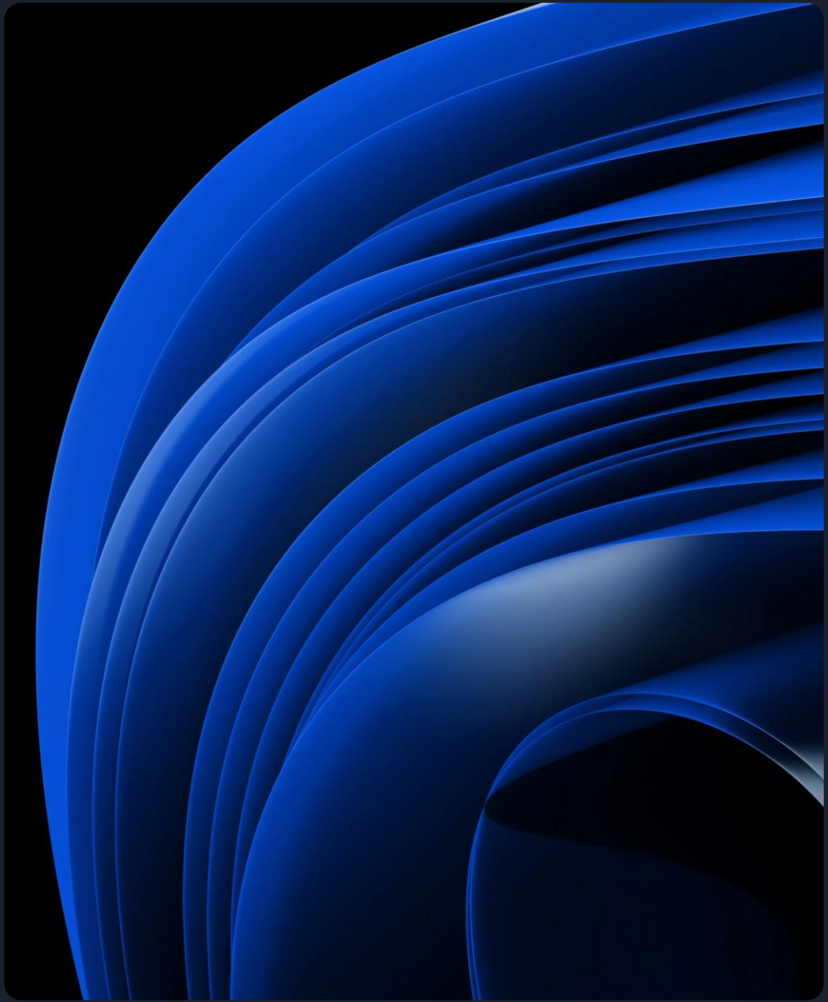
Group 6

Segmentation of Vessels in Retinal Images

Shiyu Wang
Jiacheng Ma
Joe Wang
Enhao He



Introduction

Introduction

Objective: Segment blood vessels in retinal images to support early diagnosis of eye diseases like diabetic retinopathy and glaucoma.

Dataset: **DRIVE** — 40 fundus images (33 healthy, 7 with early diabetic signs), includes expert manual segmentations.

Challenges: Low vessel-background contrast, complex vessel morphology, inconsistent illumination.

Methods:

