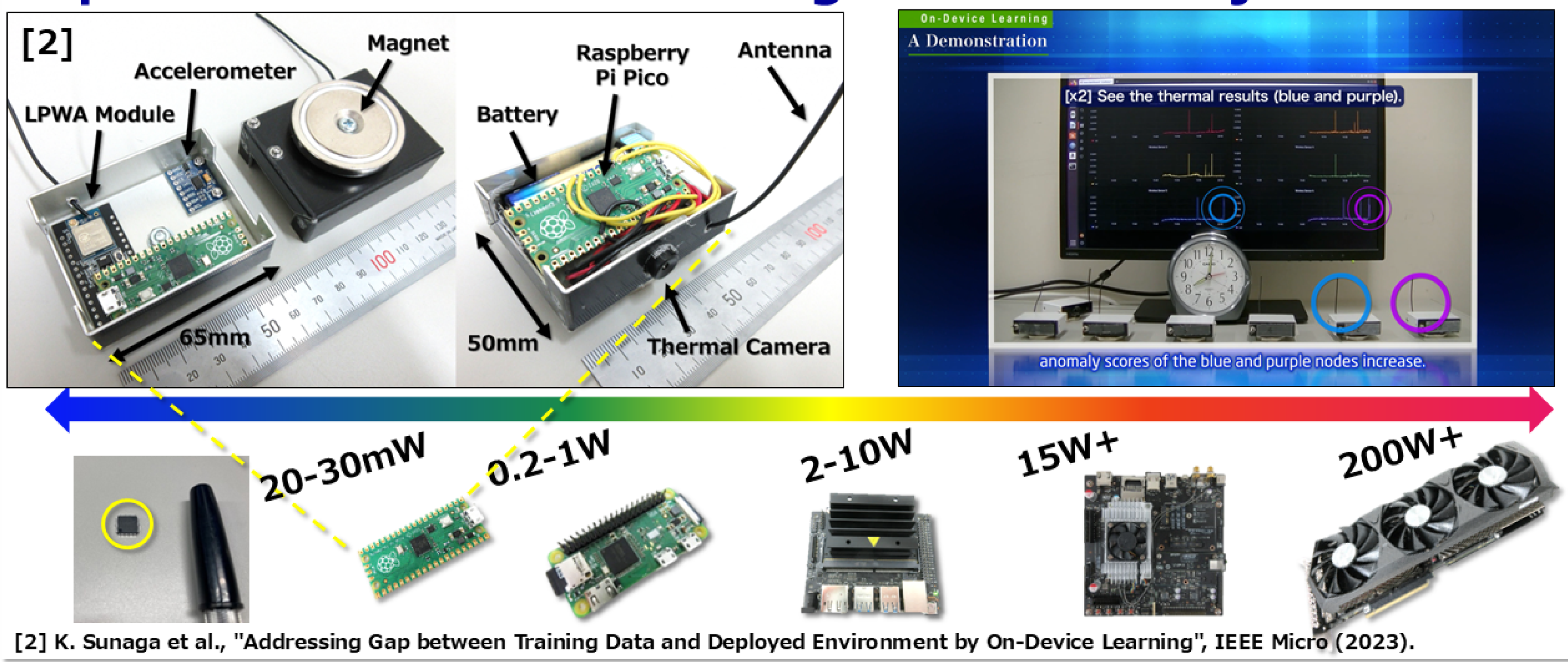
Observation: Samples from the same human subjects form clusters (e.g., Walking, Walking upstairs, Walking downstairs, Laying)

Problem: Edge AI model that has been optimized for a specific human subject may not work well for different human subjects that have not been considered yet

[1] J. Reyes-Ortiz et al., "Human Activity Recognition Using Smartphones", UCI Machine Learning Repository (2012).

