ICML International Conference On Machine Learning

Geometry-Aware Contrastive Learning for Few-Shot Automatic Modulation Recognition

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1. Introduction

- **AMR** is critical for 6G, but labeled data scarcity limits deep learning in non-cooperative scenarios.
- Existing contrastive learning methods **fail geometrically:** *isotropic augmentation is ineffective in high dimensions,* self-attention is spectrally unstable, and physical priors are fused too shallowly.
- We propose **DyCo-CL**, coupling adversarial augmentation, a spectrally-stable Swin backbone, and dynamic physics fusion, achieving *+6.27% in 1-shot AMR.*

Algorithm 1 DyCo-AMR Pre-training Algorithm

Input: f_q, f_k (encoders), m (momentum), τ (temp), ϵ, λ_{sc}

for each minibatch $\mathbf{x}$ in Dataset **do**

$\mathbf{x}_{weak} = \text{PhysAug}(\mathbf{x}), \quad \mathbf{x}_{adv} = \text{VAA}(\mathbf{x}, f_q, \epsilon)$

$\boldsymbol{q} \leftarrow f_{\boldsymbol{q}}(\mathbf{x}_{adv}), \quad \boldsymbol{k} \leftarrow f_{\boldsymbol{k}}(\mathbf{x}_{weak})$ *(k: no grad)*

$l_{\text{pos}} = \boldsymbol{q} \cdot \boldsymbol{k}^{+}, \quad l_{\text{neg}} = \boldsymbol{q} \cdot \boldsymbol{k}^{-}$

$$\mathcal{L}_{NCE} = -\log \frac{\exp(l_{\text{pos}}/\tau)}{\exp(l_{\text{pos}}/\tau) + \sum \exp(l_{\text{neg}}/\tau)}$$

$\boldsymbol{z} \leftarrow f_{\boldsymbol{q}}^{\text{proj}}(\mathbf{x})$ *(projection output, no grad)*

$\boldsymbol{z}_{adv} \leftarrow f_{\boldsymbol{q}}^{\text{proj}}(\mathbf{x}_{adv})$ *(projection output)*

$$\mathcal{L}_{SC} = 1 - \frac{\boldsymbol{z} \cdot \boldsymbol{z}_{adv}}{\|\boldsymbol{z}\| \|\boldsymbol{z}_{adv}\|}$$

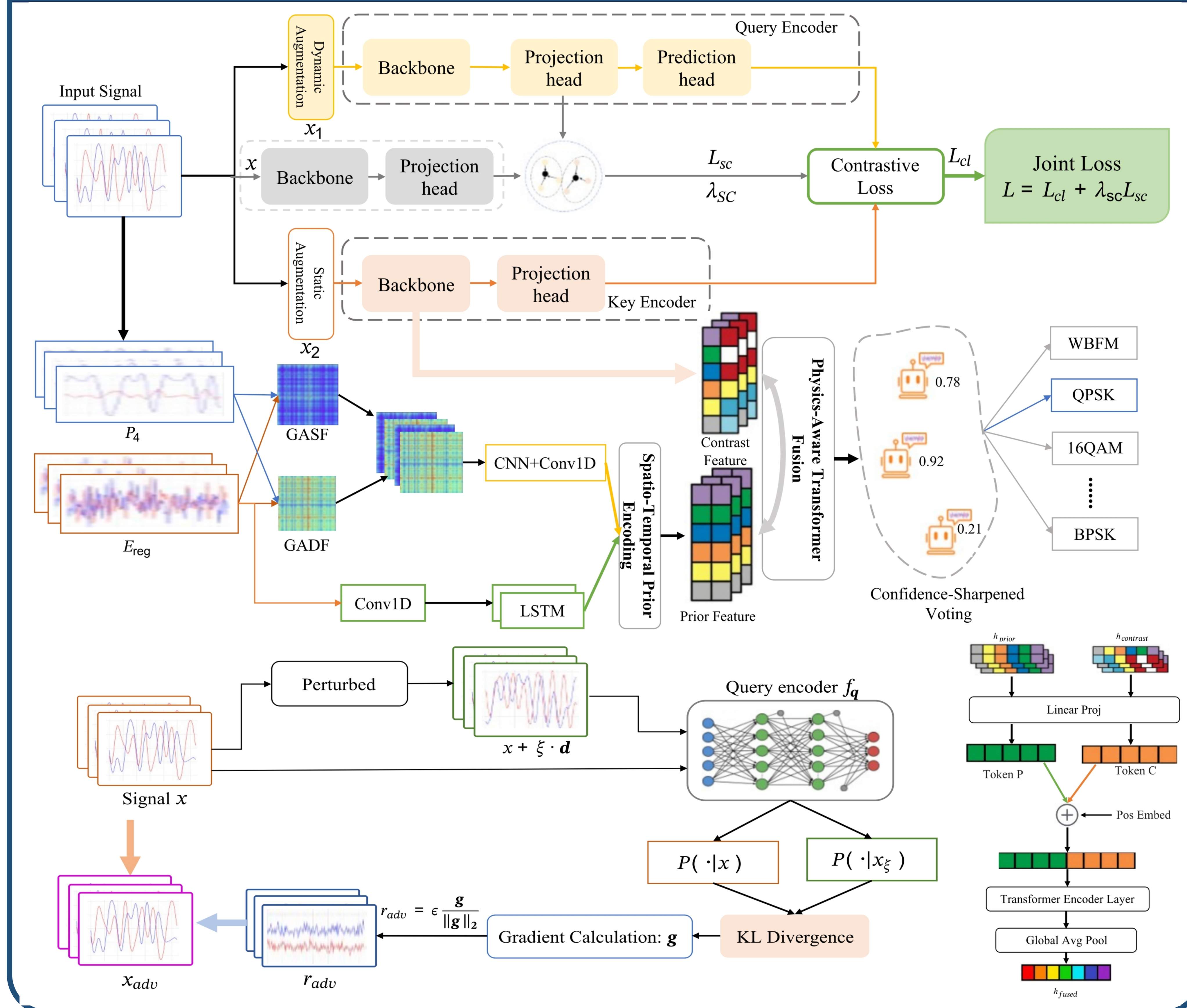
$\mathcal{L}_{total} = \mathcal{L}_{NCE} + \lambda_{sc} \cdot \mathcal{L}_{SC}$