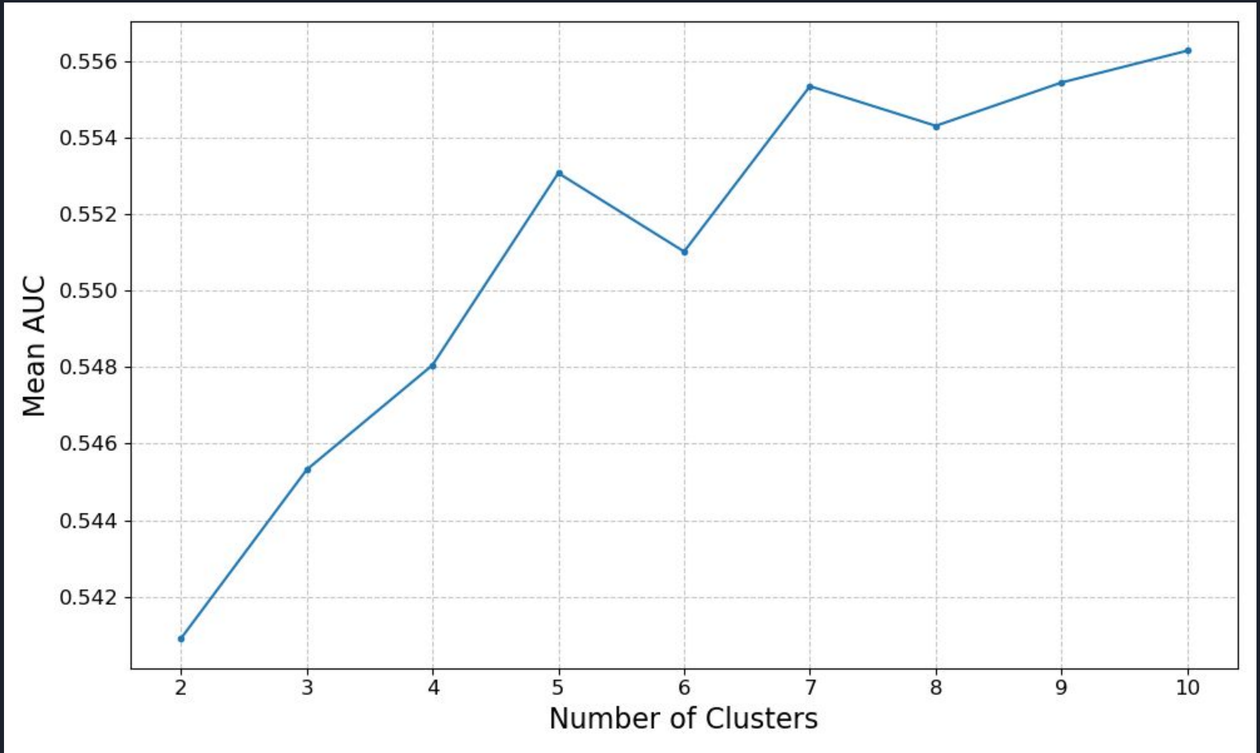
- **K-means Clustering**
- **Naive Bayes Classifier**
- **Support Vector Machine (SVM)**
- **Random Forest Classifier**

