TinyTTA: Efficient Test-time Adaptation via Early-exit Ensembles on Edge Devices

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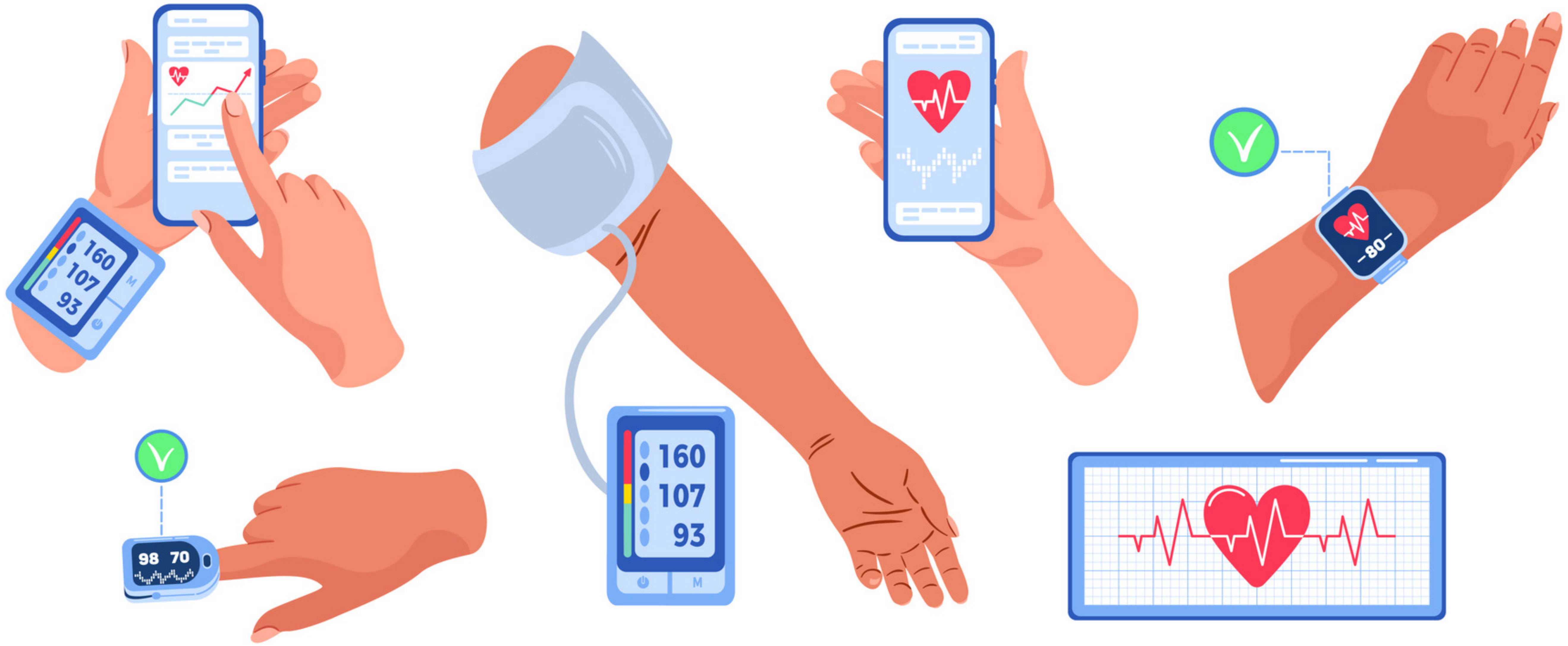
AI/Deep Learning on Edge Devices

- Deploy ML on edge devices becomes popular:

