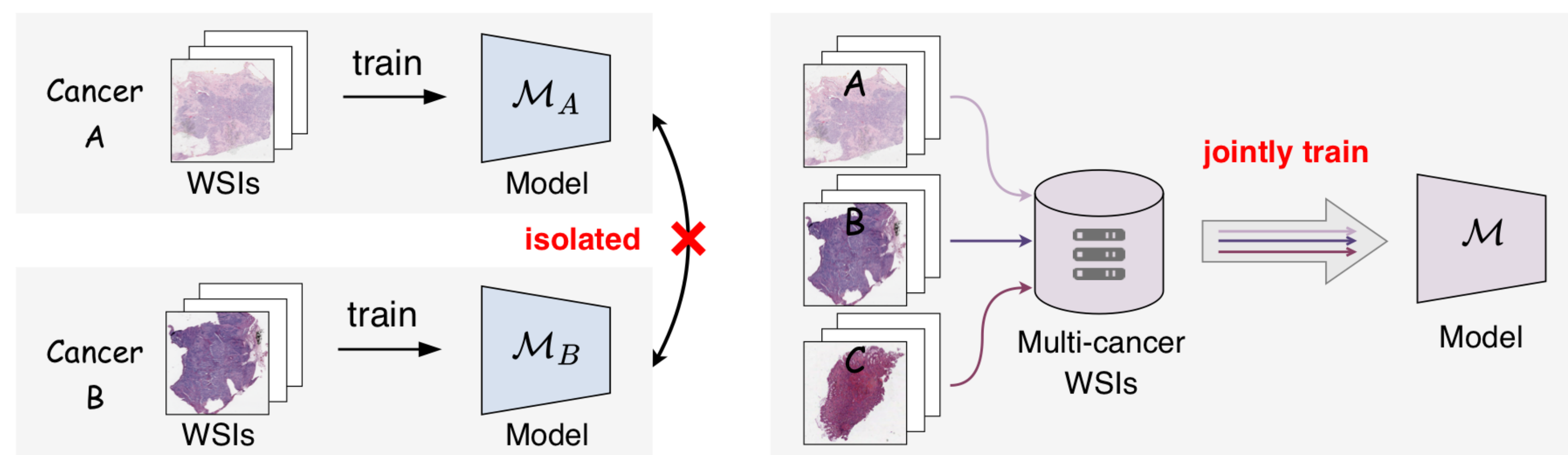


Motivation

- WSI samples are often *scarce* for one cancer type ($N \approx 1,000$), so
- Could WSI-based prognostic models *generalize well*, especially when confronted with high heterogeneity in tumors?

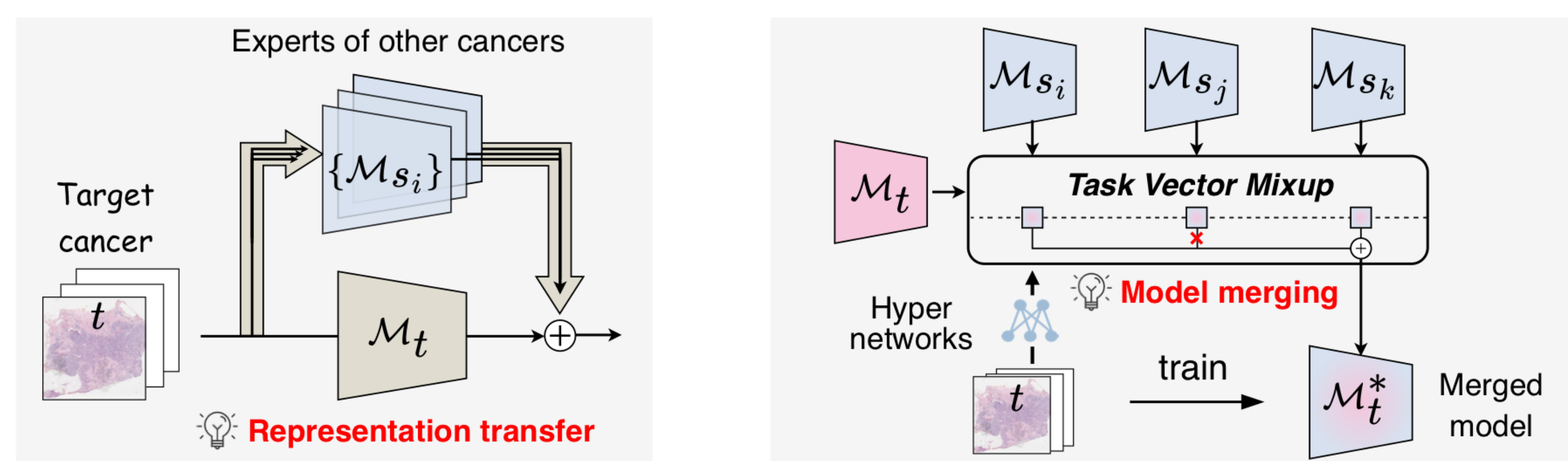
Existing approaches to addressing this problem:

