Grad-CL: Source Free Domain Adaptation with Gradient Guided Feature Disalignment

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Problem Overview

- Segmentation of fundus images: optic cup (OC) and optic disc (OD)
- Accurate diagnosis of ocular diseases.
- Source free domain adaptation (SFDA)
  - Pre-trained source model
  - Unlabeled target fundus images
- It ensures efficient data transmission as the pre trained source model (0.1-1GB) has a smaller size than the source dataset (10-100GB)
- Key approaches of SFDA
  - Pseudolabeling
  - Contrastive Learning
- Pseudolabels: Protoypye Estimation
- Contrastive: Dialignment of cup and disc features

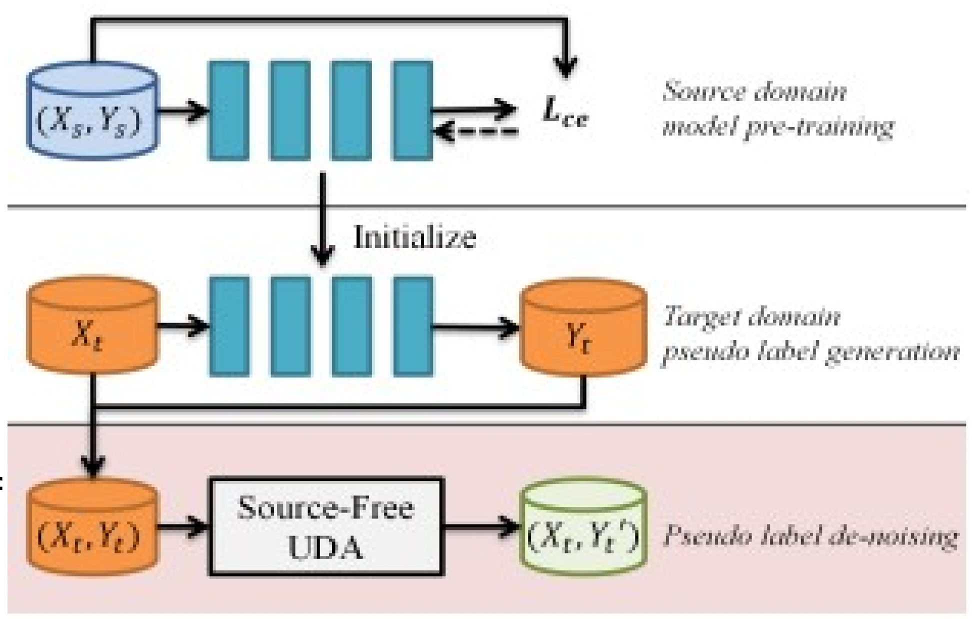

Figure: SFDA Pseudolabeling setup

Block Diagram

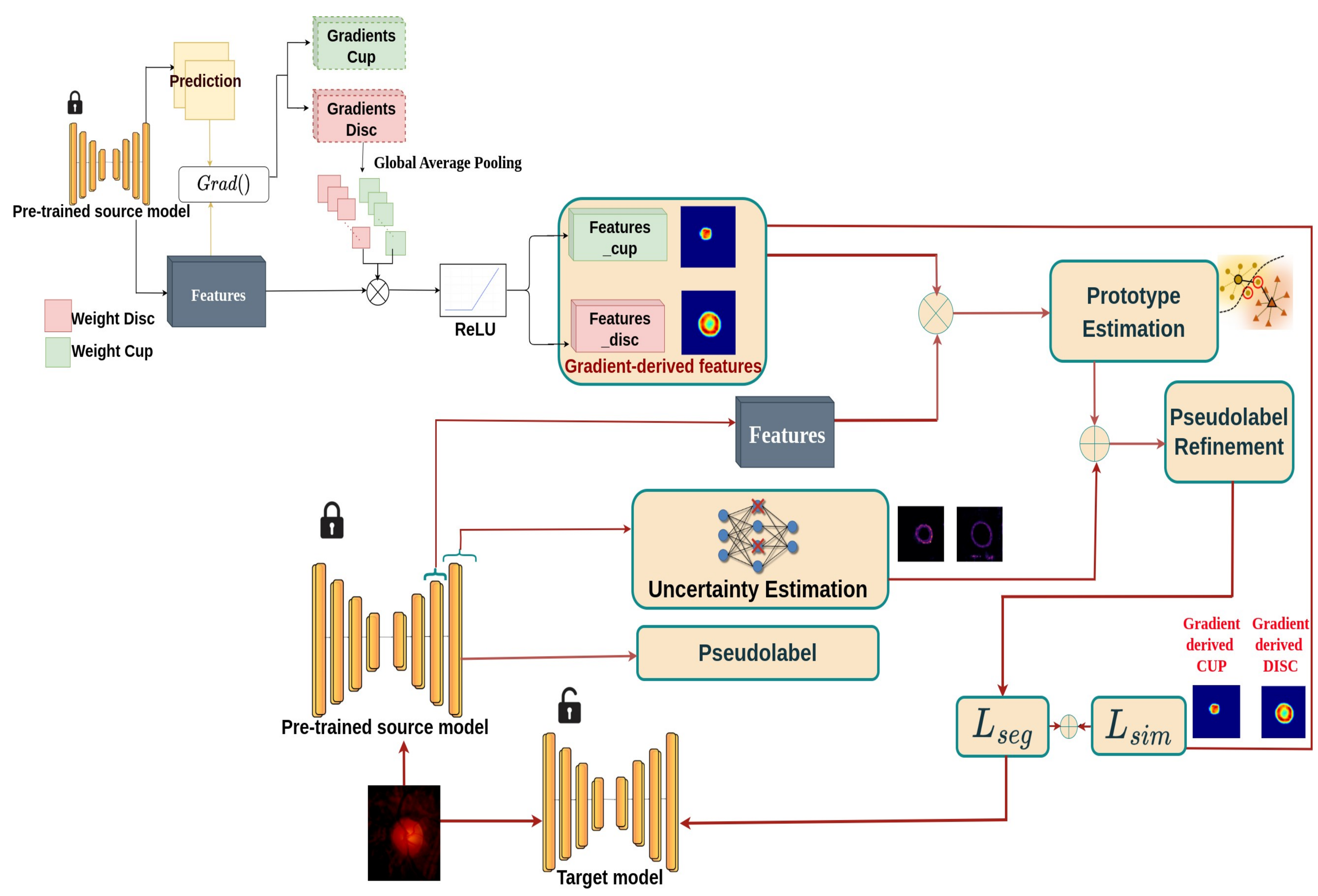