  real-time data analysis and low-latency responses

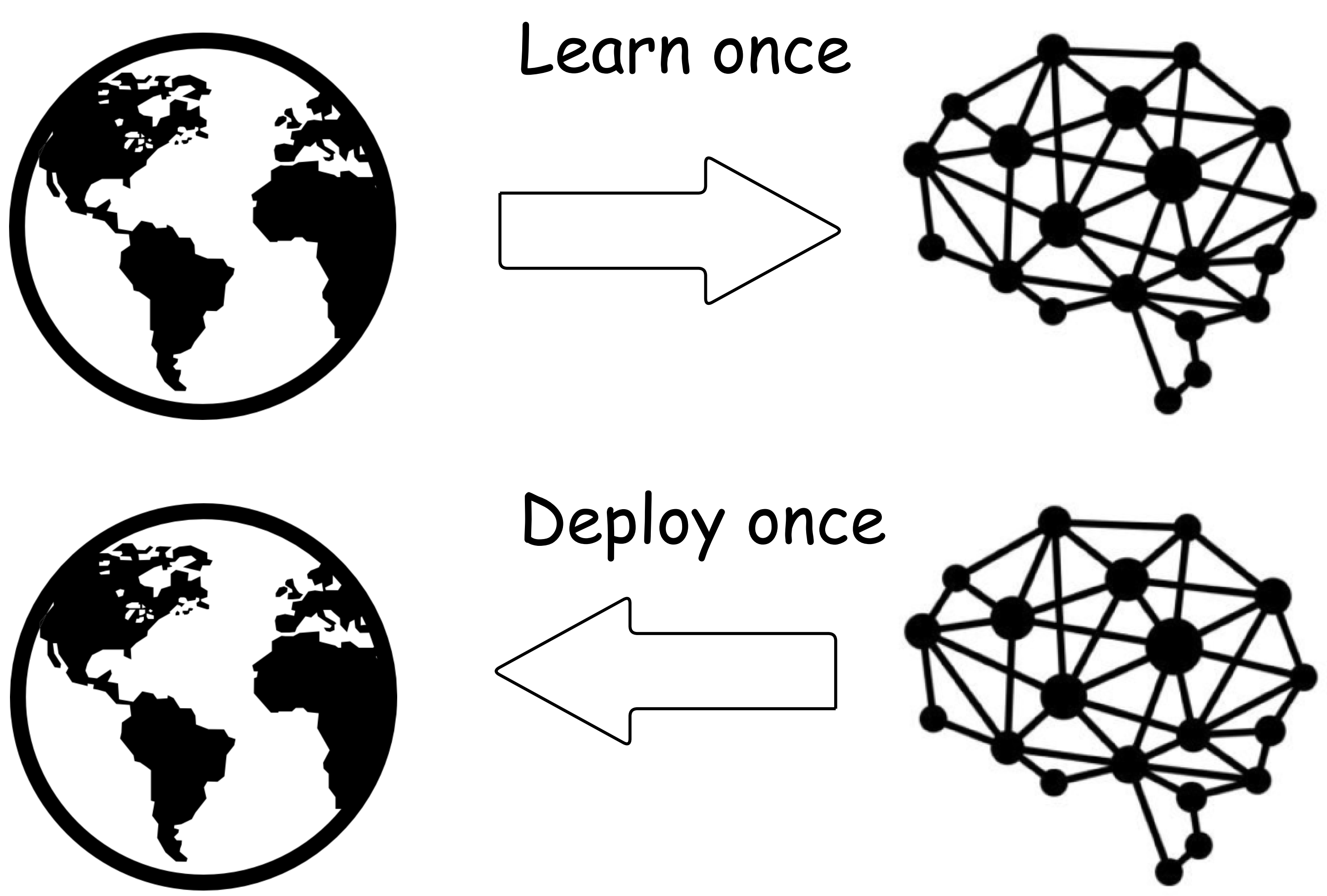
  e.g., Real-time human health monitoring and robotics



Realistic Scenarios

- Adaptive ML is essential
- Test-time adaptation (TTA) is a practical solution but challenging

Static ML



Test-Time Adaptation

Unique Challenges of TTA on Edge Devices

1. No batch normalization layers are supported on MCUs

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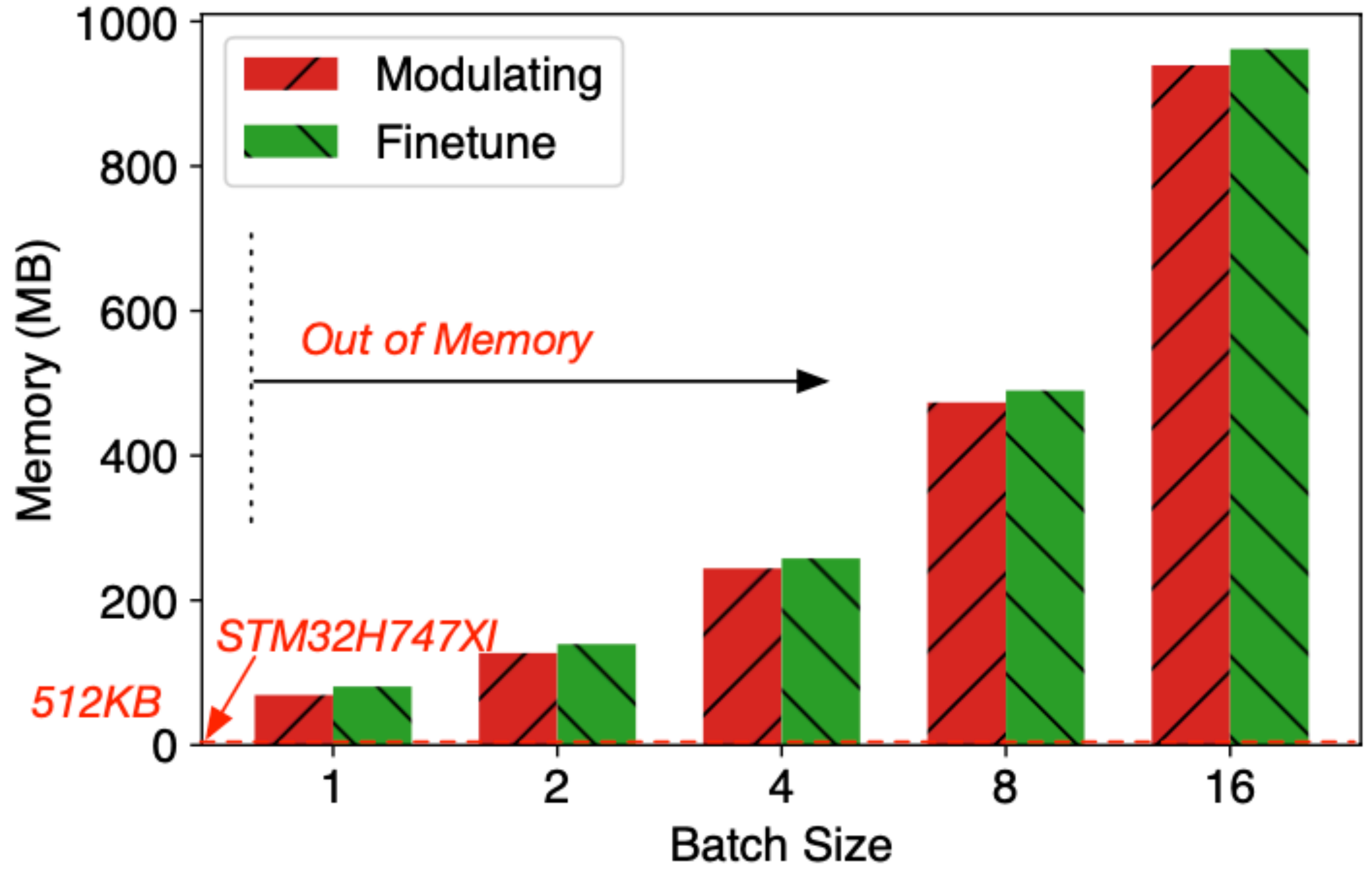
2. Adjust model parameters is expensive in terms of memory and computation



