ALFA – Leveraging All Levels of Feature Abstraction for Enhancing the Generalization of Histopathology Image Classification Across Unseen Hospitals

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ALFA Contributions

- Extension of the mDSDI [1] technique for Domain Generalization (DG) of unseen hospital image repository.
- Concatenation of disentangled Self-Supervised Learning (SSL), domain-invariant, and domain-specific representations forms the different levels of feature abstraction.
- Introduced "soft class-domain alignment" loss function that provides increased stability during optimization compared to the adversarial training.
- Tested on the PACS benchmark and a Renal Cell Carcinoma (RCC) subtyping task from The Cancer Genome Atlas (TCGA) data portal.

Feature-space representations

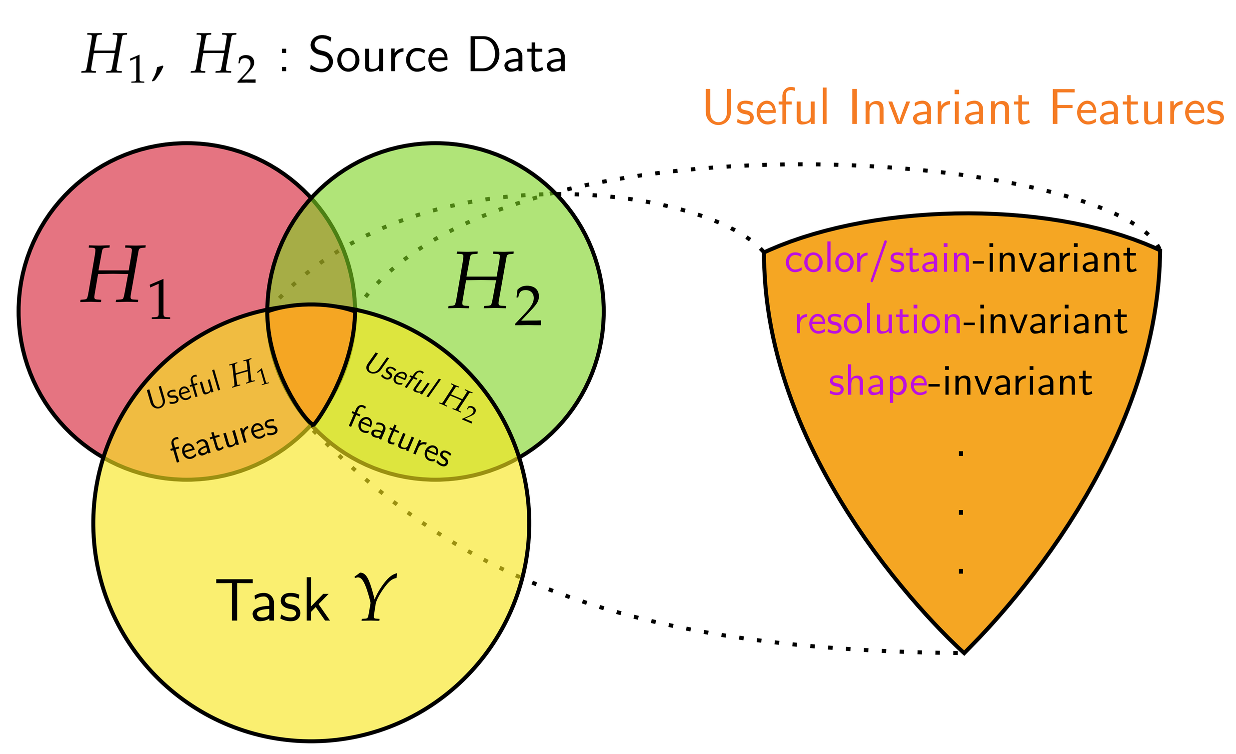

Figure 1: The Venn diagram delineates the feature space of the source hospitals (H_1 and H_2). The yellow area demarcates the label space employed in the classification task. The shared space between feature and label spaces underscores the features conducive to executing tasks within the label space.