Update f_q via Backprop: $\nabla \mathcal{L}_{total}$

Update f_k via Momentum: $\theta_k \leftarrow m\theta_k + (1-m)\theta_q$

end for

2. Method: DyCo-CL



3. Ablation Study and Hyperparameter Analysis

(a) Impact of Consistency Weight (λ_{sc})

Value	0.0	0.1	0.2	0.3	0.4	0.5	**0.6 (Default)**	0.7	0.8
Acc (%)	38.38	38.43	39.30	41.58	41.96	41.78	**43.84**	41.04	42.44
Δ	-5.46	-5.41	-4.54	-2.26	-1.88	-2.06	-	-2.8	-1.4

(d) Impact of Power Iteration Steps (I_{iter})

Iterations	**1 (Default)**	2	5
Acc (%)	**43.84**	41.71	40.82
Time	**1.0×**	1.19×	1.38×
Δ	-	-2.13	-3.02

(b) Impact of VAA Perturbation Radius (ϵ)

Value	0.1	0.2	**0.3 (Default)**	0.4	0.5
Acc (%)	43.70	43.05	**43.84**	41.34	40.95
Δ	-0.14	-0.79	-	-2.50	-2.89

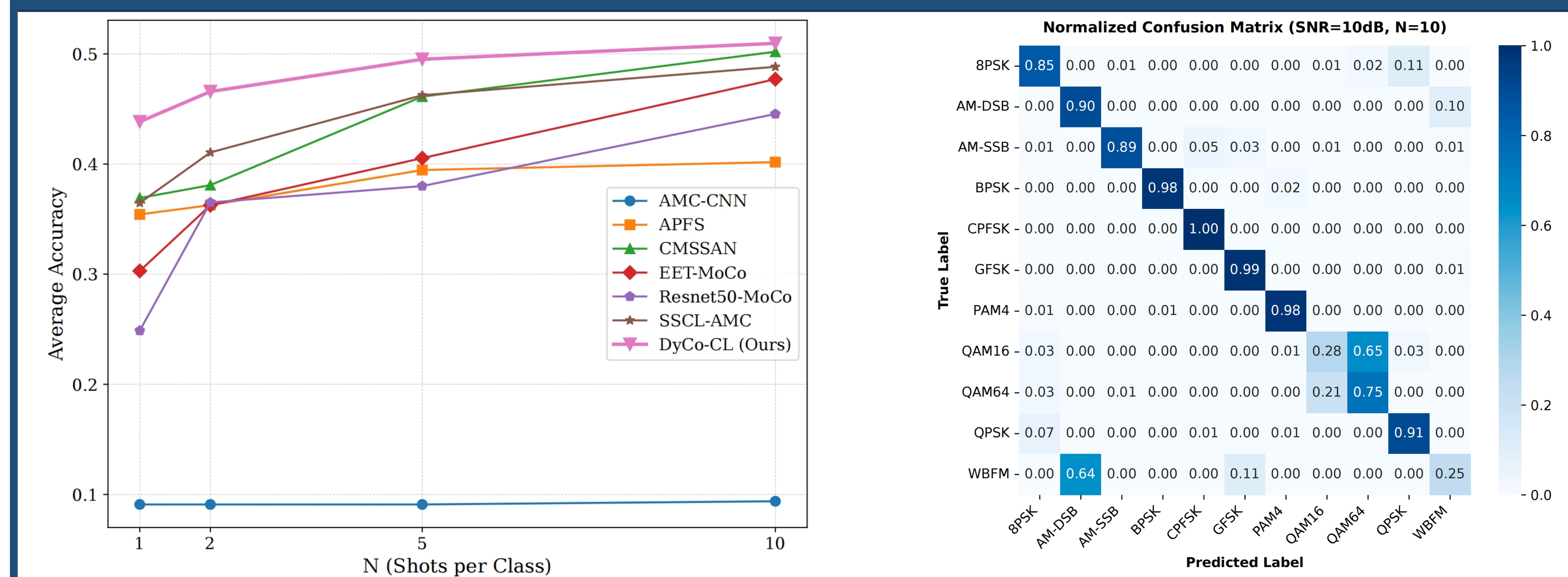
(c) Impact of Swin Window Size (M)