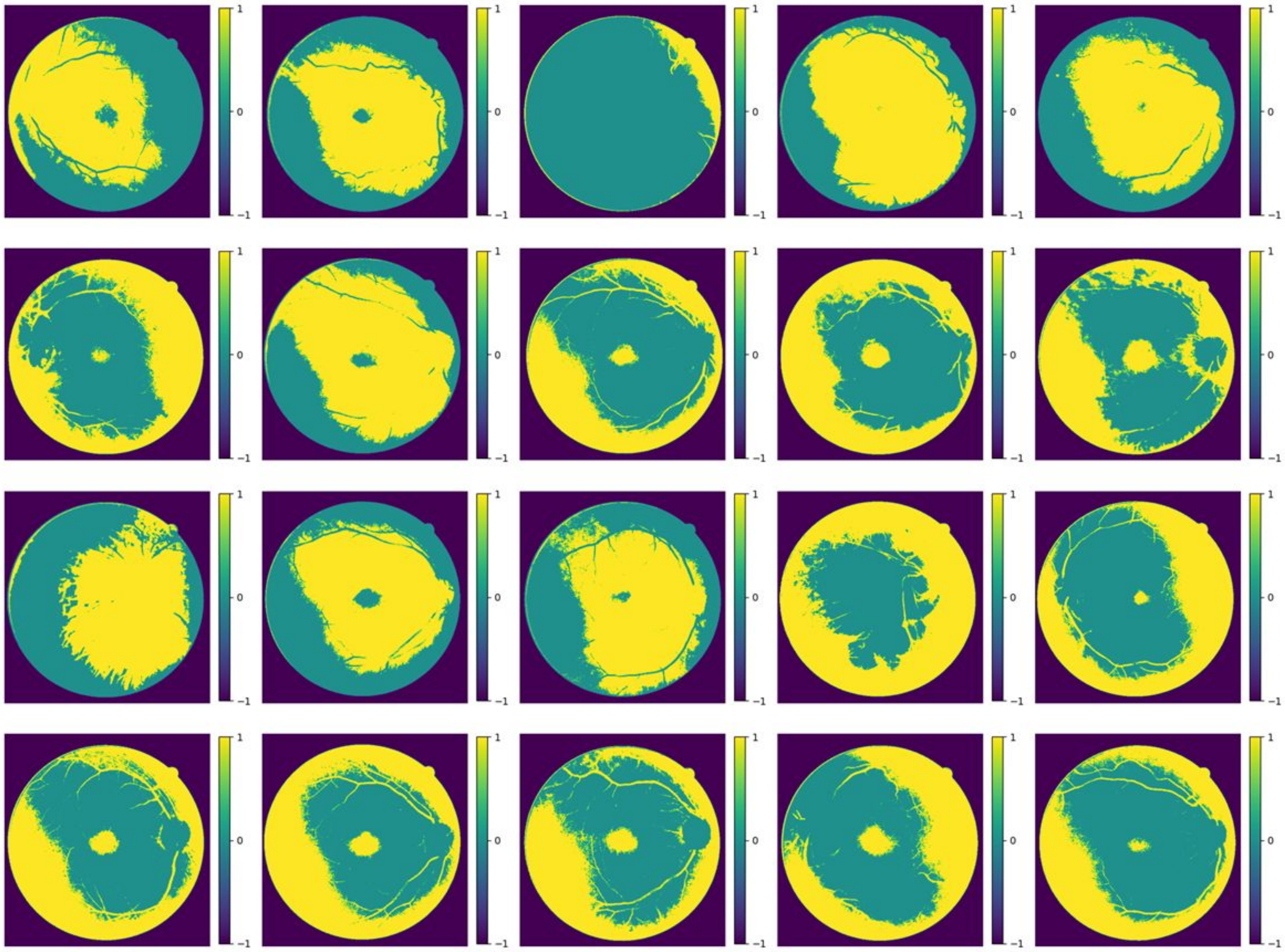
Methods & Results

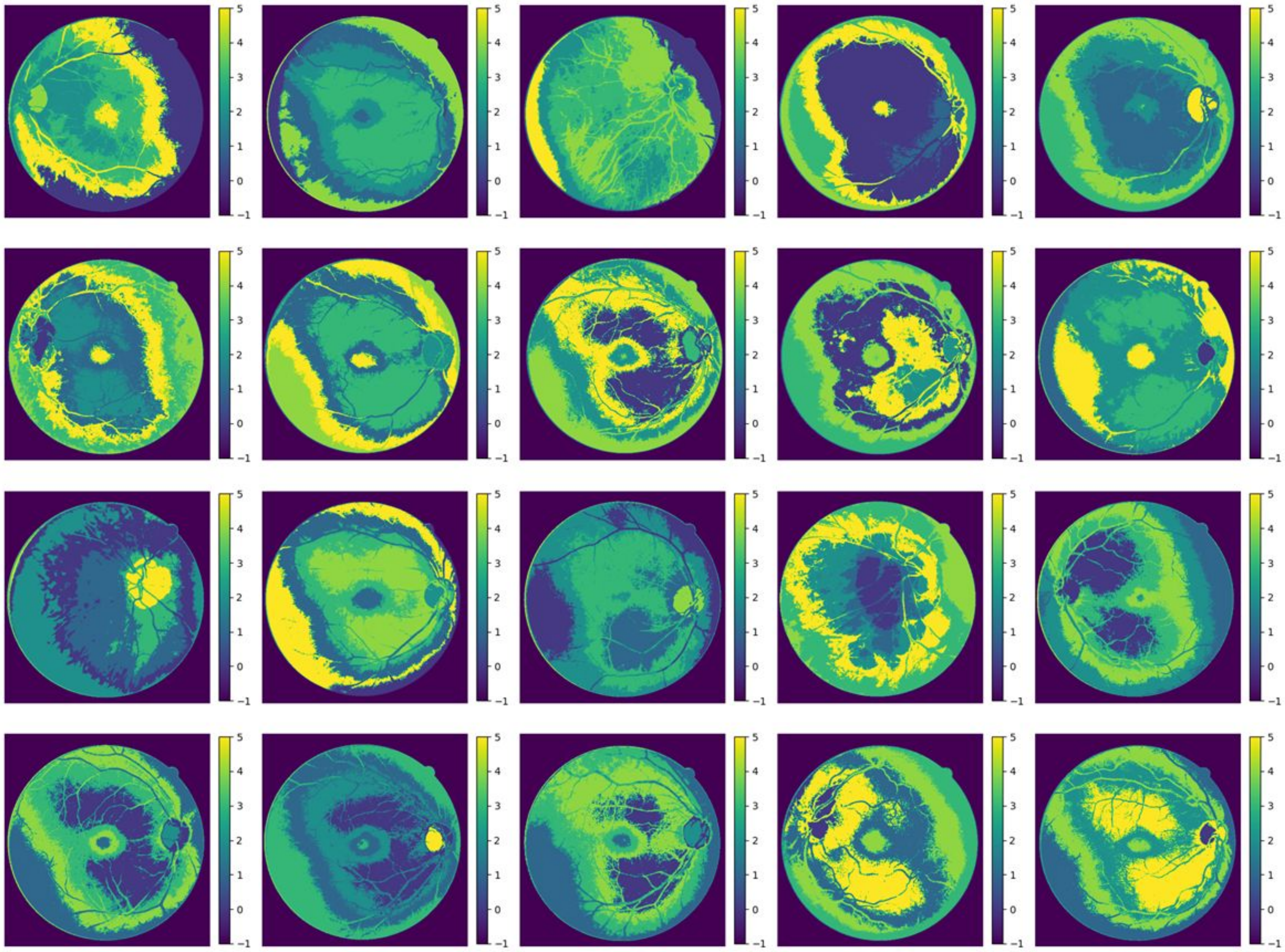
K-Means Clustering

