

Computational Framework for Automated Quantification of Panretinal Photocoagulation Technique from Ultra-Widefield Fundus Images

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Online Resource 1: Supplemental computational materials

This Online Resource provides supplemental tables referenced in the main text, plus computational implementation details, algorithm pseudocode, and code-availability information.

Supplemental tables

Table S1: Dataset characteristics

Characteristic	Value
Total images	218
Total mapped burns	93,322
Image sources	Open ultrawidefield fundus image dataset [1] UWF-RHS dataset [2] MSHF dataset [3]
Modality	Ultra-widefield fundus photography
Inclusion criteria	PRP-confirmed images with visible burns

Table S2: Variability measures (n=218)

Metric	CV	IQR	Range
Burn count	0.364	207.75	13–959
Coverage Index	0.389	0.068	0.000–0.337
Spacing Uniformity Index	0.088	0.056	0.310–0.814
Clustering Index	0.156	0.041	0.160–0.461
Quadrant Balance Index	0.138	0.118	0.250–0.980

Table S3: Literature-derived criteria adherence rates and quadrant-based attainment (n=218)

Criterion	Threshold	Adherence	Theoretical	95% CI
Burn count (ET-DRS)	1200–1600 spots	0.0%	0.0%	[0.0, 0.0]
Area coverage	$\geq 75\%$ of treatable region	0.0%	0.0%	[0.0, 0.0]
Spacing uniformity	SUI ≥ 0.7 (approx.)	71.1%	–	[65.1, 77.1]
Safety margin (PP)	≥ 2 DD from fovea	6.9%	–	[3.5, 10.2]
Safety margin (OD)	≥ 1 DD from OD	97.2%	–	[95.1, 99.4]
<i>Quadrant-based attainment (staged PRP proxy)</i>				
Burn count (1-quadrant)	≥ 300 spots	24.7%	–	[23.8, 25.5]
Burn count (2-quadrant)	≥ 600 spots	41.8%	–	[29.8, 48.3]
Burn count (3-quadrant)	≥ 900 spots	33.2%	–	[28.8, 34.4]
Burn count (4-quadrant)	≥ 1200 spots	37.0%	–	[29.7, 45.0]
Burn-count attainment (median)	–	34.0% of 1200	–	–

Note: Theoretical adherence for burn count and area coverage applies a field-of-view adjustment (observed values divided by 0.8; see Methods) as a bounded sensitivity analysis. Quadrant-based attainment reports continuous attainment as the percentage of the threshold achieved (e.g., 285 burns in a 1-quadrant case = 95% of 300 threshold), with thresholds scaled for staged PRP (1-quadrant: 300 spots; 2-quadrant: 600 spots; 3-quadrant: 900 spots; 4-quadrant: 1200 spots). Values are capped at 100%. IQR = interquartile range. CI = confidence interval. DD = disc diameter. PP = posterior pole. OD = optic disc.

Computational Framework Overview

The framework processes ultra-widefield fundus images through a pipeline that transforms raw annotations into quantitative geometric metrics. The workflow consists of four main stages:

Data Input and Preprocessing: Annotations are provided in COCO format, containing segmentation masks for PRP burns and anatomical regions (*go_zone*, posterior pole, optic disc, vessels). Burn centroids are computed from segmentation polygon areas using the centroid formula: $(x_c, y_c) = (\frac{1}{n} \sum x_i, \frac{1}{n} \sum y_i)$ for n polygon vertices.

Treatable Region Computation: The eligible treatment area is computed as the set difference: $\text{treatable} = \text{go_zone} \setminus (\text{posterior_pole} \cup \text{optic_disc} \cup \text{vessels})$. This binary mask defines the spatial domain for all coverage and safety calculations.