MCUNet

Unique Challenges of TTA on Edge Devices

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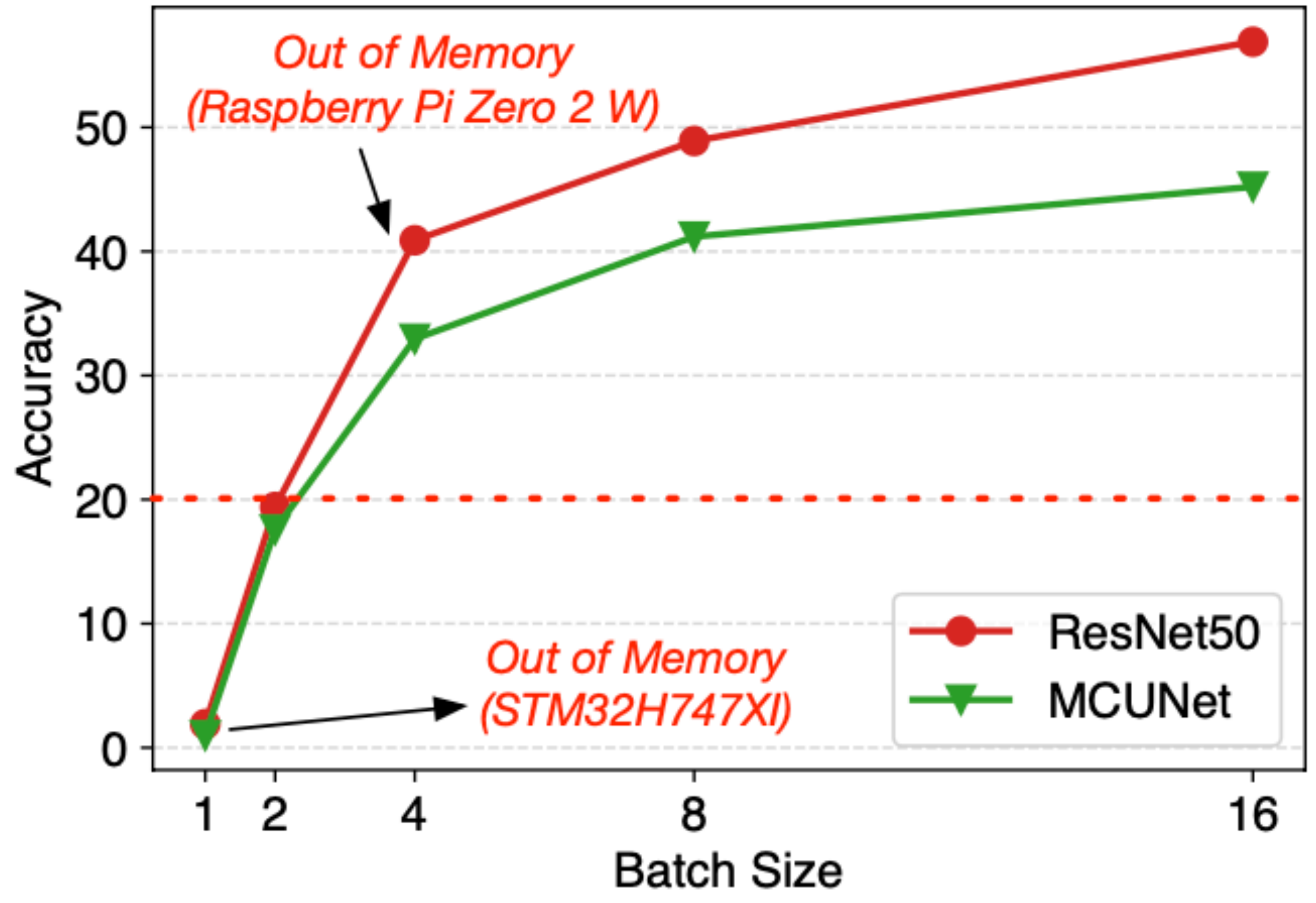
2. Adjust model parameters is expensive in terms of memory and computation