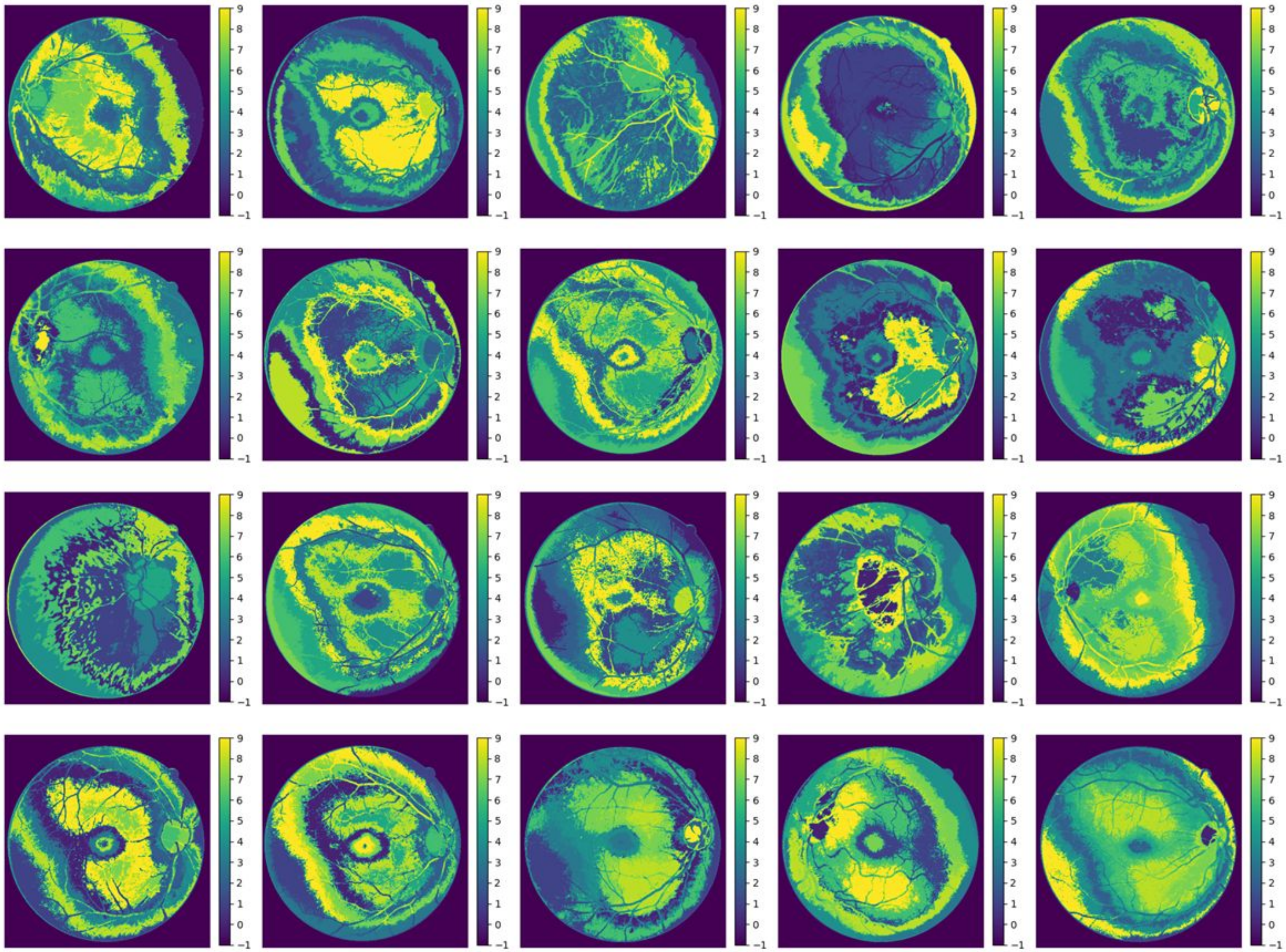
K-Means Clustering

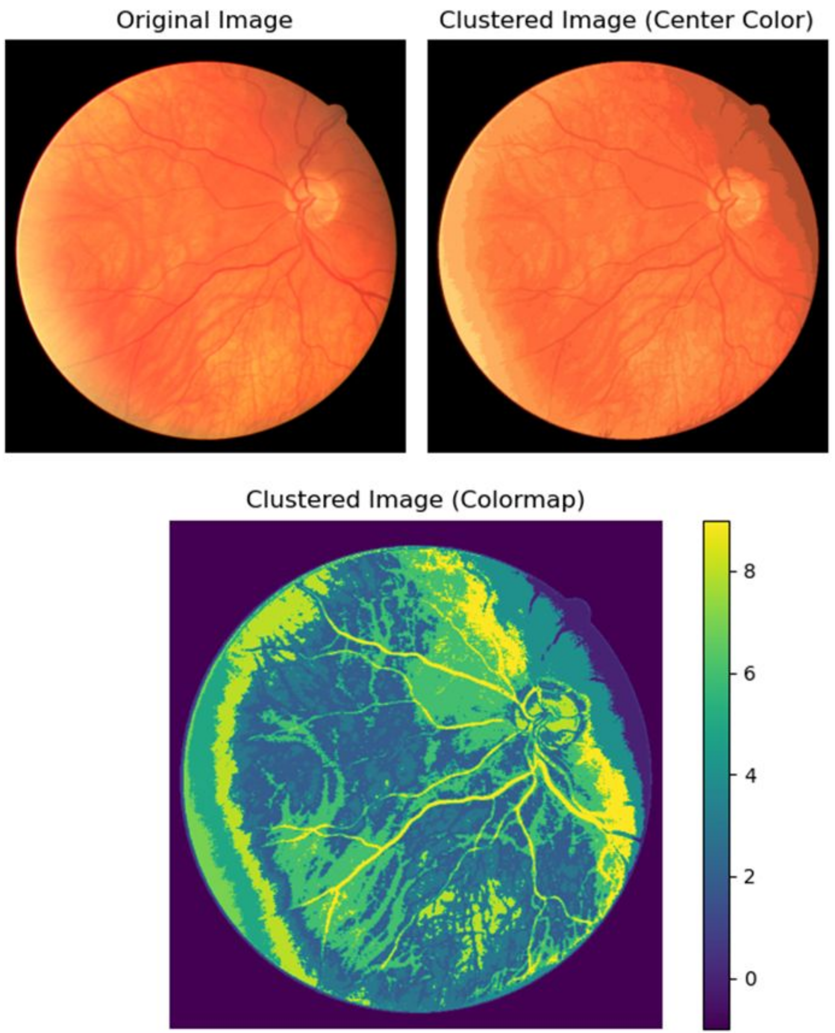
