Continual Learning in the Frequency Domain

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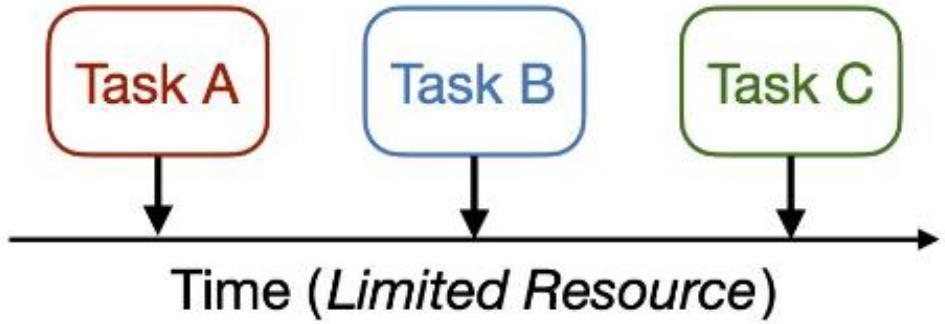
➢ Introduction

■ Continual Learning

Continual learning is designed to help models learn new tasks while retaining knowledge from previous tasks.



Continual learning requires adapting to incremental tasks with dynamic data distributions[1]

■ Challenges

- Catastrophic Forgetting
- Resource Constraints

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[1] Wang, Liyuan, et al. "A comprehensive survey of continual learning: theory, method and application.", ***IEEE TPAMI, 2024***.

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➢ Related work & Challenges

- **Catastrophic Forgetting**
  - Regularization-based methods constrain the updates to essential parameters of the model, thereby preserving important knowledge across tasks.
  - Architecture-based methods introduce task-specific components or allocate new parameters for each new task.
  - Rehearsal-based methods continuously replay samples from previous tasks to ensure that knowledge is retained.

