# MAP: Domain Generalization via Meta-Learning on Anatomy-Consistent Pseudo-Modalities

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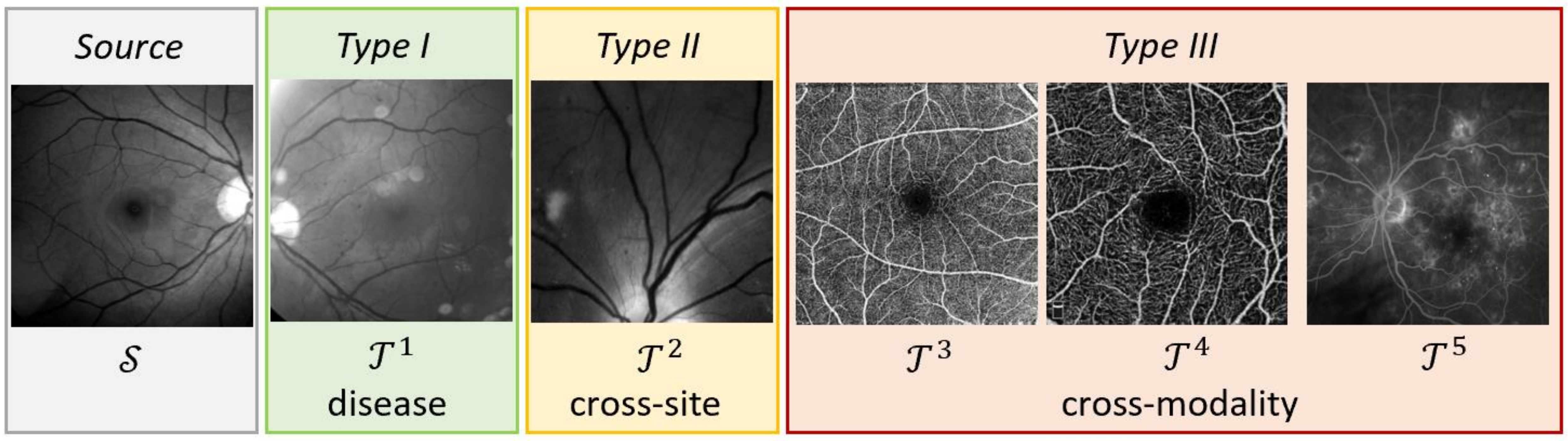
## Introduction

Deep learning models suffer from limited generalization capability to unseen domains, which has severely hindered their clinical applicability. Specifically for the retinal vessel segmentation task, although the model is supposed to learn the anatomy of the target, it can be distracted by confounding factors like intensity and contrast. In this work, we propose meta learning on anatomy-consistent pseudo-modalities (**MAP**), a method that improves model generalizability by learning structural features. We evaluate our model on 7 public datasets of various retinal imaging modalities, and we conclude that MAP has substantially better generalizability.

