MSc Thesis

Learning from Many: Domain Generalization for Medical Imaging

Abstract

Deep learning achieves good performance when training and test data share similar distribution characteristics. However, for real-world scenarios including medical imaging and natural scenes, due to significant domain shifts caused by diverse data characteristics and scanner settings, models often fail to generalize to unseen domains. To address this at the model level, domain adaptation [11, 12] and domain generalization [1, 9] have emerged as potential solutions, with domain adaptation relying on access to target data to learn target representations and domain generalization aiming to learn invariant representations and obtain robust models using only source domains. Recently, a new paradigm, test-time adaptation, further optimizes the model during online inference on the target domain to increase the performance [2, 13].

Despite advancements, existing adaptation methods struggle to address the unique challenges in the target domain. Specifically, scenarios which arise due to class imbalance, category shifts within the domains, reliance on unsupervised surrogate objectives, and non-i.i.d assumptions, that lead to error accumulation. Moreover, due to the scarcity of large annotated datasets, this limits the ability of the models to learn meaningful representations for transferring to the target domain [4]. Recent works [6] indicate that existing methods do not consistently improve performance on multi-source real-world scenarios such as medical imaging [5, 8, 10].

This Master's thesis aims to propose domain generalization and adaptation techniques to address these challenges. The research will focus on training models on multi-source data from diverse source distributions such as different scanners, pathologies, and demographics. Next, it will explore existing domain generalization algorithms, analyzing the role of entropy minimization for optimizing model performance [13, 14] and feature alignment [15]. Finally, the work seeks to introduce novel contributions through fundamental deep learning properties, aiming to enhance the adaptability and robustness of deep learning models for varied environments [3, 7]. We aspire to publish the research outcomes in a relevant academic venue.

Requirements

- Proficient in deep learning
- Interested in medical imaging and research
- Experience in practical deep learning frameworks such as PyTorch

Affiliation

Prof. Dr. Julia Schnabel
Informatik 32 - Lehrstuhl für Computational Imaging and AI in Medicine

Supervision: Sameer Ambekar, Dr. Daniel M. Lang

Application

Please send a mail, involving a CV, a current transcript of records and a brief statement on why you are interested in the project, to sameer.ambekar@tum.de.

References

[1] S. Ambekar, Z. Xiao, J. Shen, X. Zhen, and C. G. Snoek. Learning variational neighbor labels for test-time domain generalization. *arXiv preprint arXiv:2307.04033*, 2023.

[2] S. Ambekar, Z. Xiao, X. Zhen, and C. G. Snoek. Generalizeformer: Layer-adaptive model generation across test-time distribution shifts. In *2025 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pages 6548–6558. IEEE, 2025.

[3] W. Chen et al. Domain generalization by learning from privileged medical imaging information. *arXiv preprint arXiv:2311.05861*, November 2023.

[4] Z. Chen et al. Universal medical imaging model for domain generalization with data privacy. *arXiv preprint arXiv:2407.14719*, July 2024.

[5] I. Gulrajani et al. Failure to achieve domain invariance with domain generalization algorithms: An analysis in medical imaging. *Semantic Scholar*, 2021. ID: 79523b28bf5b1c7b5ee99221a4896411c9d68905.

[6] I. Gulrajani and D. Lopez-Paz. In search of lost domain generalization. In *International Conference on Learning Representations*, 2020.

[7] X. Li et al. Perturbating, tuning, and collaborating: Harnessing vision foundation models for single domain generalization on medical imaging. *Semantic Scholar*, 2023. ID: 98e7f4f464c2e890a4b32541dde474f8e5fcb7e4.

[8] Q. Liu et al. An empirical framework for domain generalization in clinical settings. *arXiv preprint arXiv:2103.11163*, April 2021.

[9] K. Muandet, D. Balduzzi, and B. Schölkopf. Domain generalization via invariant feature representation. In *International Conference on Machine Learning*, pages 10–18. PMLR, 2013.

[10] S. Niu, J. Wu, Y. Zhang, Y. Chen, S. Zheng, P. Zhao, and M. Tan. Efficient test-time model adaptation without forgetting. *arXiv preprint arXiv:2204.02610*, 2022.

[11] P. Pandey, A. K. Tyagi, S. Ambekar, and A. Prathosh. Unsupervised domain adaptation for semantic segmentation of nir images through generative latent search. In *ECCV 2020 [Spotlight]*, pages 413–429. Springer, 2020.

[12] T.-H. Vu, H. Jain, M. Bucher, M. Cord, and P. Pérez. Advent: Adversarial entropy minimization for domain adaptation in semantic segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2517–2526, 2019.

[13] D. Wang, E. Shelhamer, S. Liu, B. Olshausen, and T. Darrell. Tent: Fully test-time adaptation by entropy minimization. In *International Conference on Learning Representations*, 2021.

[14] Y. Zhang et al. Domain generalization for medical imaging classification with linear-dependency regularization. *arXiv preprint arXiv:2009.12829*, September 2020.

[15] F. Zhou, Z. Jiang, C. Shui, B. Wang, and B. Chaib-draa. Domain generalization via optimal transport with metric similarity learning. *Neurocomputing*, 456:469–480, 2021.