Disc Diameter Normalization: For each image, the optic disc diameter is computed from the annotated disc mask using the equivalent diameter method: $d_{\text{DD}} = 2 \times \sqrt{A_{\text{OD}}/\pi}$, where A_{OD} is the pixel area of the optic disc annotation. All distance measurements are normalized by this per-image value to enable anatomical scaling and comparison to guideline thresholds.

Coordinate System: All computations use pixel coordinates with origin at the top-left corner. Distances are computed using Euclidean metric: $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$.

Algorithm Pseudocode

Coverage Index Computation

1. **Input:** Burn centroids $B = \{(x_i, y_i)\}_{i=1}^n$, treatable mask M , coverage radius r_{cov}
2. **Initialize:** Build KD-tree T from burn centroids for efficient nearest-neighbor queries
3. **For each** treatable pixel $p = (x_p, y_p)$ in M :
 - Query T to find nearest burn centroid $b^* = \arg \min_{b \in B} \|p - b\|$
 - If $\|p - b^*\| \leq r_{\text{cov}}$, mark p as covered
4. **Compute:** $\text{CI} = |\text{covered pixels}| / |\text{treatable pixels}|$
5. **Output:** Coverage Index $\in [0, 1]$

Spacing Uniformity Index Computation

1. **Input:** Burn centroids $B = \{(x_i, y_i)\}_{i=1}^n$
2. **Build:** KD-tree T from all burn centroids
3. **For each** burn $b_i \in B$:
 - Query T to find nearest neighbor b_j where $j \neq i$
 - Compute distance $d_i = \|b_i - b_j\|$
4. **Compute:** Mean $\mu_d = \frac{1}{n} \sum_{i=1}^n d_i$ and standard deviation $\sigma_d = \sqrt{\frac{1}{n} \sum_{i=1}^n (d_i - \mu_d)^2}$

5. **Compute:** Coefficient of variation $CV = \sigma_d/\mu_d$
6. **Output:** $SUI = 1 - \min(1, CV)$

Safety Distance Metrics Computation

1. **Input:** Burn centroids B , exclusion zone masks (posterior pole M_{PP} , optic disc M_{OD}), disc diameter d_{DD}
2. **For each** burn $b_i \in B$:
 - Compute minimum distance to posterior pole: $d_{PP,i} = \min_{p \in M_{PP}} ||b_i - p||$
 - Compute minimum distance to optic disc: $d_{OD,i} = \min_{p \in M_{OD}} ||b_i - p||$
 - Convert to disc diameters: $d_{PP,i}^{DD} = d_{PP,i}/d_{DD}$, $d_{OD,i}^{DD} = d_{OD,i}/d_{DD}$
3. **Compute:** Minimum, 5th percentile, median, and mean for each distance distribution
4. **Output:** Safety distance statistics in disc diameters

Clustering Index Computation

1. **Input:** Burn centroids B , median burn radius r_{burn} , cluster radius multiplier $k = 8$
2. **Compute:** Cluster radius $r_{cluster} = k \times r_{burn}$
3. **Build:** KD-tree T from burn centroids
4. **For each** burn $b_i \in B$:
 - Query T to find all burns within radius $r_{cluster}$: $N_i = \{b_j : ||b_i - b_j|| \leq r_{cluster}, j \neq i\}$
 - Count neighbors: $n_i = |N_i|$
5. **Compute:** Mean $\mu_n = \frac{1}{n} \sum_{i=1}^n n_i$ and standard deviation $\sigma_n = \sqrt{\frac{1}{n} \sum_{i=1}^n (n_i - \mu_n)^2}$
6. **Compute:** Coefficient of variation $CV_n = \sigma_n/\mu_n$
7. **Output:** $CLI = CV_n$

Parameter rationale: The cluster radius multiplier $k = 8$ ($8 \times$ burn radius ≈ 4 burn diameters) provides a pragmatic starting point for quantifying local density variation, but future work should empirically optimize this parameter by correlating clustering metrics with outcomes (e.g., neovascularization regression, visual field preservation). The coefficient of variation of neighbor counts (CLI) remains interpretable regardless of k , with lower values indicating more uniform distribution.

