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NeurIPS AFTER DARK

Meta-Exploiting Frequency Prior for Cross-Domain Few-Shot Learning

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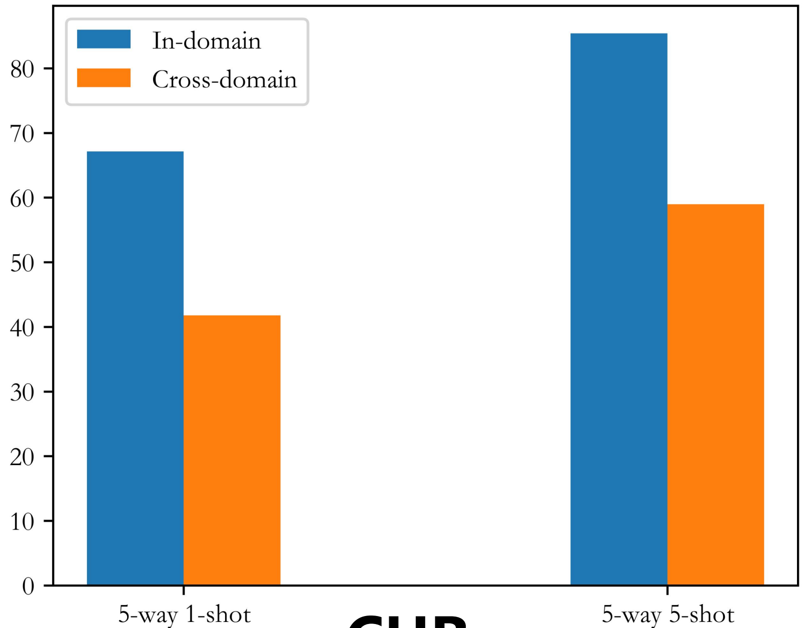
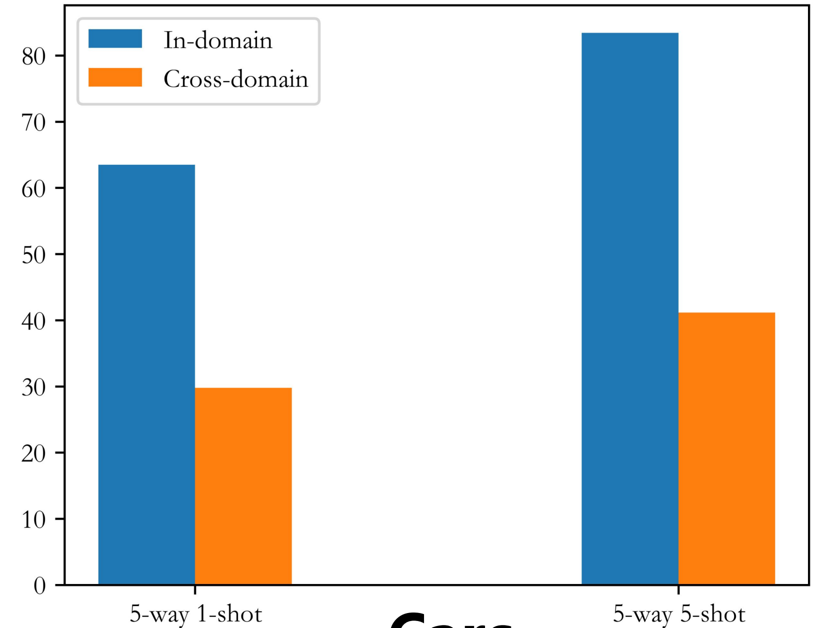
Motivation

Meta-learning offers a promising avenue for few-shot learning (FSL), enabling models to glean a generalizable feature embedding. Yet, in practical scenarios where the target task diverges from that in the source domain, meta-learning based method is susceptible to over-fitting.