Find the best n_clusters



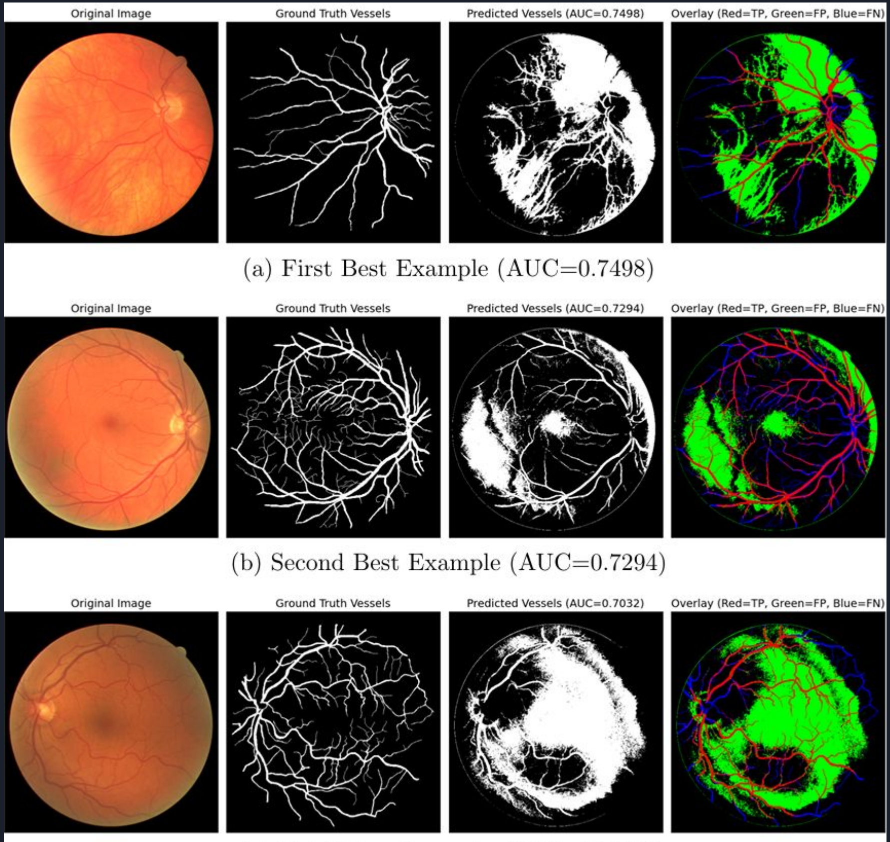

1
0
−1


5
4
3
2
1
0
−1


9
8
7
6
5
4
3
2
1
0
−1