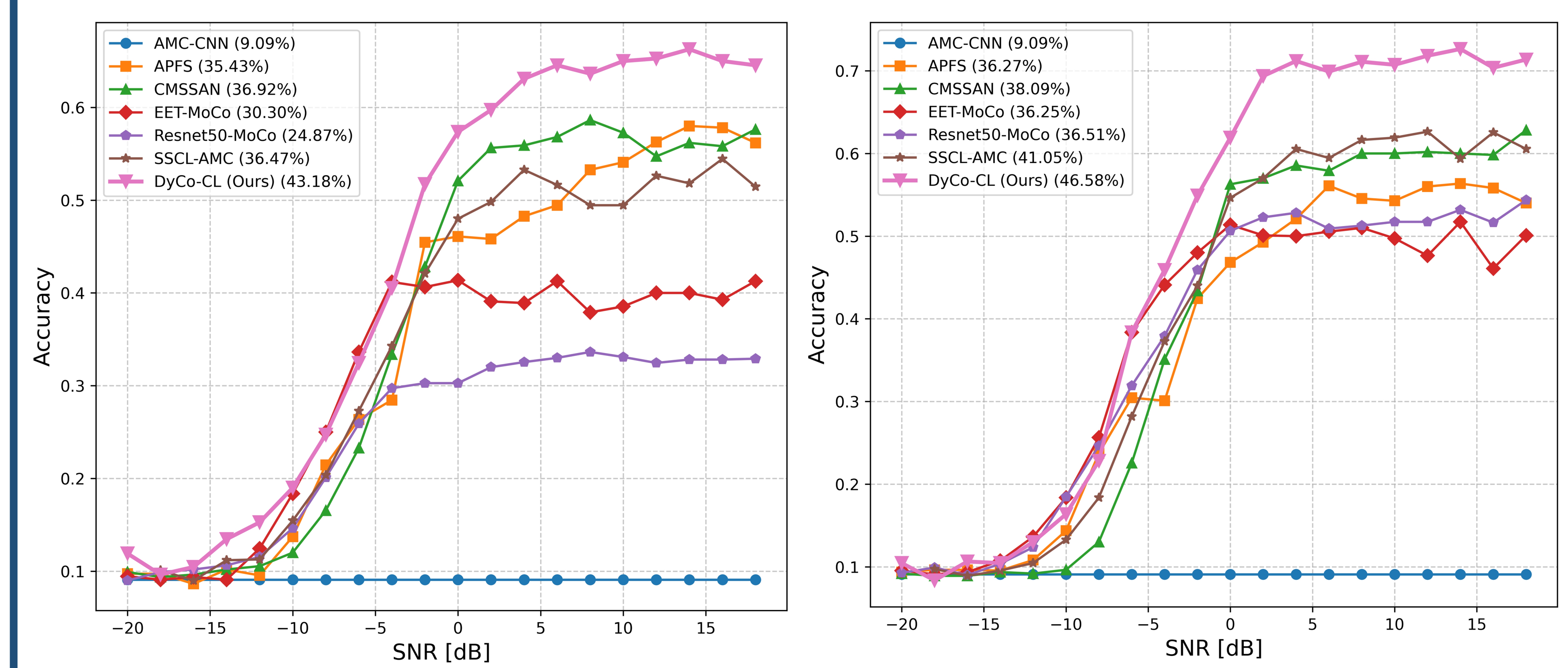
Value	1	2	4	**8 (Default)**	16
Acc (%)	39.29	39.15	38.10	**43.84**	42.63
Δ	-4.55	-4.69	-5.74	-	-1.21