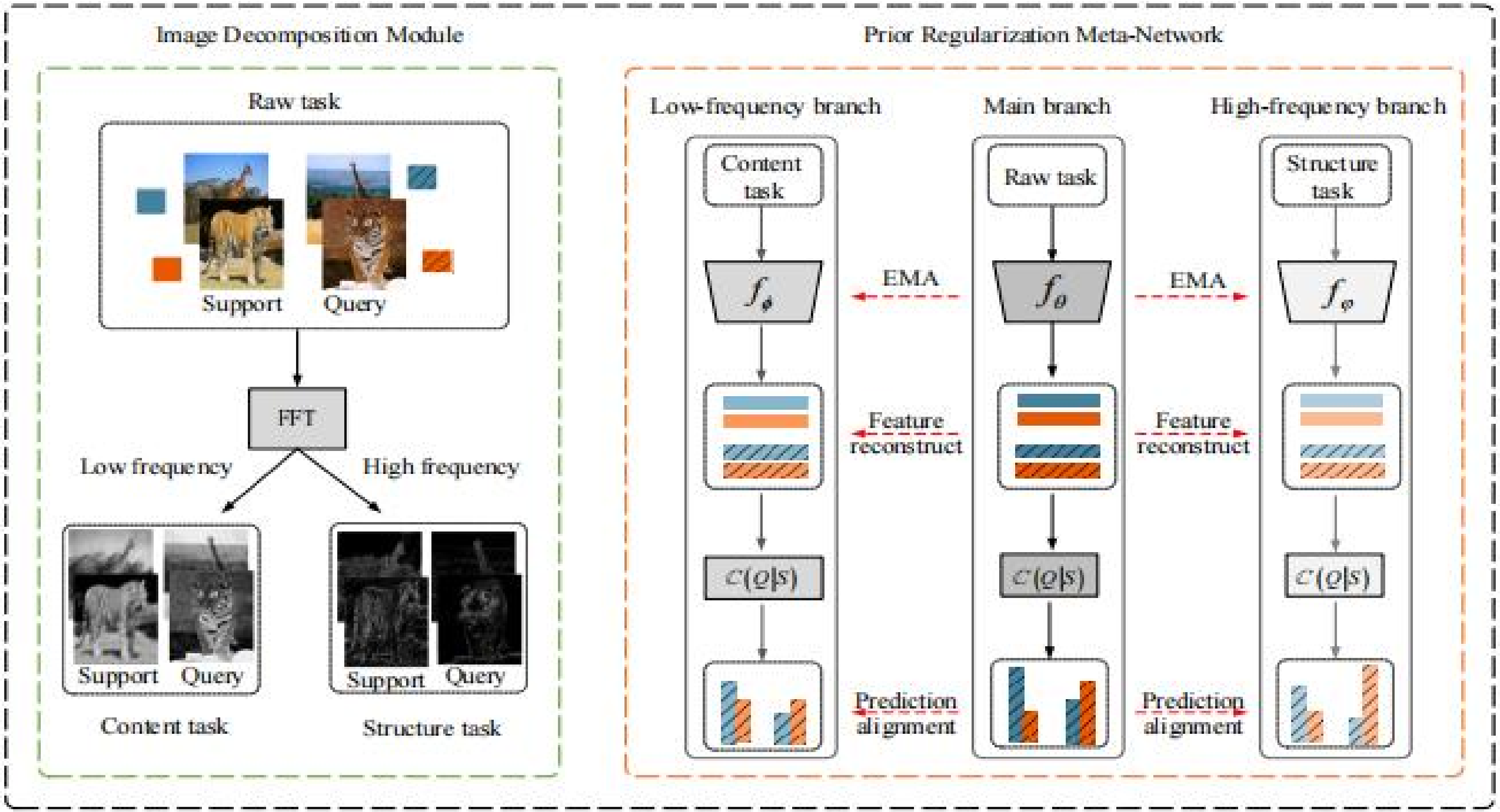
CUB



Cars

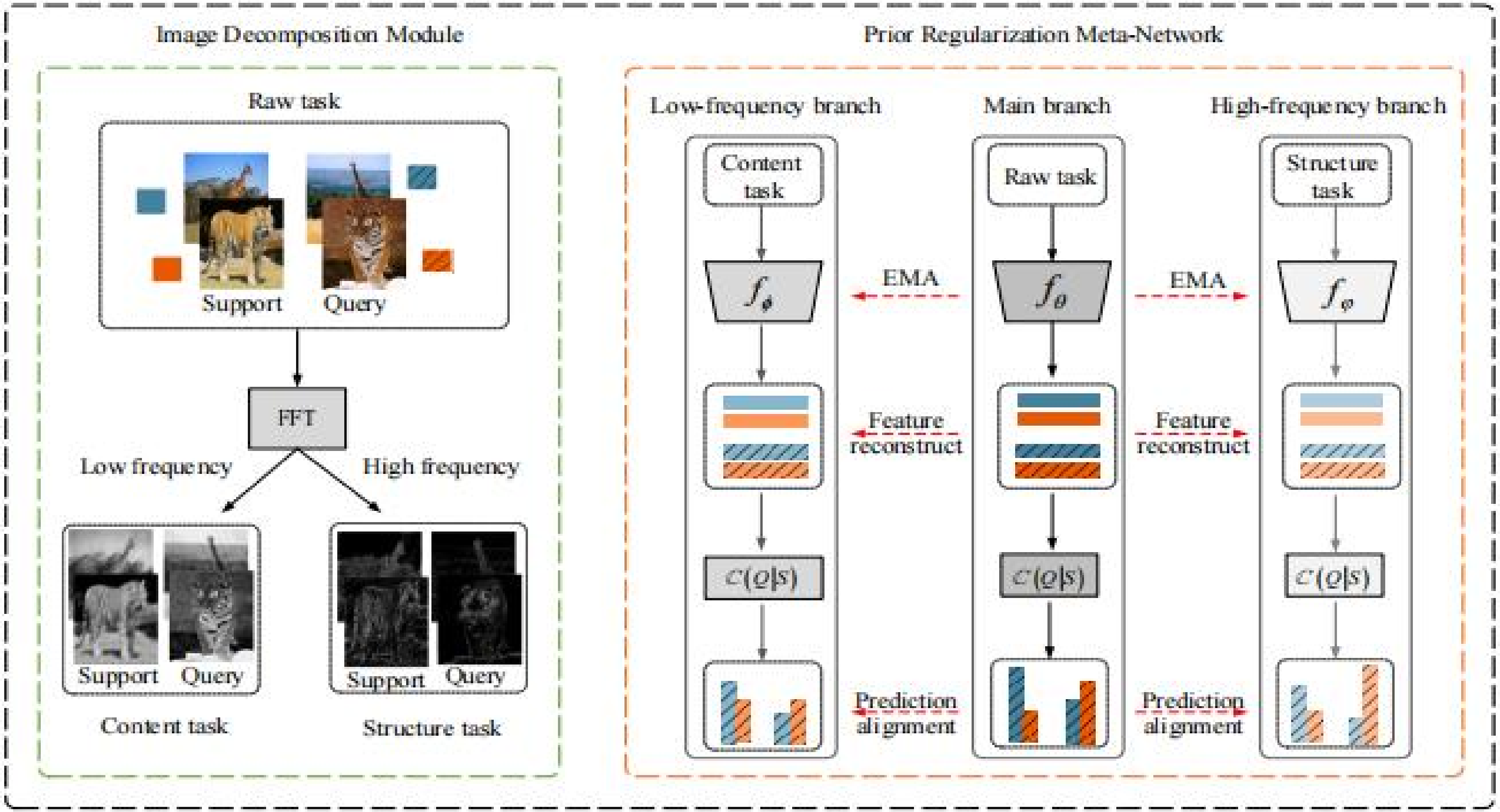
Framework

To overcome this, we introduce a novel framework, Meta-Exploiting Frequency Prior for Cross-Domain Few-Shot Learning.