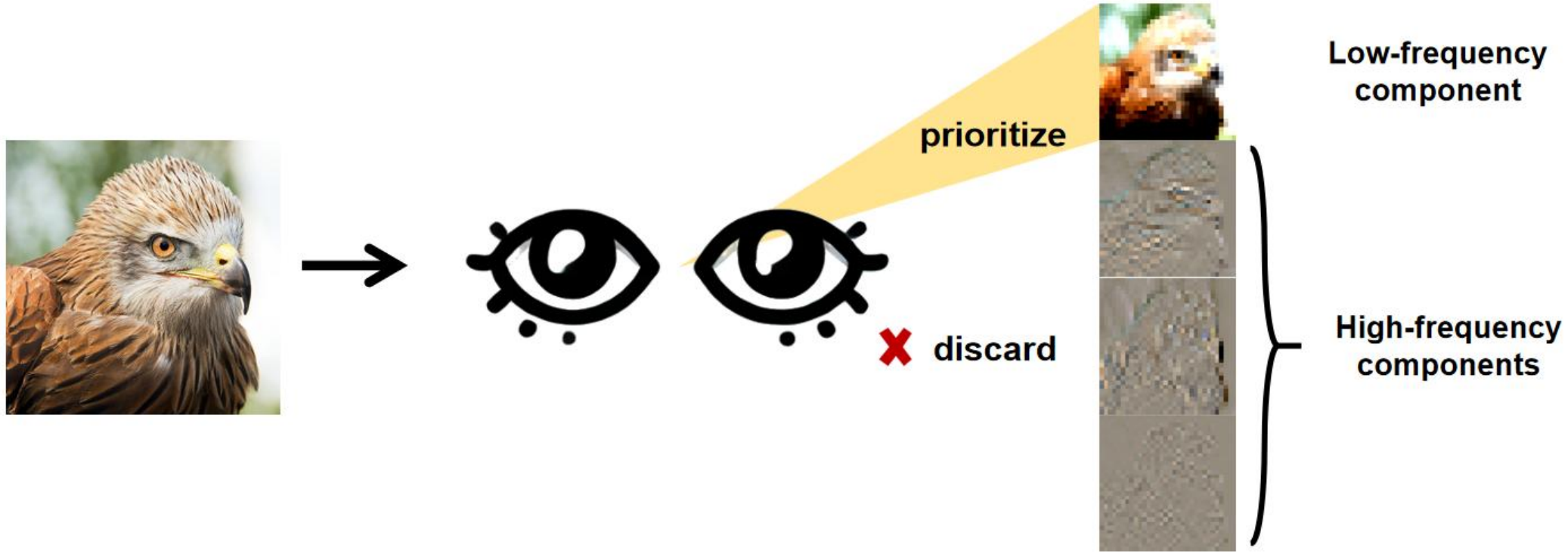
➢ Related work & Challenges

- **Resource Constraints**

Limited Memory, Storage, and Processing Capabilities

Rehearsal-based methods struggle on edge devices due to limited memory for storing samples and constrained computational resources, impacting both learning accuracy and training efficiency.

➢ Motivation



The human visual system (HVS) has evolved to handle information efficiently by focusing on essential low-frequency components and disregarding less critical details, serving as an inspiration for our framework.

➢ Method

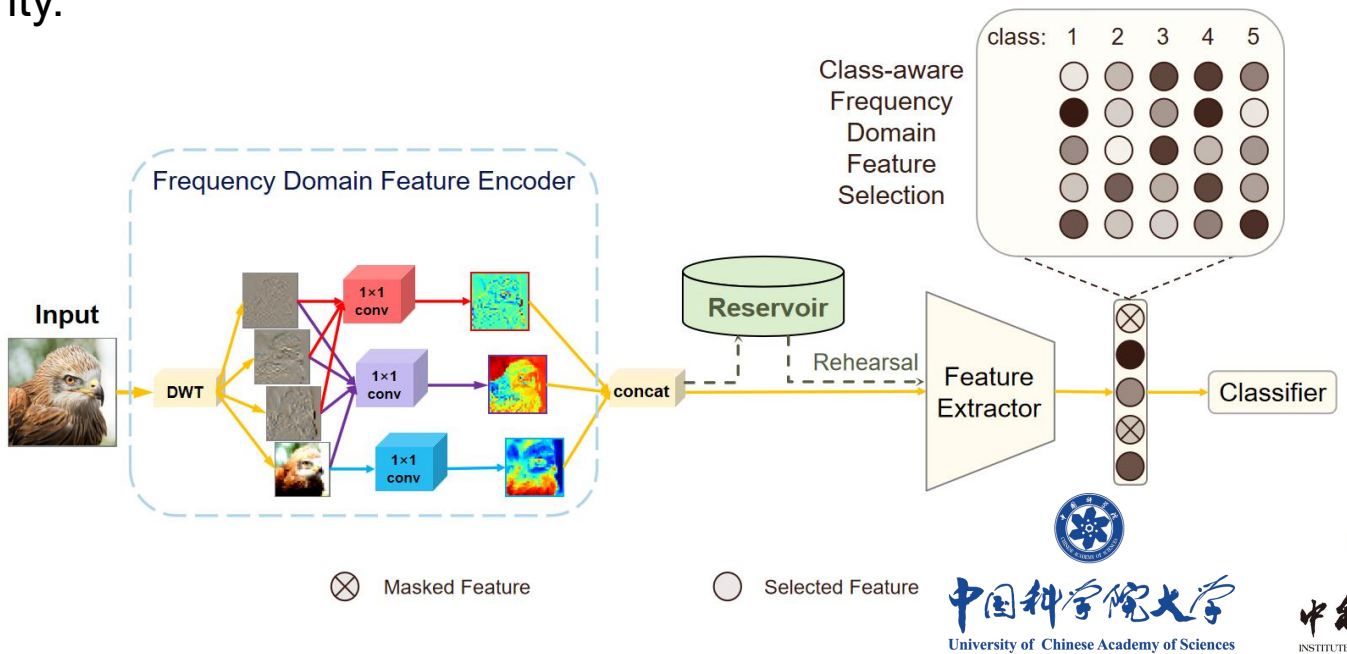
■ Continual Learning in the Frequency Domain

● The Frequency Domain Feature Encoder (FFE)

- Using wavelet transforms, FFE maps input images into the frequency domain, allowing us to reduce input feature sizes without major information loss.

