Statement of Purpose (SoP)

DSL501 : Machine Learning Project

Team Name : Ace Hunters

1 Project Details

- **Project Title :** Retina SEM : Unsupervised Retinal Vessel Segmentation via Structural Entropy Minimization
- **Own Idea:** Yes. We propose Retina SEM, an unsupervised method that segments retinal blood vessels from color fundus photographs by minimizing structural entropy to cluster vessel like patterns without any human annotated masks.

2 Problem Statement

Retinal blood vessel segmentation from colour fundus photographs underpins clinically useful biomarkers (arteriovenous ratio, calibre, tortuosity) used in screening and monitoring of diabetic and hypertensive retinopathy, glaucoma, and related conditions. Existing high-performing methods are predominantly supervised, depend on extensive pixel level annotations, and often degrade under domain shift across devices and acquisition settings.

We therefore aim to develop **Retina SEM** an **unsupervised, interpretable, graph-based** pipeline that operates without human annotated masks, partitions a superpixel graph via structural entropy minimization, and outputs accurate vessel maps suitable for downstream clinical analysis and decision support.

3 Motivation

Manual vessel annotation is slow and limits dataset scale. While **supervised deep learning approaches** can be accurate, they rely on large volumes of pixel level labels and often degrade when imaging conditions change across devices and clinics. We therefore adapt **structural entropy minimization** to fundus imaging an underexplored direction to deliver a **label efficient, interpretable** pipeline that reduces annotation cost, improves **cross dataset** robustness, and produces vessel maps ready for downstream analyses (e.g., AVR, calibre, tortuosity).

4 Methodology: The ***Retina SEM*** Pipeline

- **Preprocess:** Use green channel and CLAHE, correct illumination, apply FOV mask, optionally mask optic disc.
- **Superpixels:** Run multiscale SLIC inside FOV; superpixels serve as graph nodes.
- **Graph & cues:** Build sparse (adjacent/kNN) graph with self tuned Gaussian affinities; node features are mean intensity/color and Frangi vesselness.
- **Unsupervised grouping:** Apply SLED merge to minimize structural entropy and form coherent regions.
- **Region labeling:** Use between class variance (global thresholding) to split vessel vs. background per scale.
- **Multiscale fusion:** Weight scales by separability, fuse to a soft map, then threshold to the final binary mask.

5 Dataset Details

- **Name and source : DRIVE** (primary), **STARE**, **CHASE_DB1**. All images are treated as *unlabeled* during development; official annotations are used *only* for evaluation metrics.
- **Sizes : DRIVE**: 40 images (20/20 split) with vessel masks; **STARE**: 20 images with two manual masks each; **CHASE_DB1**: 28 images (14 subjects; left/right) with vessel masks.
- **Preprocessing used :** Keep only the retinal area (FOV), correct uneven lighting, use the green channel with CLAHE to make vessels stand out, optionally mask the optic disc, and resize all images to a common resolution before generating superpixels.
- **Why these datasets :** Standard, widely reported fundus benchmarks that enable reproducible comparison; optionally, an unlabeled local cohort may be used for qualitative stress testing while keeping the approach fully unsupervised.

6 Required Resources

Hardware

- Workstation with 8 to 16 core CPU, $\geq$32GB RAM, and $\geq$50GB storage.
- NVIDIA RTX 3060/3070 (8 to 12GB) or A2000/A4000 class GPU (*optional*) for accelerating unsupervised computations and for any optional self supervised consistency regularization experiments.

Software

- **Language/Runtime:** Python 3.10+ (Linux, Ubuntu).
- **Core Libraries:** PyTorch, torchvision, numpy, scipy, scikit image, OpenCV, albumentations.
- **Utilities:** PyTorch Lightning or native PyTorch loop, tqdm, TensorBoard/WandB, scikit learn for metrics.

Additional Tools/APIs

- Git/GitHub for version control and reproducibility; Conda/Poetry for environment management.
- LaTeX for documentation, Jupyter for exploratory analysis.
- Official dataset access (DRIVE, STARE, CHASE DB1) and optional Kaggle mirrors.

7 Novelty of Approach

We adapt SLED's structural entropy graph partitioning to *retinal* vessels, make the superpixel graph vessel aware by adding a lightweight Frangi vesselness feature per superpixel, and fuse multiple SLIC scales using simple data driven weights based on a per scale *between class separability score* computed from region statistics; optionally, a background only Isolation Forest refines faint vessels without labels.

8 Expected Outcomes

- **Performance metrics**
  - Report Dice (F1), PR AUC, and clDice, computed inside the retinal field of view (FOV) with subject wise splits.
  - Maximize Dice, PR AUC, and clDice, striving for the highest possible results while keeping cross dataset performance degradation minimal.
- **Final outputs**
  - Application demo : unsupervised, training free baseline that takes a color fundus image and outputs a vessel map; optional self supervised extensions can be explored separately.
  - Evaluation report : one table with Dice/PR AUC/clDice and 6 to 10 qualitative overlays.

9 Team Composition and Individual Contributions

- **Om Raj Singh (M25DS007)** : Postprocessing & Ablations: refine vessel masks (thresholding/morphology/CRF), calibrate outputs, and prepare final figures/tables.
- **Rohan Sinha (M25DS008)** : Preprocessing: normalization, color constancy, FOV preparation, optic disc masking; two view augmentations for self supervised add ons.
- **Sarvesh Badoni (M25DS011)** : Graph Construction & SLED Optimization: multi scale SLIC superpixels, vessel aware features (Frangi), structural entropy minimization, and region labeling.
- **Vedant Tawri (M25DS016)** : Data Management & Evaluation: dataset curation, subject wise splits, FOV masking; metric scripts (Dice/PR AUC/clDice) and results consolidation.

10 References

1. Zeng, G., Peng, H., Li, A., Liu, Z., Liu, C., Yu, P. S., He, L. “Unsupervised Skin Lesion Segmentation via Structural Entropy Minimization on Multi-Scale Superpixel Graphs.” *ICDM*, 2023.
2. Ma, Y., Hua, Y., Deng, H., Song, T., Wang, H., Xue, Z., Cao, H., Ma, R., Guan, H. “Self-Supervised Vessel Segmentation via Adversarial Learning.” *ICCV*, 2021.
3. Chen, T., Kornblith, S., Norouzi, M., Hinton, G. “A Simple Framework for Contrastive Learning of Visual Representations.” *ICML*, 2020.
4. Shit, S., Paetzold, J. C., Sekuboyina, A., Ezhov, I., Unger, A., Zhylka, A., Pluim, J. P. W., Bauer, U., Menze, B. “clDice: A Novel Topology-Preserving Loss Function for Tubular Structure Segmentation.” *CVPR*, 2021.
5. Cervantes, J., García-Lamont, F., Yee-Rendón, A., Espejel-Cabrera, J. E., Jalili, L. D., *et al.* “A Comprehensive Survey on Segmentation Techniques for Retinal Vessel Segmentation.” *Neurocomputing*, 2023.