Retina SEM: Unsupervised Retinal Vessel Segmentation via Structural Entropy Minimization

DSL501: Machine Learning Project

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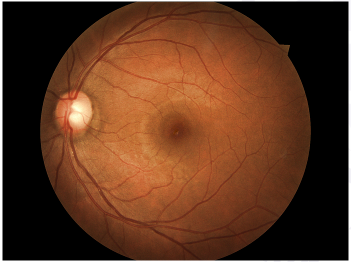
What are color fundus photographs?

- Retinal photos are circular images of the back of the eye, showing very thin blood vessels.
- Doctors use accurate vessel maps to screen diseases such as diabetes, glaucoma, and hypertension.
- Color fundus photographs provide a non-invasive way to monitor eye and systemic health.



Left Eye Fundus

Right Eye Fundus

Problem and Motivation

Problem statement

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

Motivation

- **No labels needed**: removes the biggest bottleneck.
- **Generalizes better**: uses image structure; robust across cameras & clinics.
- **Interpretable**: transparent steps clinicians can audit and trust.
- **Practical payoff**: faster to deploy, easier to explain, real world ready.

Flowchart: Retina SEM Pipeline

I. Preprocessing
– Green channel
– CLAHE
– Illum. correction
– FOV mask; (opt.) OD

II. Superpixel Graph
– Multi-scale SLIC (S/M/L)
– Node = superpixel
– Edges: color/texture + spatial

III. SE-Guided Segm.
– Minimize structural entropy
– Auto #regions (no fixed K)
– Split by between-class variance

IV. Multi-Scale Segm.
– Isolation Forest (per scale)
– Compile outlier scores $\rightarrow$ fused map
– Threshold & clean $\rightarrow$ vessel mask

Preprocessing

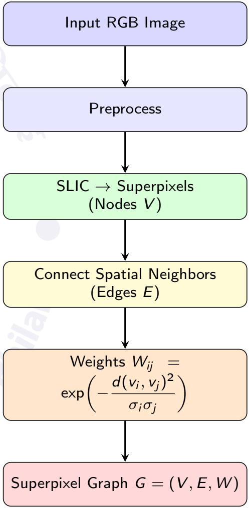
- **Green channel** : keep only green; vessels show highest contrast.
- **CLAHE** : boost local contrast so thin vessels pop; limit noise.
- **Illumination correction** : normalize center edge brightness.
- **FOV mask** : keep circular retina; drop borders/artifacts.
- **Optic disc** : mask bright disc to avoid false positives.

Superpixel Graph Construction

- **SLIC** to obtain superpixels $\Rightarrow$ nodes V.
- Connect spatial neighbors (radius r).
- Similarity weights:

$$W_{ij} = \exp\left(-\frac{d(v_i, v_j)^2}{\sigma_i\, \sigma_j}\right)$$

- Result: **Superpixel graph** $G = (V, E, W)$.



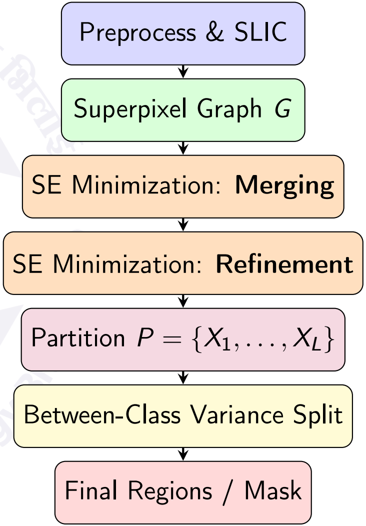
Structural Entropy Guided Segmentation

- **Setup:** Convert image $\rightarrow$ superpixel graph $G = (V, E, W)$
  - Nodes $v \in V$: SLIC superpixels;
  - Edges E: connect spatially near superpixels;
  - Weights W_{ij}: similarity (e.g., color distance with local scaling).
- **Goal:** Find a partition $P = \{X_1, \ldots, X_L\}$ of G that **minimizes structural entropy (SE)**.
  - Low SE $\Rightarrow$ modules (regions) are *homogeneous* internally, *well separated* externally.
  - **Adaptive L:** number of regions emerges from optimization (no fixed K).
- **Two stage optimization on an encoding tree**
  - *Merging stage:* greedily merge module-pairs (X, Y) that yield the largest SE decrease.
  - *Refinement stage:* reassign individual nodes v_i between modules if SE decreases further.
- **After partition: Homogeneous Region Bisection**
  - Choose a color channel, compute each region's mean intensity;
  - **Maximize between-class variance** to split regions into foreground/background.

SE-Guided Segmentation : Algorithmic Flow

Pipeline

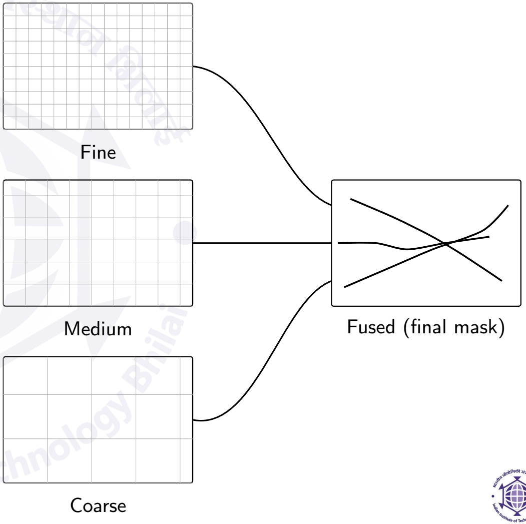
1. **Graph Build:** SLIC $\Rightarrow$ superpixels; connect spatial neighbors; W_{ij} by feature similarity.
2. **SE Minimization (2 stages):**
   - *Merging:* While $\exists$ modules X, Y with positive SE-decrease, merge (X, Y) that *maximally* reduces SE.
   - *Refinement:* For each node v_i, move it from current X to best Y if SE decreases (iterate until convergence).
3. **Region Bisection:** Arrange region means; choose threshold τ that maximizes between-class variance $\Rightarrow$ two classes.
4. **Output:** Segmentation with *adaptive* number of regions; clear boundaries from SE-optimal modules.



Multi-Scale Segmentation

What it means

- Segment the image at **different levels of detail (scales)** by varying **superpixel size**.
- **Fine scale**: many small superpixels $\Rightarrow$ captures thin capillaries / lesion edges.
- **Medium scale**: balances detail and stability.
- **Coarse scale**: fewer large superpixels $\Rightarrow$ captures big vessels / regions and suppresses noise.



Datasets

- **DRIVE** — Digital Retinal Images for Vessel Extraction.
- **STARE** — Structured Analysis of the Retina.
- **CHASE_DB1** — Child Heart and Health Study in England .

We treat the pipeline as **unsupervised**; public masks are used *only* for reporting metrics.

What's new in *our* Retina-SEM

- **First to use SLED on retina (unsupervised):** We apply the SLED (Structural Entropy Minimization) framework to retinal vessel segmentation in an *unsupervised* setting; prior works are supervised deep learning or other unsupervised methods, but none used SLED for retina.
- **Code release:** We will provide reproducible code for retinal vessel segmentation using this SLED approach.

Expected Output

- **Executable notebook demo**: input fundus $\rightarrow$ output vessel mask.
- **Compact evaluation report**: one concise table (Dice, clDice)
- **Reproducible codebase**: preprocessing, SLIC, graph+SE, fusion, evaluation.

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Thank you!

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