3. Poor performance with small batch size when computational resources are limited



Prior Works & Limitations

Finetune-based

- Update entire model

- Suffer from intensive memory usage

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Finetune-based	Modulating-based	Memory-efficient TTA
• Update entire model	• Update normalization layers only and freeze other layers	• Update enabled with low memory on GPUs
• Suffer from intensive memory usage	• Suffer from intensive memory usage	• Remain memory intensive on CPUs

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• Update entire model	• Update normalization layers only and freeze other layers	• Update enabled with low memory on GPUs
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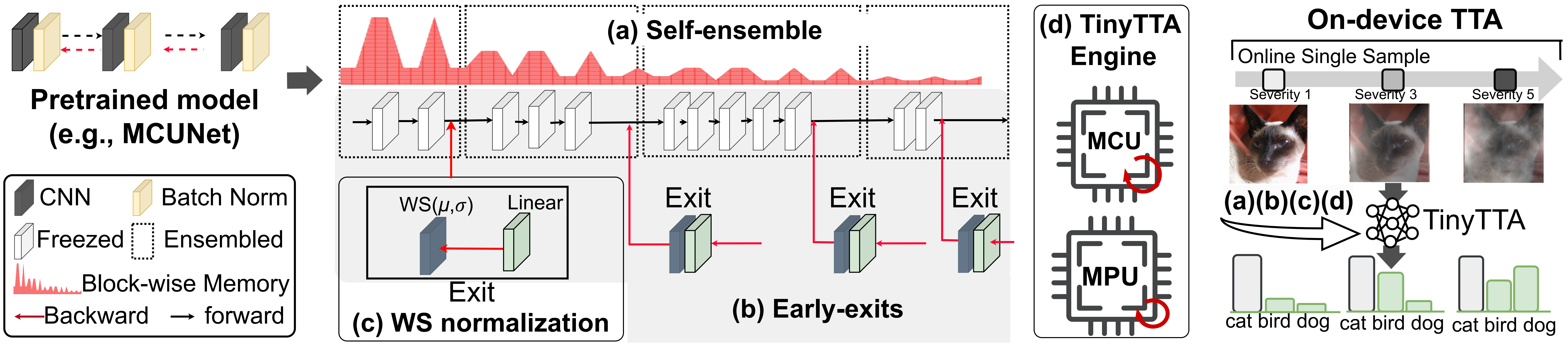
- Model collapse with batch size of one
- Normalization layers are unavailable on MCUs