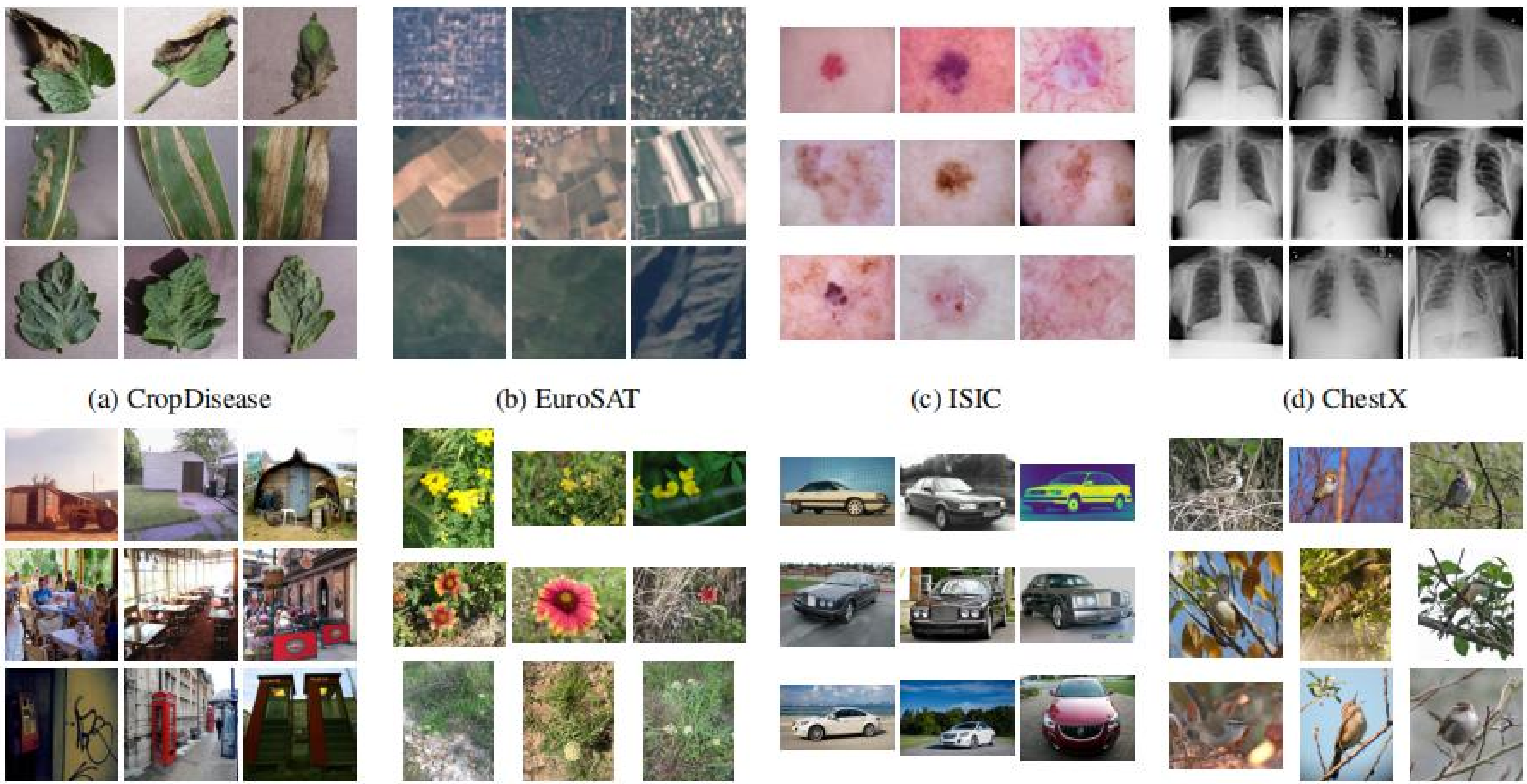
Framework

Our method consists of an Image Decomposition Module (IDM) and a Prior Regularization Meta-Network (PRM-Net).



Results

Eight benchmarks.