## Domains

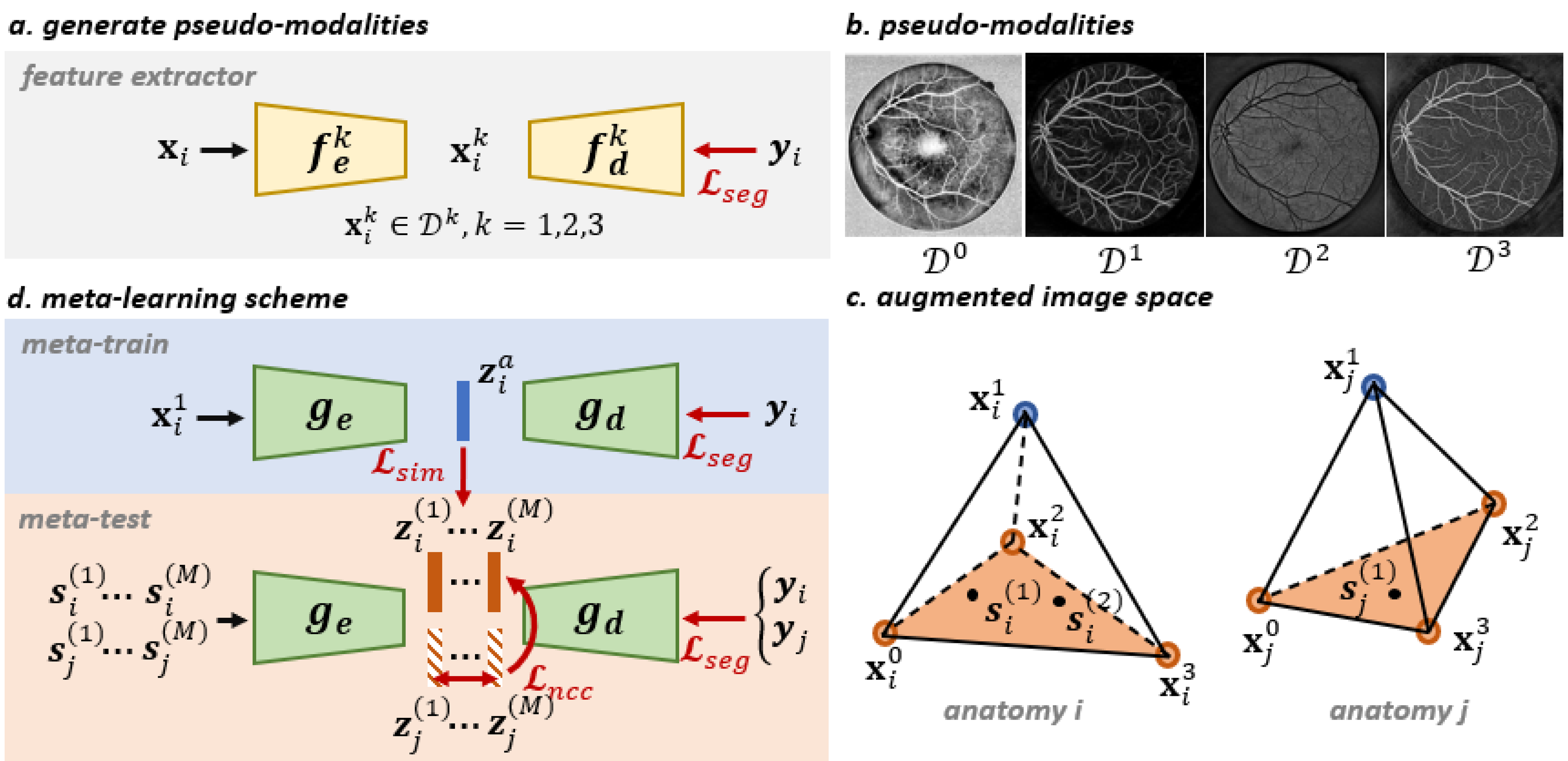



## Experiment Setting

We train the model on healthy fundus data which is relatively easy to label. And test on three different types of domain shift.

- ***Type I:*** Same modality but with unseen diseases such as AMD and diabetic retinopathy [5]
- ***Type II:*** Same modality from different sites [6]
- ***Type III:*** Different modalities e.g., OCT-A and FA. [7,8,9]

## Methods




### (a, b). Generate Anatomy-consistent Pseudo-modalities

With the model presented in [4], given one input fundus image we can generate four types pseudo-modalities with the vessel structure unchanged.

### (c). Augment image space with Dirichlet mix-up

To enrich the meta-test data, we form a linear image space with Dirichlet mix-up.

### (d). Meta-learning with $\mathcal{L}_{sim}$ and $\mathcal{L}_{ncc}$

The latent vector $\boldsymbol{z}_i$ is supposed to represent the anatomy i, we set the constraints to guarantee they can form a cluster close to $\boldsymbol{z}_i^a$.

## Experiment Results

- **Ablation study**

We prove the three major components are proved to be effective to improve the performance.

| Episodic | $\mathcal{L}_{sim}$ | $\mathcal{L}_{ncc}$ | Type I | Type II | Type III | Average |
|---|---|---|---|---|---|---|
| - | - | - | 62.93 | 60.04 | 63.94 | 62.95 |
| - | - | ✓ | 64.73 | 62.48 | 68.06 | 66.02 |
| ✓ | - | - | **67.50** | 63.40 | 64.25 | 65.19 |
| ✓ | ✓ | - | 64.75 | 66.24 | 68.30 | 66.77 |
| ✓ | - | ✓ | 66.10 | 66.99 | 69.71 | 68.05 |
| ✓ | ✓ | ✓ | 67.39 | **66.99** | **71.60** | **69.43** |

- **Evaluation**

**MAP** outperforms the competing methods with (1) domain regularization, (2) data augmentation, (3) meta-learning, and (4) shape modelling approaches.

| Method | ARIA | | PRIME-FP20 | OCTA 500 | ROSE | RECOVERY |
|---|---|---|---|---|---|---|
| | amd | diabetic | | | | |
| *baseline* | 63.82 | 65.19 | 47.31 | 73.16 | 67.41 | 51.25 |
| Regular[1] | 64.89 | 66.97 | 55.76 | 73.54 | 68.36 | 55.20 |
| BigAug[2] | 65.55 | 67.27 | 59.97 | 76.88 | 69.32 | **63.20** |
| MASF[3] | 65.33 | 67.75 | 65.96 | 77.65 | 67.25 | 50.74 |
| VFT[4] | 61.81 | 64.05 | 54.64 | 77.91 | 72.81 | 48.28 |
| MAP | **66.69**$^{\sim}$ | **68.08**$^{\sim}$ | **68.21**$^{\dagger}$ | **78.71**$^{\dagger}$ | **74.25**$^{\dagger}$ | 61.85$^{\dagger}$ |
| *oracle* | 73.34 | 70.65 | 77.80 | 86.57 | 76.03 | 74.54 |

Dice score (%). **Boldface**: best result. Underline: second-best result. ~: p-value ≥ 0.05. ⱡ: p-value ≪ 0.05.

## Conclusions

- We presented **MAP**, a method that approaches the domain generalization problem by implicitly encouraging the model to learn about domain invariant features.
- Our results indicate that enforcing domain-invariance between anatomy-consistent pseudo-modalities makes our model more robust across different domain shifts.

## References

[1] Aslani et al. *ISBI (2020)*
[2] Zhang et al. *TMI (2020)*
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[4] Hu et al., *MIDL (2022)*
[5] Farnell et al. *(2008)*
[6] Ding et al. *TMI (2020)*
[7] Li et al. *TMI (2020)*
[8] Ma et al. *TMI (2020)*
[9] Ding et al. *TMI (2020)*

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