TinyTTA

- Efficient, batch-agnostic, and robust TTA on edge devices



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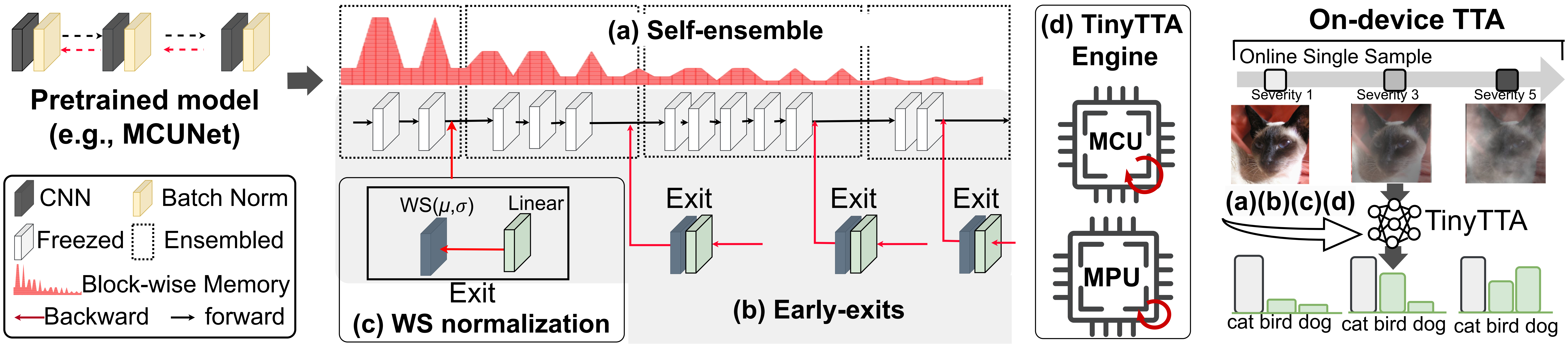
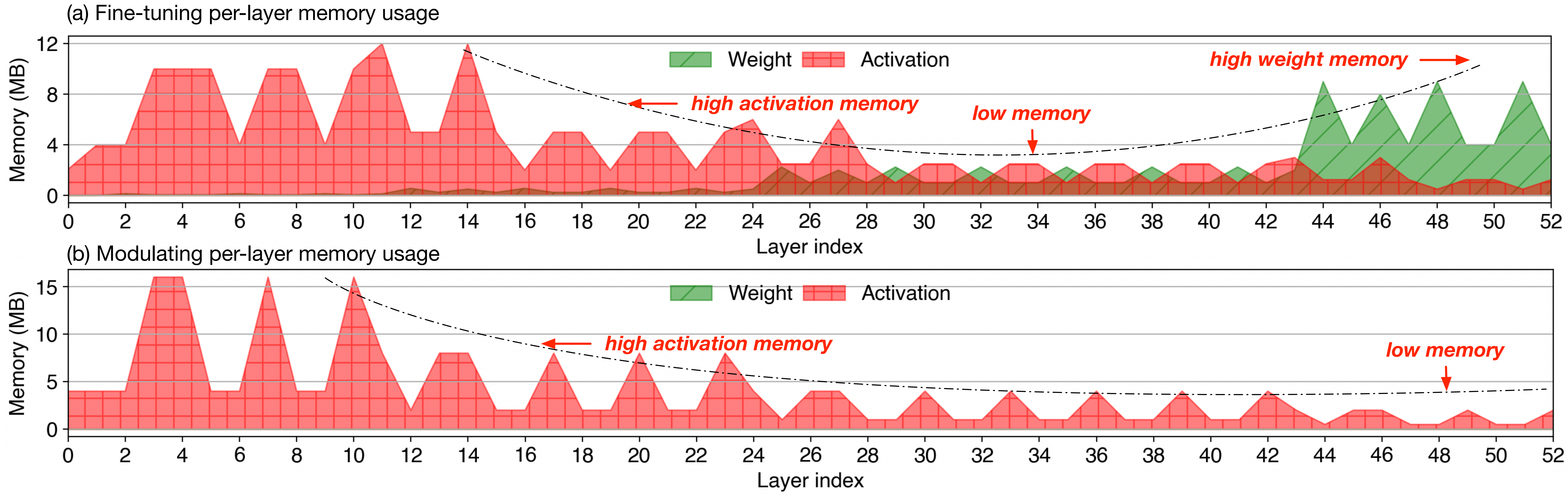


- Early-exit ensemble to co-optimize memory footprint and accuracy
- TinyTTA Engine to enable TTA on MCUs

Batch-Agnostic Early-exit Ensembles

- Co-optimizes memory footprint and accuracy



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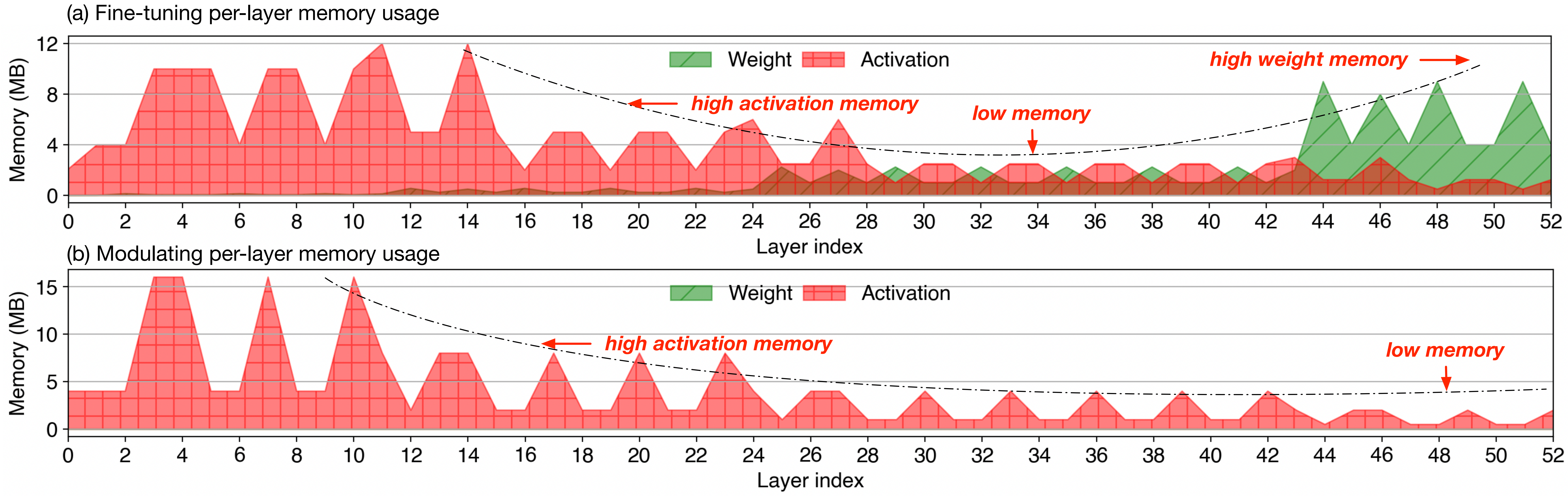

latent representation of submodules

submodule output

$$\boldsymbol{p}_i^k = \frac{\exp\left(\boldsymbol{z}_i^k\right)}{\sum_{j=1}^{C} \exp\left(\boldsymbol{z}_j^k\right)}$$