(a) CropDisease (b) EuroSAT (c) ISIC (d) ChestX

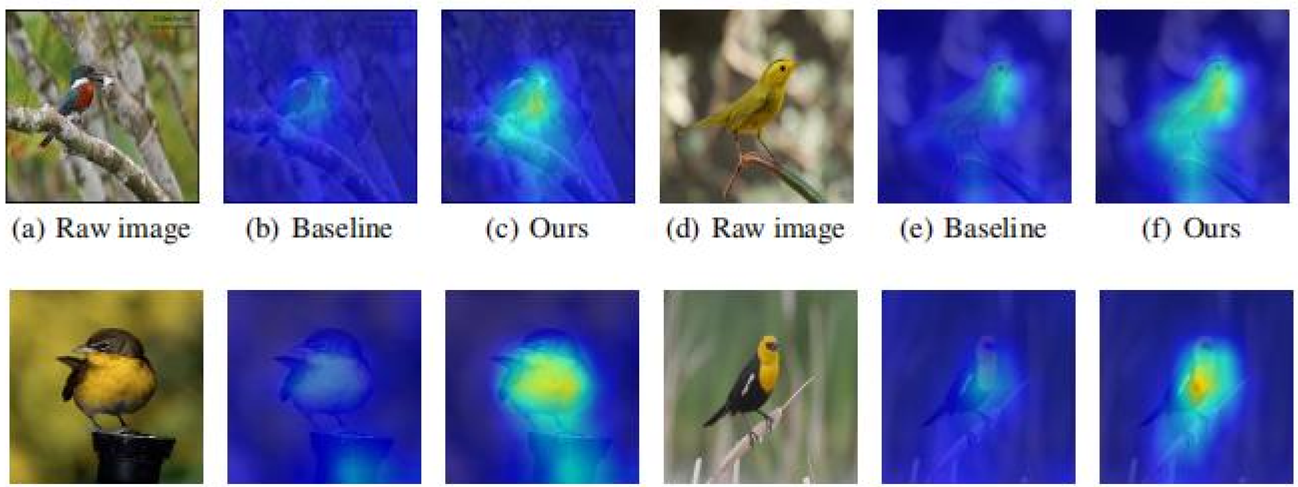
(e) Places (f) Plantae (g) Cars (h) CUB

Results

Comparison with the baseline and ablation study

Table 3: Ablation study. Average classification accuracies (%) are provided. ✔ indicates that this component is used, vice versa. The best results are in bold.

		CUB		Places		Plantae		CropDisease		Ave.	
Method		1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
Pretraining baseline		46.90	68.05	50.24	71.43	38.47	57.08	69.89	89.80	51.37	71.59
Meta baseline		47.05	67.99	51.09	71.74	39.26	57.82	70.22	89.54	51.90	71.77
Ours		**51.55**	**73.61**	**52.06**	**73.78**	**41.55**	**61.39**	**71.47**	**90.68**	**54.16**	**74.87**
Alignment	Reconstruction	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
✔	✗	50.79	72.65	51.42	73.22	41.05	60.93	70.80	90.11	53.51	74.22
✗	✔	50.55	71.39	51.96	72.60	41.11	60.22	70.04	89.44	53.41	73.41
✔	✔	51.55	73.61	52.06	73.78	41.55	61.39	71.47	90.68	54.16	74.87



(a) Raw image (b) Baseline (c) Ours (d) Raw image (e) Baseline (f) Ours

(g) Raw image (h) Baseline (i) Ours (j) Raw image (k) Baseline (l) Ours

Figure 2: Feature visualization for Baseline and the proposed method.

Results

Comparison with state-of-the-art methods in 5-way 1-shot setting

Table 1: Comparison with state-of-the-art methods on 5-way 1-shot cross-domain FSL. Average classification accuracies (%) are provided. † stands for exploiting the full data of FSL task. * means that the feature embedding network needs to be fine-tuned (Ft) on each target domain tasks. The best results are in bold.

Methods	Ft	CUB	Cars	Places	Plantae	Chest	ISIC	EuroSAT	CropDisease	Ave.
MatchingNet Vinyals et al. [2016]	✗	35.89	30.77	49.86	32.70	20.91	29.46	50.67	48.47	37.34
RelationNet Sung et al. [2018]	✗	41.27	30.09	48.16	31.23	21.95	30.53	49.08	53.58	38.24
GNN Garcia and Bruna [2018]	✗	44.40	31.72	52.42	33.60	21.94	30.14	54.61	59.19	41.00
FWT Tseng et al. [2019]	✗	45.50	32.25	53.44	32.56	22.00	30.22	55.53	60.74	41.53
LRP Sun et al. [2021]	✗	48.29	32.78	**54.83**	37.49	22.11	30.94	54.99	59.23	42.58
ATA Wang and Deng [2021]	✗	45.00	33.61	53.57	34.42	22.10	33.21	61.35	67.47	43.84
AFA Hu and Ma [2022]	✗	46.86	34.25	54.04	36.76	22.92	33.21	63.12	67.61	44.85
LDP-net Zhou et al. [2023]	✗	49.82	35.51	53.82	39.84	**23.01**	33.97	**65.11**	69.64	46.34
Ours	✗	**51.55**	**37.04**	52.06	**41.55**	22.82	**33.98**	64.31	**71.47**	**46.85**
ATA† Wang and Deng [2021]	✗	50.26	34.18	57.03	39.83	21.67	**34.70**	65.94	77.82	47.68
AFA† Hu and Ma [2022]	✗	50.85	38.43	60.29	40.27	21.69	34.25	66.17	72.44	48.05
RDC† Li et al. [2022]	✗	47.77	38.74	58.82	41.88	**22.66**	32.29	67.58	80.88	48.83
GNN+wave-SAN† Fu et al. [2022]	✗	50.25	33.55	57.75	40.71	22.93	33.35	69.64	70.80	47.37
LDP-net† Zhou et al. [2023]	✗	55.94	37.44	62.21	41.04	22.21	33.44	**73.25**	81.24	50.85
StyleAdv† Fu et al. [2023]	✗	48.49	34.64	58.58	41.13	22.64	33.96	70.94	74.13	48.06
Ours†	✗	**59.48**	**38.86**	**62.90**	**44.06**	22.48	34.28	69.56	**84.01**	**51.95**
Fine-tuning* Guo et al. [2020]	✓	43.53	35.12	50.57	38.77	22.13	34.60	66.17	73.43	45.54
ATA*† Wang and Deng [2021]	✓	51.89	38.07	57.26	40.75	22.45	35.55	70.84	82.47	49.91
RDC*† Li et al. [2022]	✓	50.09	39.04	61.17	41.30	22.32	36.28	70.51	85.79	50.81