The visual differences in digital pathology

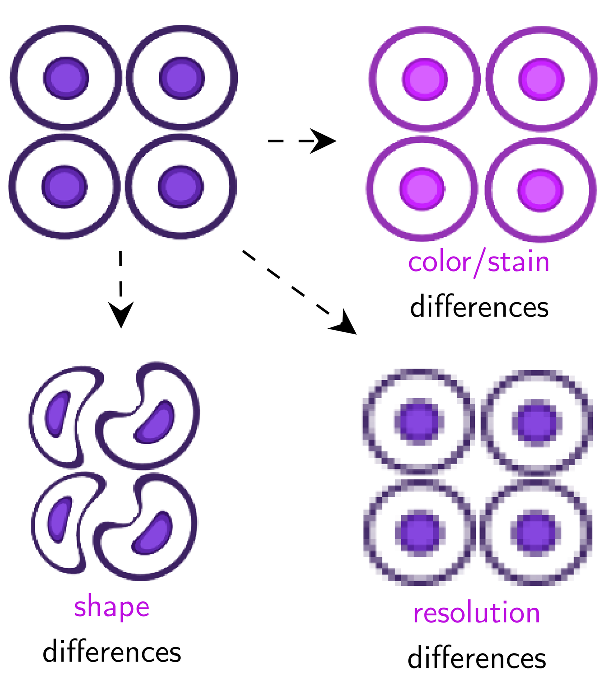

Figure 2: Different distribution shifts happening in digital pathology setups.

Methodology of ALFA

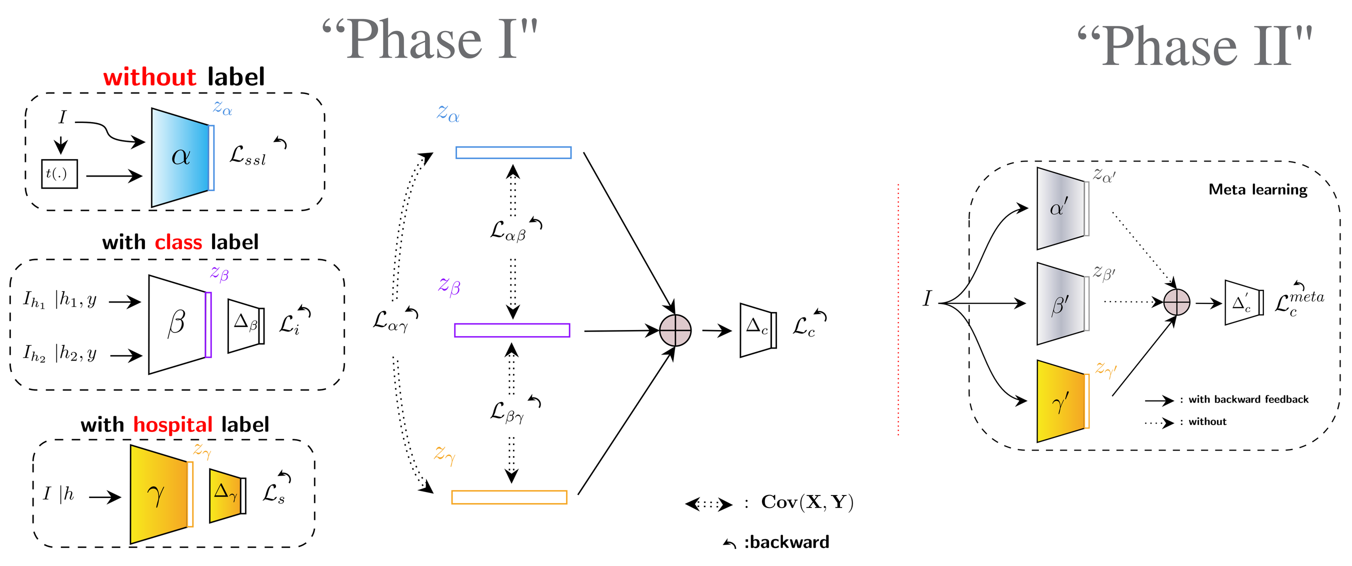

Figure 3: ALFA has two phases: In Phase I, three feature extractors extract different levels of feature abstraction, and disentangled features are concatenated for classification. In Phase II, updated feature extractors' representations are concatenated and fed into the updated classifier to update parameters in a Meta-learning fashion while α' and β' feature extractors remain frozen.