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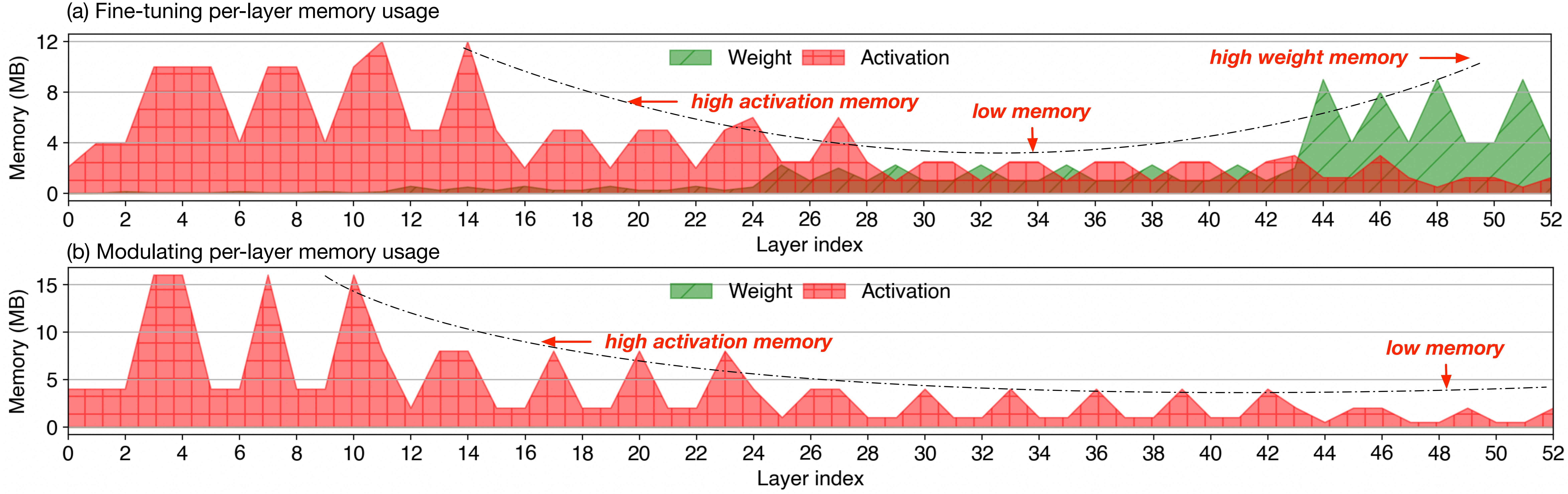

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Align latent representations

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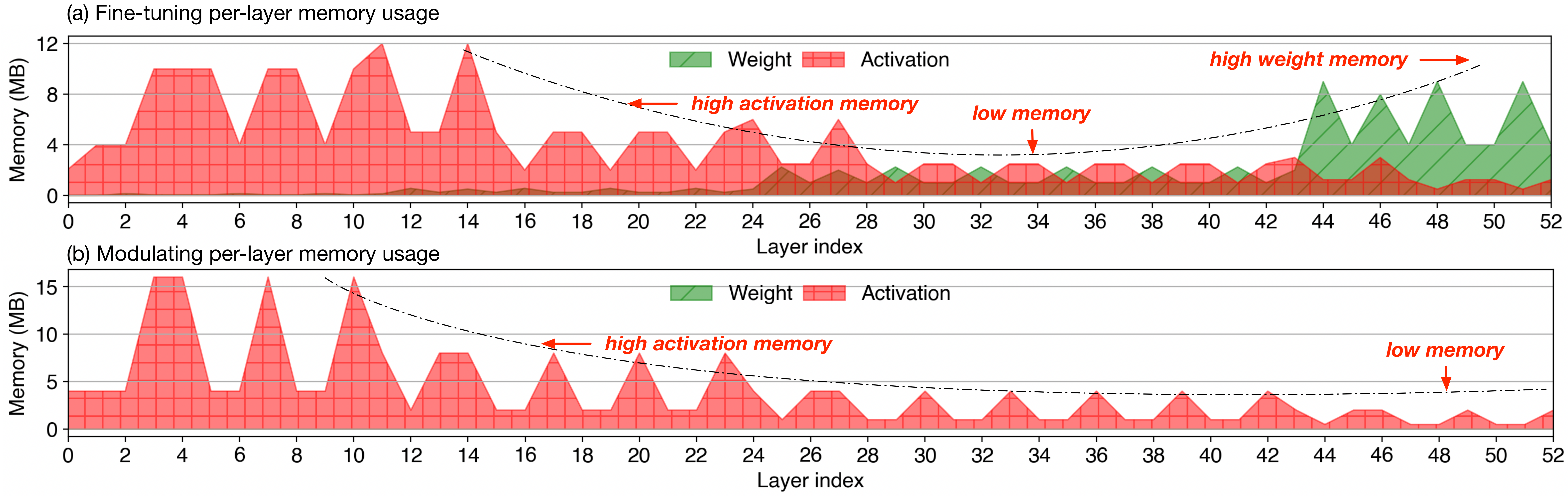