- Multi-cancer joint training: expensive computational costs
- Representation transfer: extensive model inference



(a) Cancer-specific learning

(b) Multi-cancer joint learning



(c) Cross-cancer knowledge transfer

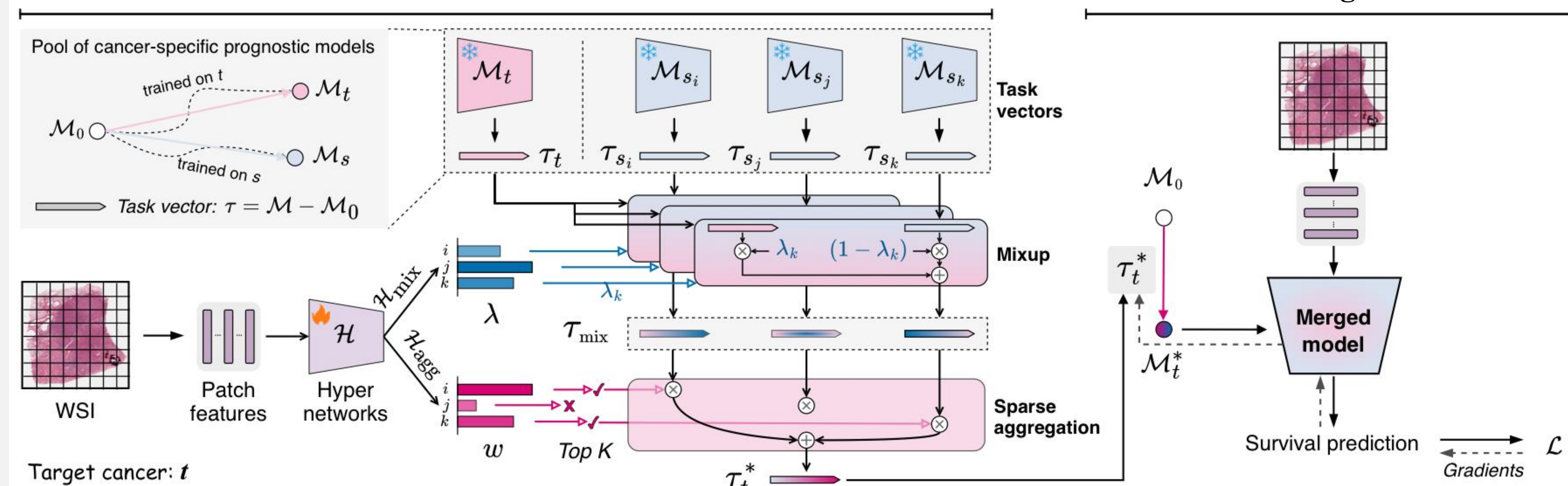
The proposed STEP:

- A lightweight, model merging-based approach
- Efficient cross-cancer knowledge transfer
- Better overall performance on 13 datasets



Method

STEPH (Sparse Task Vector Mixup with Hypernetworks)