On-device learning (ODL) for data drifts

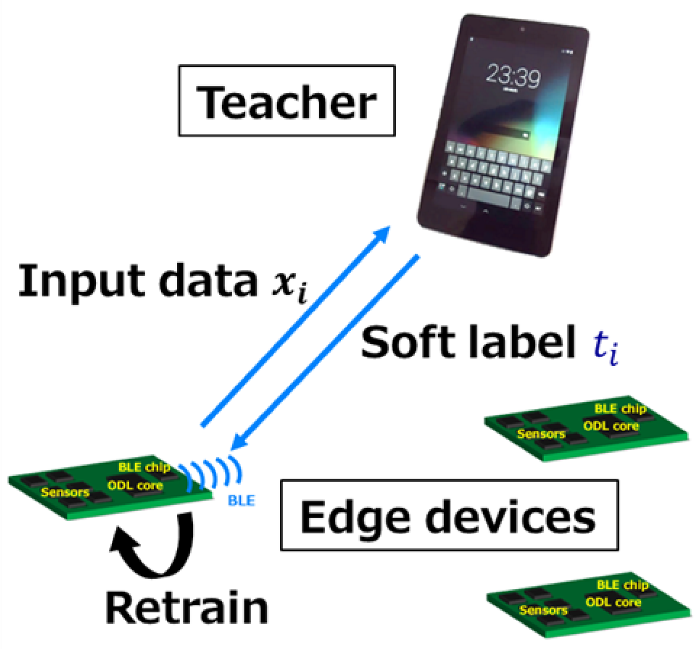
- Motivation for ODL: Addressing the gap between pre-trained model and target human subjects



[2] K. Sunaga et al., "Addressing Gap between Training Data and Deployed Environment by On-Device Learning", IEEE Micro (2023).

Supervised on-device learning (ODL)

- Ask a nearby teacher device to get teacher labels and update on-device models to address data drifts

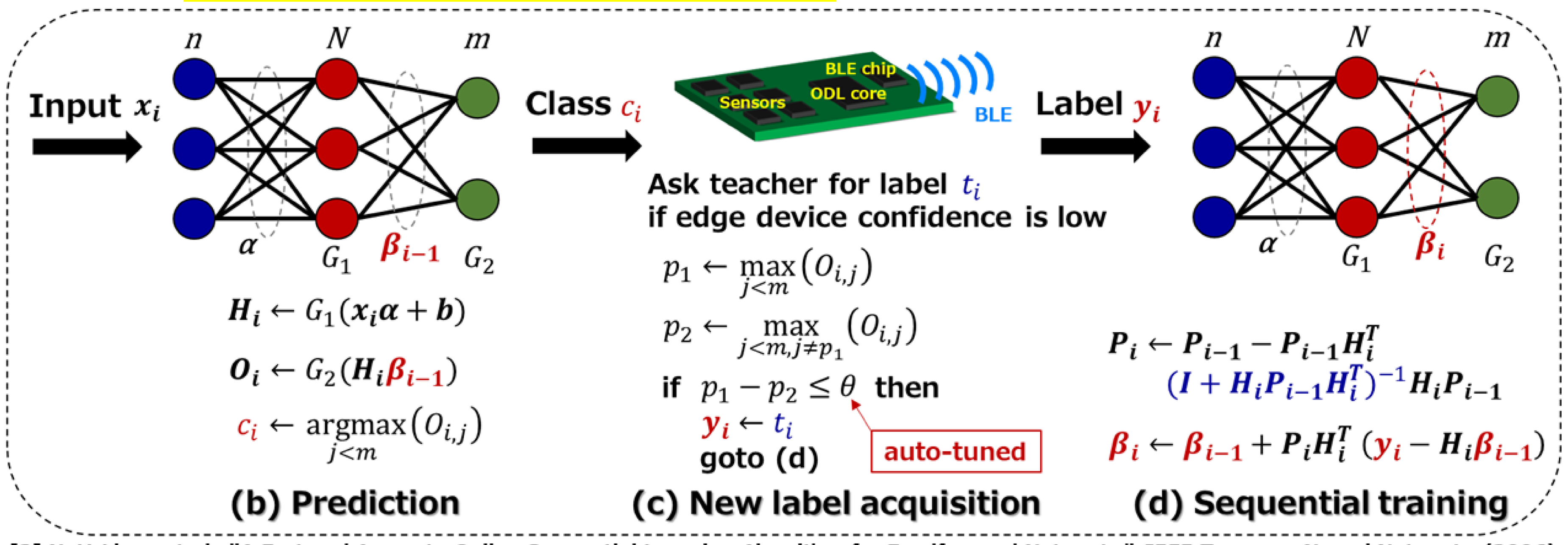


(a) Architecture

```
x_i ← Sense()
if mode = predicting then
    if IsDrift(x_i) then
        mode ← training
    end if
    return Predict(x_i)                      → Fig (b)
else if mode = training then
    y_i ← LabelAcquire(Predict(x_i))         → Fig (c)
    SequentialTrain(x_i, y_i)                → Fig (d)
    if IsTrainDone() then
        mode ← predicting
    end if
end if
```