● The Class-aware Frequency Domain Feature Selection (CFFS)

- CFFS balances feature reusability and minimizes interference by selecting frequency components based on class similarity.



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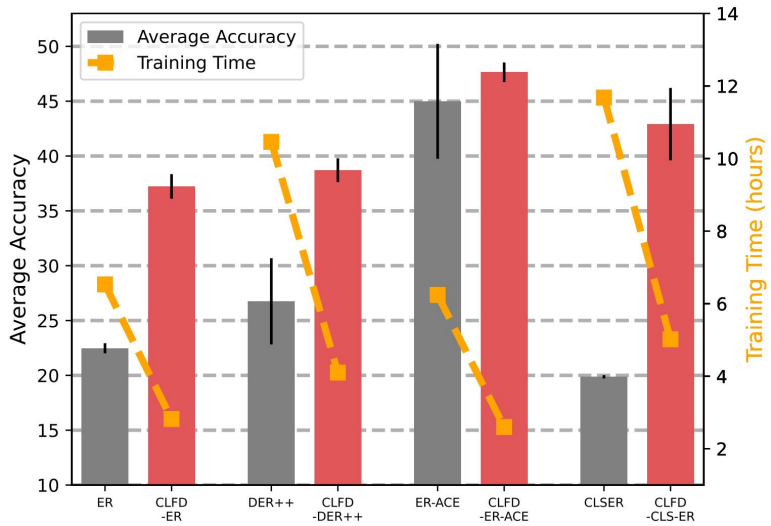
➢ Experiments

Achieving substantial improvements in training speed, memory usage, and accuracy, demonstrating practical feasibility for real-world applications.



Buffer	Method	S-CIFAR-10			S-Tiny-ImageNet		
		Class-IL	Task-IL	Mem	Class-IL	Task-IL	Mem
–	JOINT	92.20±0.15	98.31±0.12	-	59.99±0.19	82.04±0.10	-
	SGD	19.62±0.05	61.02±3.33	-	7.92±0.26	18.31±0.68	-
–	oEWC [41]	19.49±0.12	68.29±3.92	530MB	7.58±0.10	19.20±0.31	970MB
	SI [50]	19.48±0.17	68.05±5.91	573MB	6.58±0.31	36.32±0.13	1013MB
	LwF [30]	19.61±0.05	63.29±2.35	316MB	8.46±0.22	15.85±0.58	736MB
50	ER [38]	29.42±3.53	86.36±1.43	497MB	8.14±0.01	26.80±0.94	1333MB
	DER++ [6]	42.15±7.07	83.51±2.48	646MB	8.00±1.16	23.53±2.67	1889MB
	ER-ACE [7]	40.96±6.00	85.78±2.78	502MB	6.68±2.75	35.93±2.66	1314MB
	CLS-ER [4]	45.91±2.93	89.71±1.87	1016MB	11.09±11.52	40.76±9.17	3142MB
50	CLFD-ER	45.56±3.71	84.45±0.85	205MB	7.61±0.03	34.67±1.91	514MB
	CLFD-DER++	51.02±2.76	81.15±1.92	241MB	10.69±0.27	31.55±0.39	658MB
	CLFD-ER-ACE	**52.74**±1.91	87.13±0.41	204MB	10.71±2.91	38.05±11.98	514MB
	CLFD-CLS-ER	50.13±3.67	85.30±1.01	401MB	**12.61**±0.95	37.80±3.08	1032MB
125	ER [38]	38.49±1.68	89.12±0.92	497MB	8.30±0.01	34.82±6.82	1333MB
	DER++ [6]	53.09±3.43	88.34±1.05	646MB	11.29±0.19	32.92±2.01	1889MB
	ER-ACE [7]	56.12±2.12	90.49±0.58	502MB	11.09±3.86	41.85±3.46	1314MB
	CLS-ER [4]	53.57±2.73	90.75±2.76	1016MB	16.35±4.61	46.11±7.69	3142MB
125	CLFD-ER	55.76±1.85	88.29±0.16	205MB	8.89±0.07	42.40±0.83	514MB
	CLFD-DER++	58.81±0.29	84.76±0.66	241MB	15.42±0.37	40.94±1.30	658MB
	CLFD-ER-ACE	58.68±0.66	89.35±0.34	204MB	15.88±2.51	44.71±10.54	514MB
	CLFD-CLS-ER	**59.98**±1.38	87.09±0.43	401MB	**18.73**±0.91	49.75±2.01	1032MB