Network training

Key formulations

$$\lambda = \mathcal{H}_{\text{mix}}(X)$$

$$\tau_{\text{mix}} = \lambda \tau_t + (1 - \lambda) \tau_s$$

$$w = \mathcal{H}_{\text{agg}}(X)$$

$$\tau_t^* = \sum_j w_j \tau_{\text{mix},j}$$

$$\mathcal{M}_t^* = \mathcal{M}_0 + \tau_t^*$$

$$\mathcal{L} = \mathcal{L}_{\text{sl}} + \mathcal{L}_{\text{aux}}$$

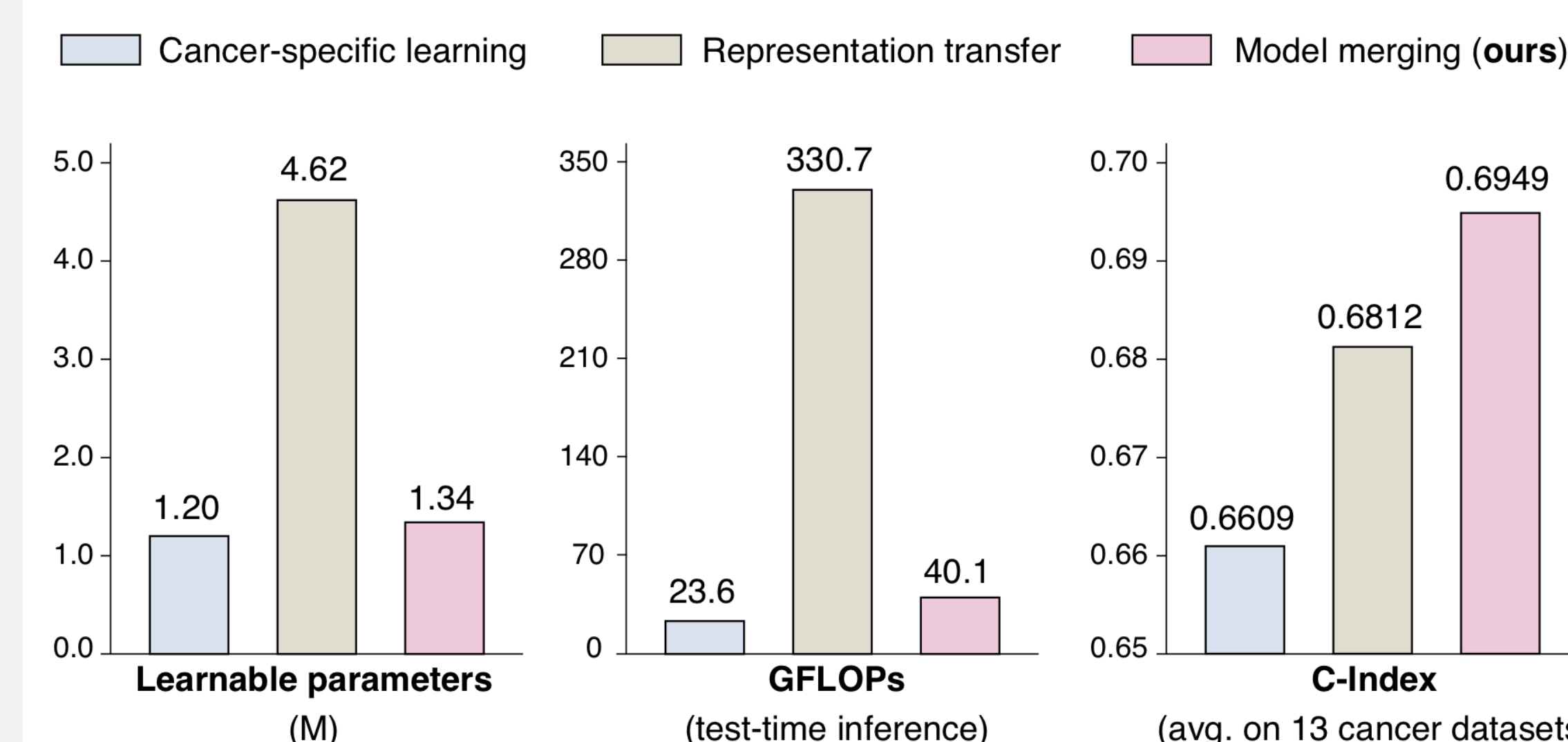
$$\mathcal{L}_{\text{aux}} = \beta \mathcal{L}_{\text{mix}} + \gamma \mathcal{L}_{\text{agg}}$$

$$= \beta \frac{\sum_j \lambda_j^2}{K} + \gamma (\log \sum_i e^{w_i})^2$$

Experiments & results

Comparison with existing approaches

- improves by 5.14% and 2.01% on average
- less computational costs at inference
- performs better than existing model merging-based approaches



Ablation study

Ablation	Avg.	
- On task vector mixup		
w/o mixup	fix $\lambda = 0$ (only $\{\tau_{s_i}\}$)	0.6860
	fix $\lambda = 0$ ($\tau_t \in \{\tau_{s_i}\}$)	0.6895
	fix $\lambda = 1$ (only τ_t)	0.6851
w/ mixup	trainable param. λ	0.6921
	hypernetwork-driven λ	0.6949
- On task vector aggregating		
w/o sparsity	hypernetwork-driven w	0.6912
w/ sparsity	trainable param. w	0.6490
	hypernetwork-driven w	0.6949

Visualization of task vector mixture