Quadrant Balance Index Computation

1. **Input:** Burn centroids B , image center or posterior pole centroid (c_x, c_y)
2. **For each** burn $b_i = (x_i, y_i) \in B$:
 - Compute relative position: $\Delta x = x_i - c_x$, $\Delta y = y_i - c_y$
 - Assign quadrant:
 - If $\Delta x \geq 0$ and $\Delta y \geq 0$: quadrant 1
 - If $\Delta x < 0$ and $\Delta y \geq 0$: quadrant 2
 - If $\Delta x < 0$ and $\Delta y < 0$: quadrant 3
 - If $\Delta x \geq 0$ and $\Delta y < 0$: quadrant 4
3. **Count:** Burns per quadrant: q_1, q_2, q_3, q_4
4. **Compute:** Mean $\mu_q = \frac{1}{4}(q_1 + q_2 + q_3 + q_4)$ and standard deviation $\sigma_q = \sqrt{\frac{1}{4} \sum_{j=1}^4 (q_j - \mu_q)^2}$
5. **Compute:** Coefficient of variation $CV_q = \sigma_q / \mu_q$
6. **Output:** QBI = $1 - CV_q$

Software and Implementation Details

Programming Language and Libraries: All computations were implemented in Python 3 using the following scientific computing libraries:

- **NumPy:** Array operations, mathematical functions, and numerical computations
- **SciPy:** Spatial data structures (KD-tree via `scipy.spatial.cKDTree`), distance computations, and statistical functions
- **OpenCV:** Image processing, mask operations, and geometric transformations
- **Pandas:** Data manipulation and tabular data structures for metric aggregation

Code Availability Statement

The computational framework for metric computation is implemented in Python and follows the algorithms described above. However, the automated burn segmentation model used for initial annotation assistance is currently under active development and undergoing validation studies. The burn segmentation module described in this manuscript will be made publicly available in the repository https://github.com/brendan12fox/PRP_Burn_Segmentation following additional validation and preparation for release. The authors plan to release the trained model, inference pipeline, and supporting documentation required to reproduce the segmentation component of the study. The anticipated public release date is May 2026, and updates will be posted in the repository as the module is finalized.

The metric computation algorithms described in this supplementary section can be implemented using the pseudocode provided above. We are working toward making a complete

software package available that includes both the segmentation pipeline and metric computation framework. Interested researchers may contact the corresponding author for access to the current implementation or for updates on code availability.

Data Availability

The ultra-widefield fundus images analyzed in this study were obtained from three publicly available datasets:

- Open ultrawidefield fundus image dataset [1]
- UWF-RHS dataset [2]
- MSHF dataset [3]

Annotation data (COCO format) and computed metrics for the 218 images analyzed in this study are available upon reasonable request from the corresponding author.

References

- [1] Shucheng He, Xin Ye, and Lijun Shen. Open ultrawidefield fundus image dataset with disease diagnosis and clinical image quality assessment [dataset], 2024. Open ultrawidefield fundus image dataset with disease diagnosis and clinical image quality assessment.
- [2] Renkai Wu, Pengchen Liang, Yiqi Huang, Qing Chang, and Huiping Yao. Automatic segmentation of hemorrhages in the ultra-wide field retina: Multi-scale attention subtraction networks and an ultra-wide field retinal hemorrhage dataset. *IEEE Journal of Biomedical and Health Informatics*, 2024. UWF-RHS dataset: Ultra-wide field retinal hemorrhage segmentation dataset.
- [3] Kai Jin, Zhiyuan Gao, Xiaoyu Jiang, Yaqi Wang, Xiaoyu Ma, and Yunxiang Li. Mshf: A multi-source heterogeneous fundus (mshf) dataset for image quality assessment [dataset], 2022. MSHF dataset: Multi-source heterogeneous fundus image quality assessment.