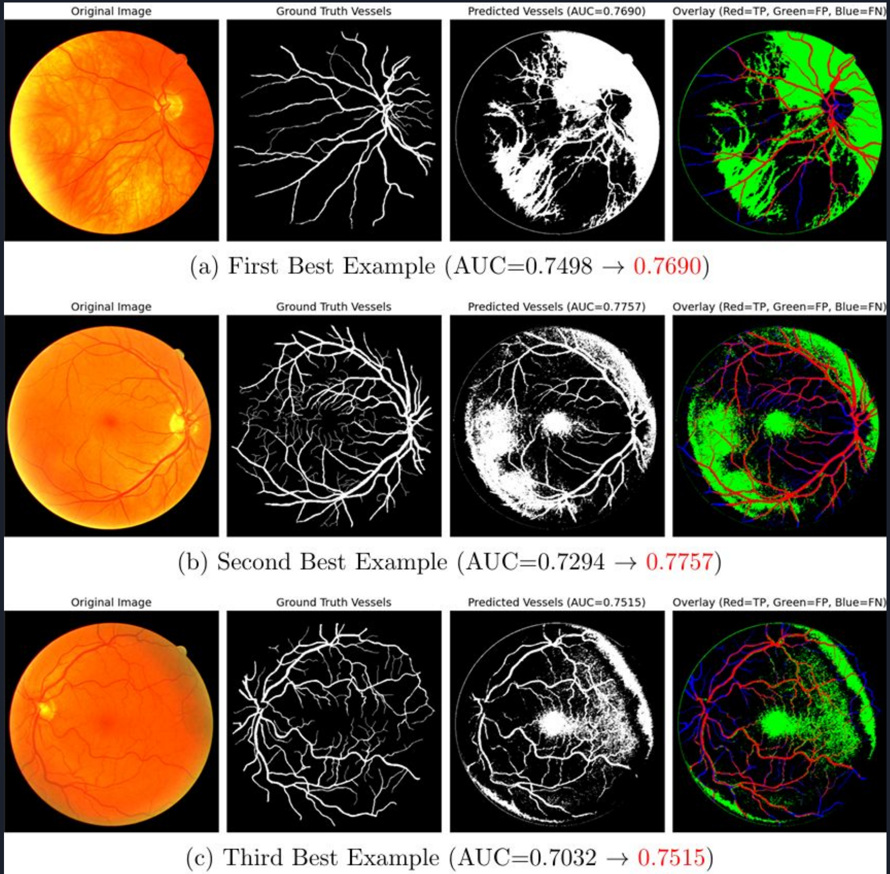

Original Image
Clustered Image (Center Color)
Clustered Image (Colormap)
8
6
4
2
0