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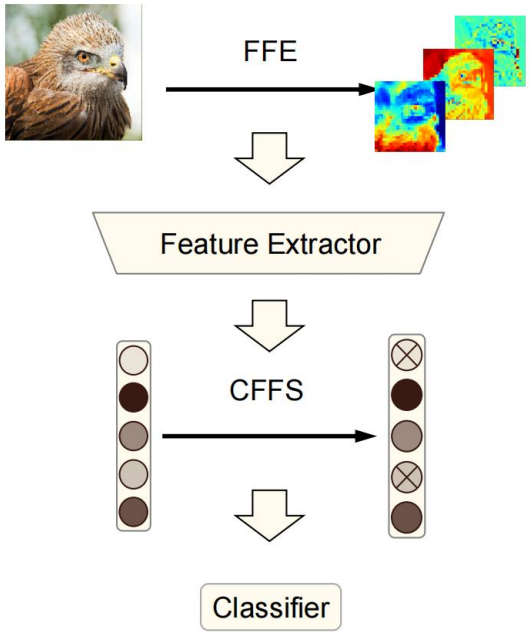
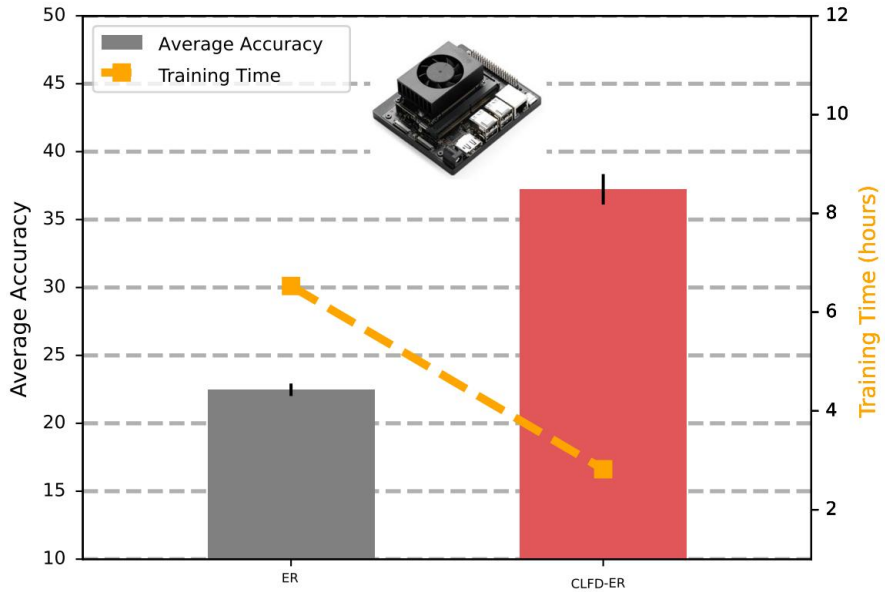
➢ Conclusion

■ Continual Learning in the Frequency Domain

- Our framework leverages frequency domain transformations for efficient continual learning, addressing both catastrophic forgetting and the unique resource limitations of edge computing.





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Thank You!

For further details, feel free to get in touch with us

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https://github.com/EMLS-ICT CAS/CLFD.git

https://arxiv.org/abs/2410.06645