Supervised ODL w/ auto data pruning

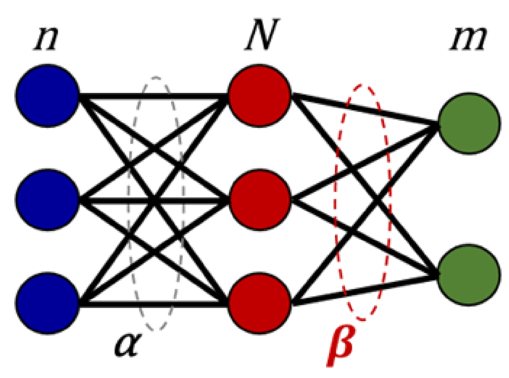
- Ask a teacher if confidence of locally-predicted label is low and sequentially update the model by OS-ELM [3]
- The confidence threshold θ is auto-tuned

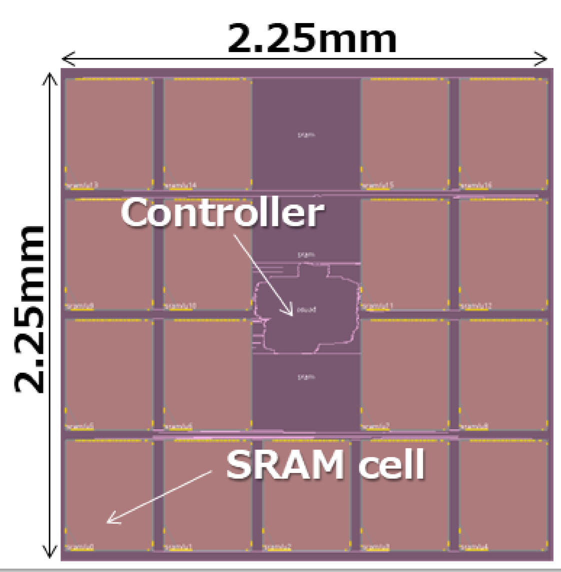


[3] N. Y. Liang et al., "A Fast and Accurate Online Sequential Learning Algorithm for Feedforward Networks", IEEE Trans. on Neural Networks (2006).

Tiny ODL core: Memory size reduction

- **NoODL**: Prediction-only MLP (a single hidden layer)
- **ODLBase**: MLP with OS-ELM based ODL capability
- **ODLHash**: ODL + Weight α is replaced with a hash function to reduce memory size





- Memory size of ODL core [kB]

N	32	64	128	256	512
NoODL	74.82	147.40	292.55	582.85	1163.46
ODLBase	83.01	180.16	423.62	1107.14	3260.61
ODLHash	11.20	36.55	**136.39**	532.68	2111.68

Comm. size saving by auto data pruning

- Accuracy before/after data drift

  NoODL: Accuracy drops after data drift

  ODLBase & ODLHash: Accuracy recovers by ODL

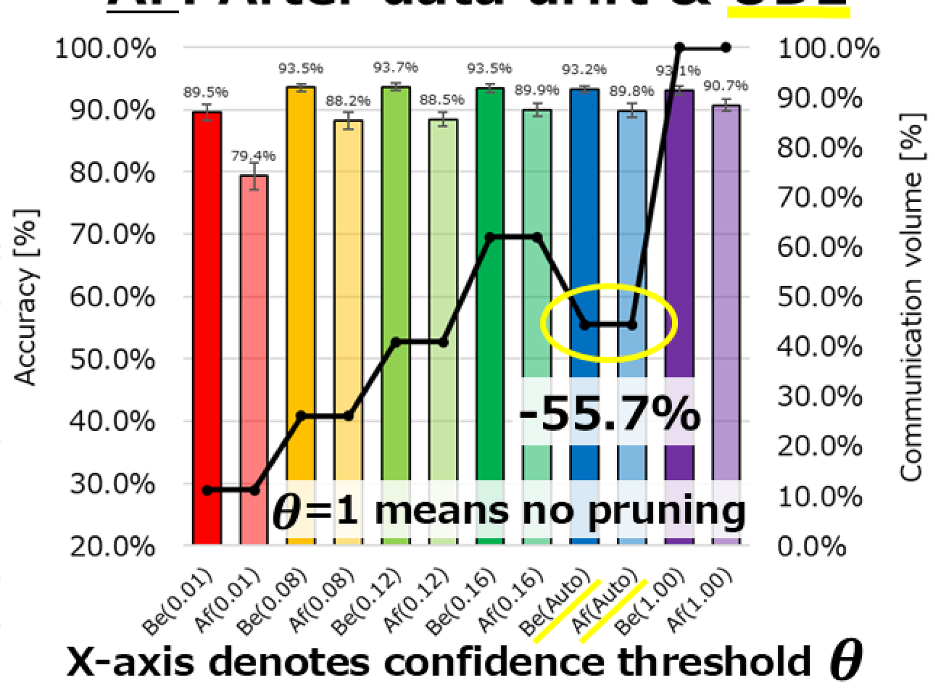
	Before [%]	After [%]
NoODL (N = 128)	92.9±0.8	82.9±1.4
ODLBase (N = 128)	93.4±0.6	90.8±1.7
ODLHash (N = 128)	93.1±0.8	90.7±1.0
NoODL (N = 256)	95.1±0.3	83.7±1.0
ODLBase (N = 256)	95.2±0.3	92.5±0.6
ODLHash (N = 256)	95.1±0.4	92.3±0.7
DNN (561,512,256,6)	94.1±1.0	85.2±1.3