Optimized K-Means Algorithm



(c) Third Best Example (AUC=0.7032)

Optimized K-Means Algorithm

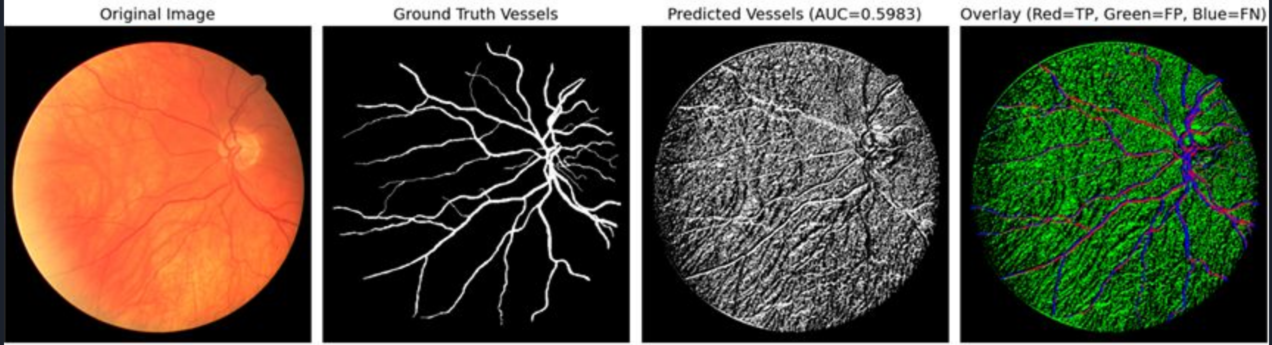


(a) First Best Example (AUC=0.7498 → 0.7690)

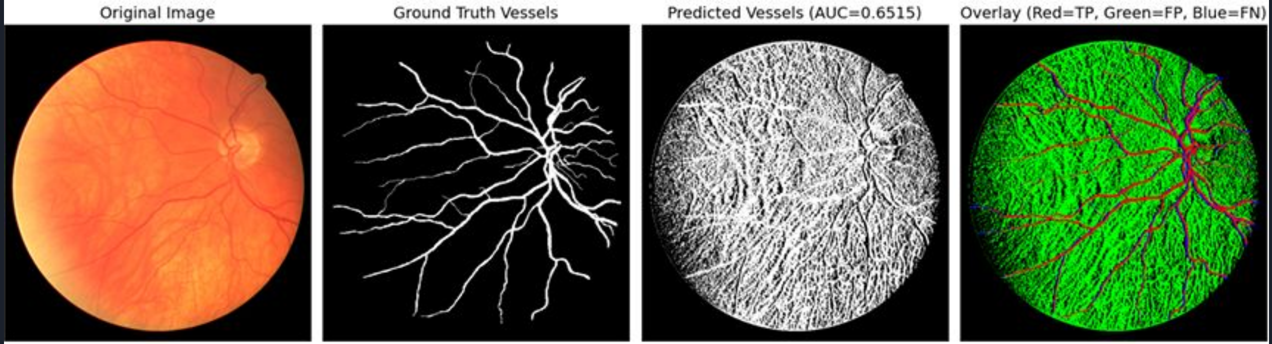
(b) Second Best Example (AUC=0.7294 → 0.7757)

(c) Third Best Example (AUC=0.7032 → 0.7515)

Direction-enhanced K-Means Clustering

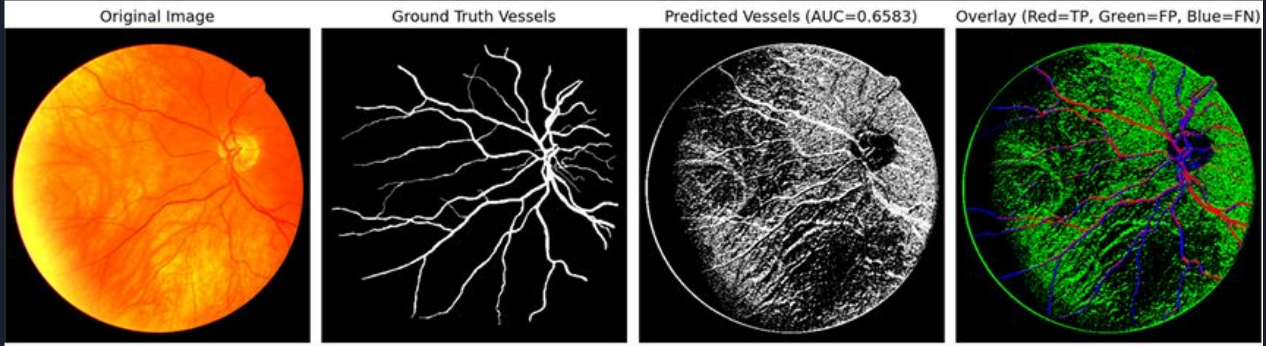


(a) Merging Top 3 Clusters (AUC=0.5983)