Figure: Overview of the proposed Grad-CL method. Target image is given to pre-trained source model to obtain pseudolabels by thresholding. Thereafter, target domain adaptation has two steps

a)Pseudolabel Refinement: It is done with uncertainty estimation and gradient derived prototype estimation

b) Contrastive Loss Module: Cosine Similarity L_{sim} is applied between modified gradient derived features of cup and disc

Motivation

- Usage of **gradients derived features** of optic cup and disc for:
  - Pseudolabel Refinement
  - Contrastive Learning Module
- **Grad-CAM** to identify the features that have more impact on identifying optic cup and disc regions.

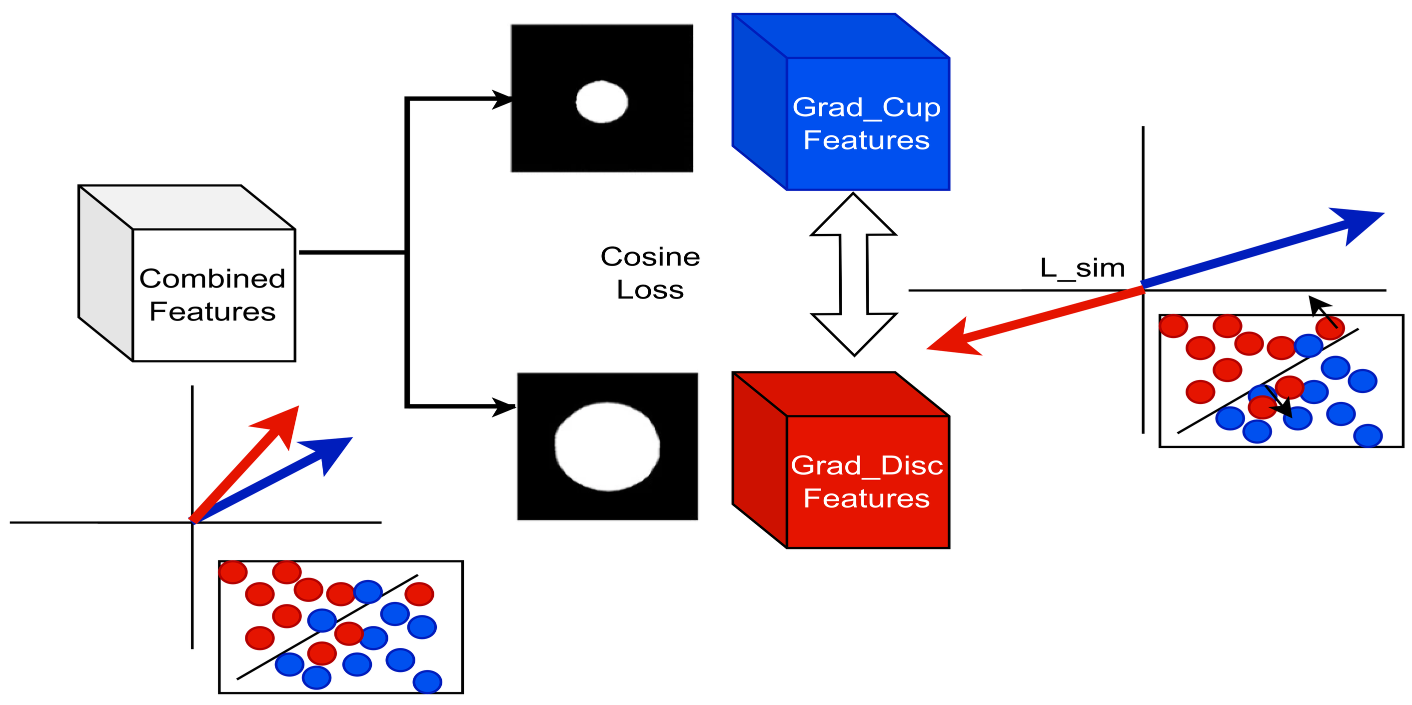

Figure: Extraction of the prominent features of optic cup and disc and visualization of contrastive cosine similarity loss L_sim