Results on RCC subtyping

Table 1: Results on RCC subtyping task

Target	Source	Accuracy (%) ERM	Accuracy (%) mDSDI [1]	Accuracy (%) HA [2]	Accuracy (%) ALFA	AUROC (%) ERM	AUROC (%) mDSDI [1]	AUROC (%) HA [2]	AUROC (%) ALFA	Recall (%) ERM	Recall (%) mDSDI [1]	Recall (%) HA [2]	Recall (%) ALFA
IGC	{NCI, MSKCC, H-MD}	75.86	86.20	70.42	86.21	93.23	95.78	88.36	95.33	57.14	82.88	62.38	85.39
NCI	{IGC, MSKCC, H-MD}	81.82	72.73	83.38	86.36	96.49	94.46	97.32	97.83	83.08	71.46	85.48	86.41
MSKCC	{IGC, NCI, H-MD}	86.73	85.71	88.19	84.69	95.91	95.89	96.47	95.99	82.99	87.05	85.32	87.99
H-MD	{IGC, NCI, MSKCC}	72.49	51.72	75.29	65.52	85.38	88.37	90.16	90.48	72.96	51.85	78.42	66.67
Average		79.22 ±5.36	74.09 ±13.72	79.32 ±6.49	80.69 ±8.61	92.75 ±4.34	93.62 ±3.02	93.08 ±3.34	94.90 ±2.66	74.07 ±10.38	73.31 ±13.36	77.90 ±8.44	81.62 ±8.50

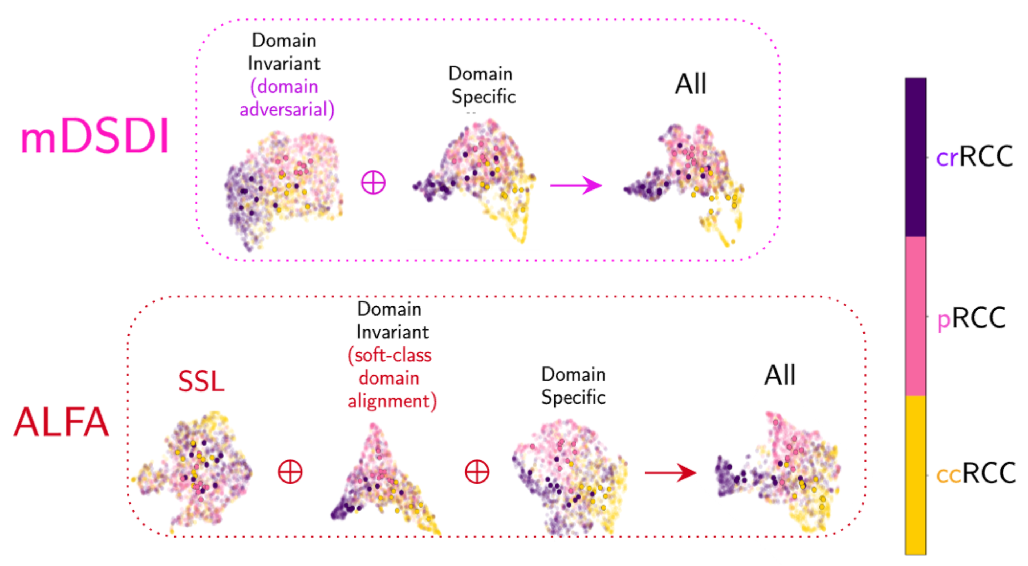

Figure 4: 2D feature embeddings for the feature extractors in mDSDI [1] versus in ALFA: (target hospital: 'NCI'). 'All' is the concatenation of domain-specific and domain-invariant representations for the mDSDI [1] (up), and SSL, domain-invariant, and domain-specific representations for ALFA (bottom).

References

[1] Bui, Manh-Ha, et al. "Exploiting domain-specific features to enhance domain generalization." Advances in Neural Information Processing Systems 34 (2021): 21189-21201.

[2] Sikaroudi, Milad, et al. "Hospital-agnostic image representation learning in digital pathology." EMBC 2022. IEEE.