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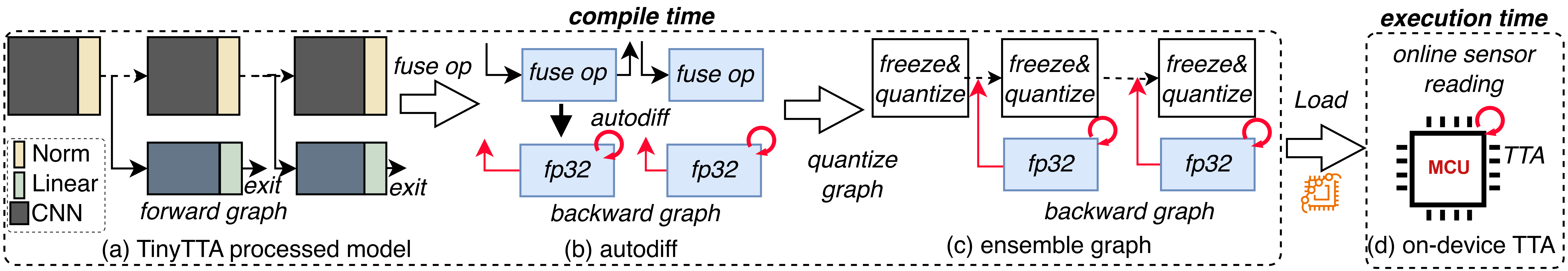
Weight standar-dization exits

$$\widetilde{\boldsymbol{W}} = \frac{\boldsymbol{W} - \boldsymbol{\mu}_w}{\boldsymbol{\sigma}_w + \epsilon}$$

TinyTTA Engine

- First-of-its-kind TTA engine on MCUs
- Optimized to mitigate resource limitations during TTA



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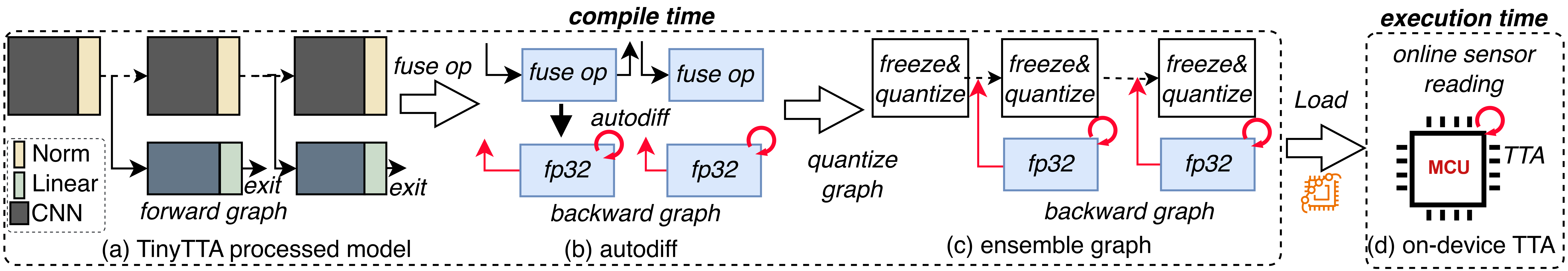


- BP operators support for Tensorflow Lite Micro
- Layer-wise update strategy to optimize memory efficiency