ODL can address data drift issues

- Comm. size reduction

  BE: Before data drift

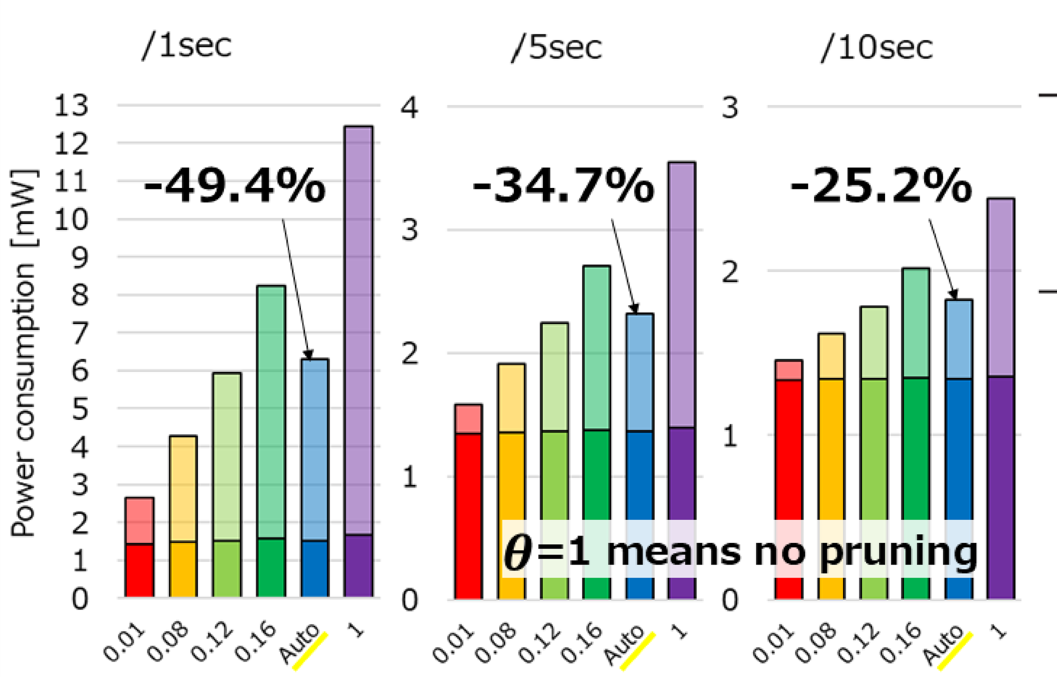
  AF: After data drift & ODL



X-axis denotes confidence threshold θ

Power saving by auto data pruning

- Sensing frequencies: /1sec, /5sec, and /10sec



X-axis denotes confidence threshold θ

- ODL core parameters

Core size	2.25mm × 2.25mm
Prediction time	36.40 [msec]
Seq. train time	171.28 [msec]
Prediction power	3.39 [mW]
Seq. train power	3.37 [mW]
Idle power	3.06 [mW]
Sleep power	1.33 [mW]

- BLE chip parameters

  Chip: nRF52840

  Data rate: 1Mbps

  TX power: 1dBm

  Voltage: 3.0V

Tiny supervised ODL: Our contributions

- Our tiny supervised ODL core that supports the automatic data pruning consumes only 3.39mW of power and only 136.39kB of memory.
- Although our ODL core is smaller than the NoODL baseline, our ODL core can recover accuracy by ODL when data drift occurs.
- Our automatic data pruning reduces the communication volume by 55.7% and training mode power significantly with 0.9% accuracy loss.

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