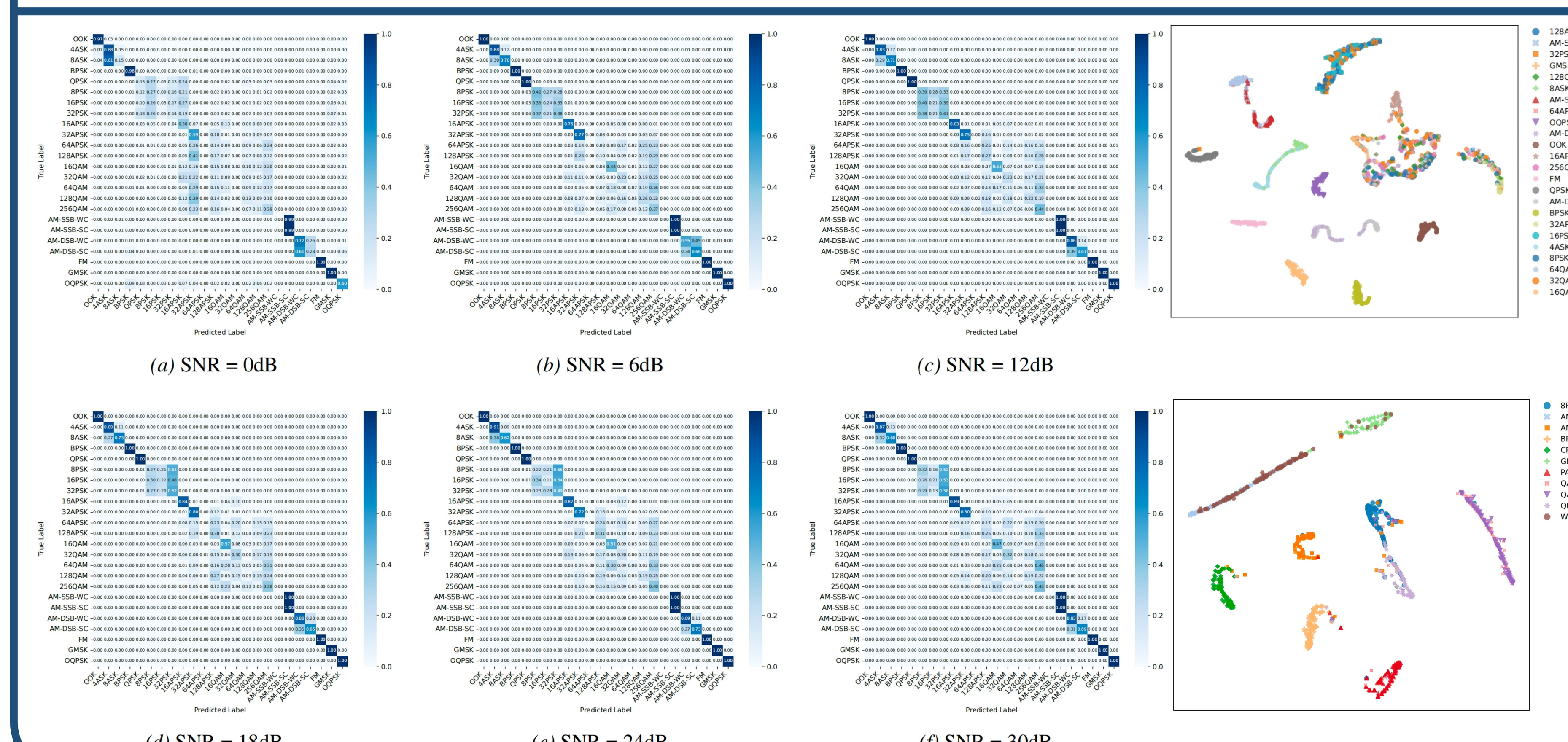
Category	Model Variant	Acc (%)	Δ
Full Method	**DyCo-CL**	**43.84**	-
Backbone & Module	w/o Dynamic-Consistency	34.94	−8.90
	w/o Swin (ResNet18)	39.45	−4.39
Fusion Strategy	Stage I → Concat	39.47	−4.37
	Stage II → Concat	40.12	−3.72
	All Stages → Concat	38.32	−5.52

Model	Params (M)	FLOPs (M)	Storage (MB)	Latency (ms)	Throughput (samples/s)
APFS	1.09	50.27	4.4	42.5	23.49
CMSSAN	0.123	2.33	0.5	0.007	140335
EET-MoCo	1.005	11.340	4.1	1.37	729
ResNet50-MoCo	23.520	101.900	94.1	0.06	17280
SSCL-AMC	1.515	36.934	6.1	2.01	498
DyCo-CL	**1.443**	**14.46**	**5.8**	**0.60**	**1672**

4. Main Results







paper: https://arxiv.org/abs/2605.26600