Experimental Setup

- **Datasets**

(1) CIFAR10C
(2) CIFAR100C
(3) OfficeHome
(4) PACS

- **Baselines**

(1) Tent (Modulating)
(2) Tent (Finetune)
(3) EATA
(4) CoTTA
(5) EcoTTA

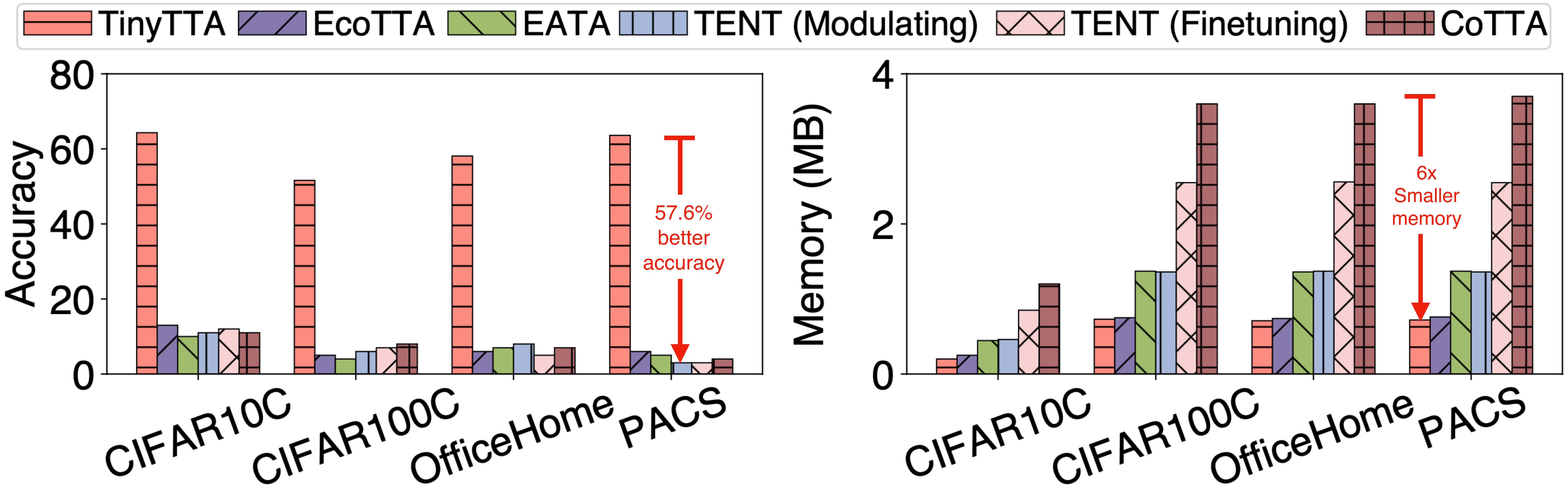
- **Architectures**

(1) MCUNet
(2) MobileNetV2_×05
(3) EfficientNet_b1
(4) RegNet-200m

- **Hardwares**

(1) MCU: STM32H747
(2) MPU: RaspberryPi Zero 2 W

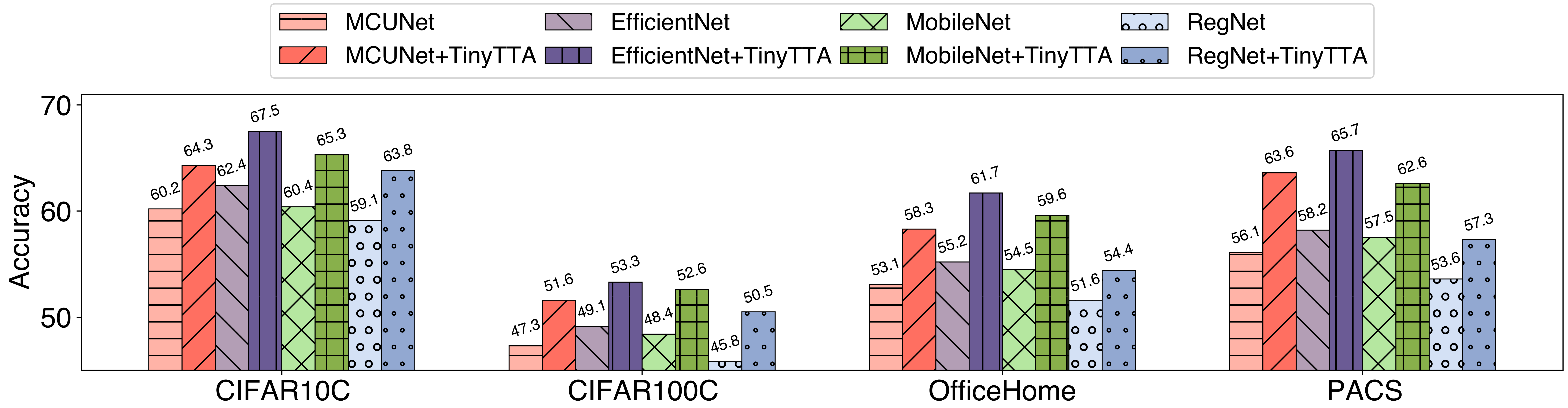
Results



TinyTTA achieves up to 57.6% higher accuracy compared to TENT (Modulating) with a batch size of one

TinyTTA achieves up to 6x lower memory usage compared to CoTTA with a batch size of one

Results



TinyTTA achieves an average of 4.3% higher accuracy compared to a model without update with a batch size of one

TinyTTA is the only framework capable of performing TTA under an MCU's 512 KB memory constraint

Table 2: MCU deployment of the baseline and TinyTTA on STM32H747 using MCUNet and CIFAR10C.

System	Accuracy	SRAM	Flash	Latency	Energy
Inference Only	60.2%	**82.8KB**	**290KB**	55.8ms	12.7mJ
TinyTTA (update)	**64.3%**	123KB	375KB	**50.7ms**	**11.5mJ**

Summary & Take-away Messages

S1. TinyTTA enables efficient, batch-agnostic and robust on-device TTA for the first time

T1. Self-ensemble framework and early-exit policy is effective in ensuring high TTA accuracy

T2. TinyTTA Engine enables TTA for diverse MCU applications

Thank you!

Any questions?
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