Results

Comparison with state-of-the-art methods in 5-way 5-shot setting

Table 2: Comparison with state-of-the-art methods on 5-way 5-shot cross-domain FSL. Average classification accuracies (%) are provided. † stands for exploiting the full data of FSL task. * means that the feature embedding network needs to be fine-tuned (Ft) on each target domain tasks. The best results are in bold.

Methods	Ft	CUB	Cars	Places	Plantae	Chest	ISIC	EuroSAT	CropDisease	Ave.
MatchingNet Vinyals et al. [2016]	✗	51.37	38.99	63.16	46.53	22.40	36.74	64.45	66.39	48.75
MAML Finn et al. [2017]	✗	-	-	-	-	23.48	40.13	71.70	78.05	-
RelationNet Sung et al. [2018]	✗	56.77	40.46	64.25	42.71	24.07	38.60	65.56	72.86	50.66
MetaOptNet Lee et al. [2019]	✗	-	-	-	-	22.53	36.28	64.44	68.41	-
GNN Garcia and Bruna [2018]	✗	62.87	43.70	70.91	48.51	23.87	42.54	78.69	83.12	56.77
FWT Tseng et al. [2019]	✗	64.97	46.19	70.70	49.66	24.28	40.87	78.02	87.07	57.72
LRP Sun et al. [2021]	✗	64.44	46.20	74.45	54.46	24.53	44.14	77.14	86.15	58.94
ATA Wang and Deng [2021]	✗	66.22	49.14	75.48	52.69	24.32	44.91	83.75	90.59	60.89
AFA Hu and Ma [2022]	✗	68.25	49.28	**76.21**	54.26	25.02	46.01	**85.58**	88.06	61.58
LDP-net Zhou et al. [2023]	✗	70.39	52.84	72.90	58.49	**26.67**	48.06	82.01	89.40	62.60
Ours	✗	**73.61**	**54.22**	73.78	**61.39**	26.53	**48.70**	81.24	**90.68**	**63.77**
ATA† Wang and Deng [2021]	✗	65.31	46.95	72.12	55.08	23.60	45.83	79.47	88.15	59.56
AFA† Hu and Ma [2022]	✗	65.86	47.89	72.81	55.67	23.47	46.29	80.12	85.69	59.73
RDC† Li et al. [2022]	✗	63.39	52.75	72.83	55.30	25.10	42.10	79.12	88.03	59.83
GNN+wave-SAN† Fu et al. [2022]	✗	70.31	46.11	76.88	57.72	25.63	44.93	85.22	89.70	62.06
LDP-net† Zhou et al. [2023]	✗	73.34	53.06	75.47	59.64	**26.88**	48.44	84.05	91.89	64.10
StyleAdv† Fu et al. [2023]	✗	68.72	50.13	**77.73**	61.52	26.07	45.77	**86.58**	**93.65**	63.77
Ours†	✗	**76.68**	**55.44**	76.98	**63.08**	26.45	**49.07**	83.22	93.09	**65.50**
Fine-tuning* Guo et al. [2020]	✓	63.76	51.21	70.68	56.45	25.37	49.51	81.59	89.84	61.05
NSAE(CE+CE)* Liang et al. [2021]	✓	68.51	54.91	71.02	59.55	27.10	54.05	83.96	93.14	64.03
ConFeSS* Das et al. [2021]	✓	-	-	-	-	27.09	48.85	84.65	88.88	-
ATA*† Wang and Deng [2021]	✓	70.14	55.23	73.87	59.02	24.74	49.83	85.47	93.56	63.98
RDC*† Li et al. [2022]	✓	67.23	53.49	74.91	57.47	25.07	49.91	84.29	93.30	63.21

The proposed method achieves state-of-the-art performance on a eight cross-domain FSC benchmarks.

Conclusions

Thanks!