Proposed Method: Grad-CL

- **Gradient-guided pseudolabel refinement:** Enhances pseudolabel quality using gradient-based feature extraction and prototype estimation.
  - Uncertainty based filtering
  - Gradient guided prototype
- **Contrastive feature disalignment:** Encourages inter-class separation between OC and OD regions by minimizing cosine similarity between class-specific gradient-derived features.
- Gradient derived features $\tilde{e}^{disc}_v$, $\tilde{e}^{cup}_v$ are combination of:
  - Combined features (OC+OD): e_v
  - Gradient highlighted feature maps: e^{cup}_{GCv} ,e^{disc}_{GCv}
  - Gradient derived features

$$\tilde{e}^{cup}_v = e_v + e^{cup}_{GCv}, \quad \tilde{e}^{disc}_v = e_v + e^{disc}_{GCv}$$

- Total loss is combination of:
  - Standard cross entropy loss with **uncertainty** and **gradient based protoptype masking**
  - Contrastive cosine similarity loss between the embeddings highlighting cup and disc

$$Lsim = \frac{\tilde{e}^{cup}_v \cdot \tilde{e}^{disc}_v}{max\left(\|\tilde{e}^{cup}_v\|_2, \|\tilde{e}^{disc}_v\|_2, \varepsilon\right)}$$

where ε prevets division by zero.

Results

Methods	Optic Disc		Optic Cup	
	DICE %	ASD	DICE %	ASD
RIM-ONE-r3				
W/o adaptation	83.18	24.15	74.51	14.44
TT-SFUDA arxiv	85.00	17.05	76.62	10.31
TENT arxiv	82.92	23.63	72.95	14.00
PLPB WACV2024	92.89	6.52	77.94	10.07
DPL MICCAI2021	90.13	9.43	79.78	9.01
Grad-CL (proposed)	**94.99**	**5.02**	**80.51**	**9.50**

Methods	Optic Disc		Optic Cup	
	DICE %	ASD	DICE %	ASD
Drishti-GS				
W/o adaptation	93.84	9.05	83.36	11.39
TT-SFUDA arxiv	95.22	6.00	80.67	13.00
TENT arxiv	94.06	7.56	80.12	13.52
PLPB WACV2024	96.51	**4.01**	83.56	11.11
DPL MICCAI2021	96.39	4.08	83.53	11.39
Grad-CL (proposed)	**96.58**	4.09	**84.67**	**10.28**

Quantitative Performance of the different state-of-the-art UDA and SFDA methods on the target datasets: RIM-ONE-r3 and Drishti-GS; Source: Refuge

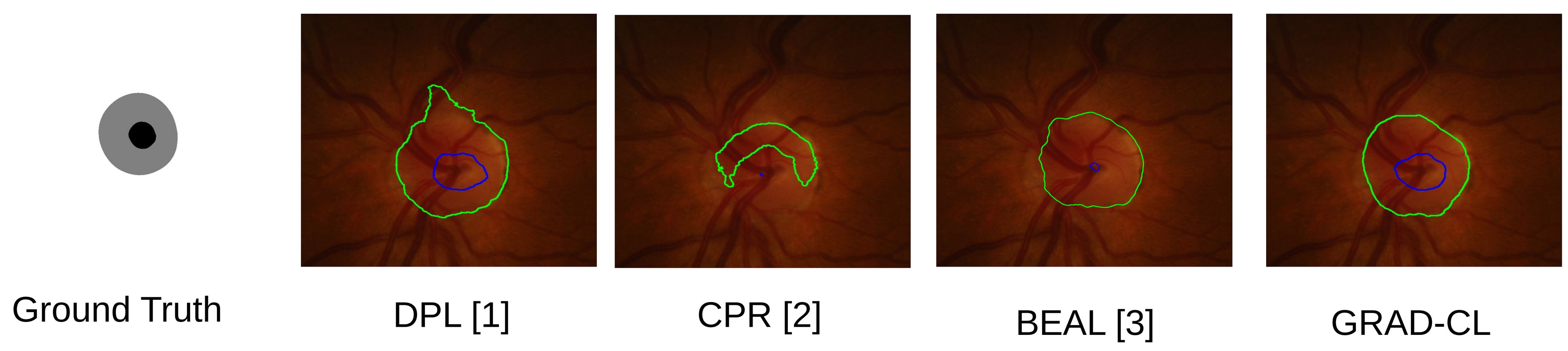

Figure: Overlaying the final segmentation on an image from the RIM-ONE-r3 dataset.

Conclusion

- Inclusion of feature gradient information in prototype estimation and cosine-similarity contrastive loss improves the results.
- Divergence between gradient based activations of cup and disc is crucial for segmentation.

References

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