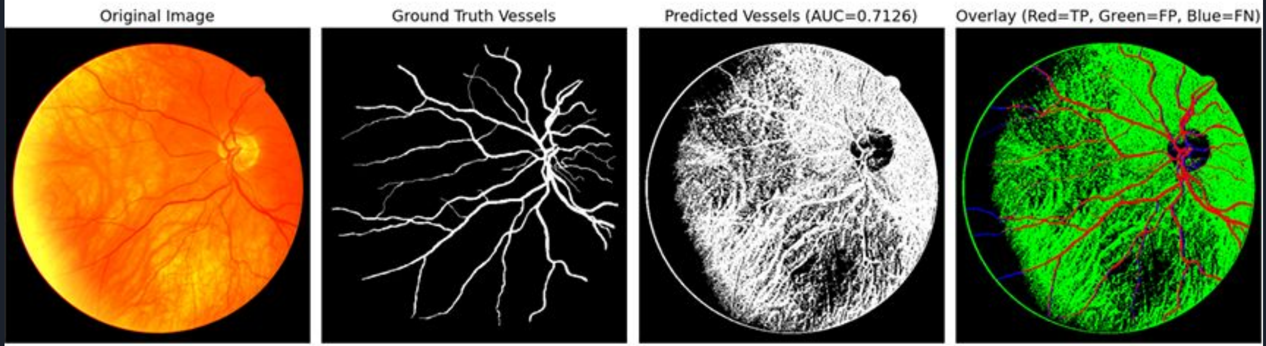


(b) Merging Top 5 Clusters (AUC=0.6515)

Direction-enhanced K-Means Clustering



(a) Merging Top 3 Clusters (AUC=0.5983 → 0.6583)



(b) Merging Top 5 Clusters (AUC=0.6515 → 0.7126)

Comparison

Metric	Classic K-means	Optimized K-means
Accuracy	$0.8062 \rightarrow 0.8404$	$0.6193 \rightarrow 0.6938$
Sensitivity	$0.2228 \rightarrow 0.2805$	$0.5862 \rightarrow 0.6138$
Specificity	$0.8898 \rightarrow 0.9200$	$0.6247 \rightarrow 0.7057$
F1 Score	$0.2270 \rightarrow 0.3115$	$0.2802 \rightarrow 0.3393$
AUC value	$0.5563 \rightarrow 0.6003$	$0.6054 \rightarrow 0.6598$

Naives bayes

Naives bayes

Preprocessing:

- CLAHE (Contrast Limited Adaptive Histogram Equalization) for local contrast enhancement (LAB color space)
- Extracted RGB pixel features **within the Field of View (FOV)**
- Vessel pixels labeled from manual annotations

Class Imbalance Handling:

- All vessel pixels retained
- Equal number of background pixels sampled
- Resulted in a balanced dataset for fair training

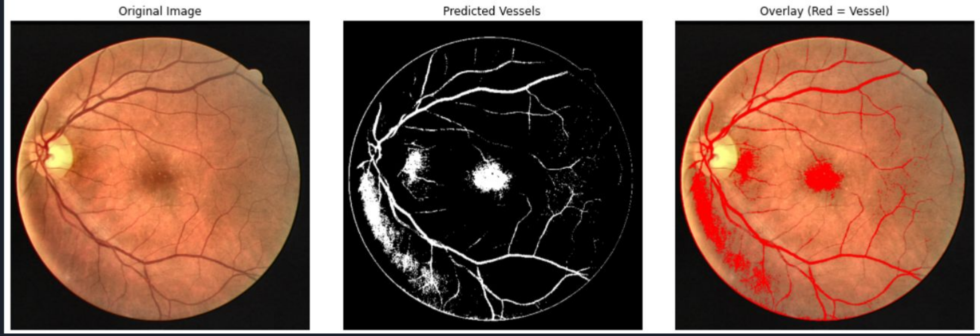
Model: Gaussian Naive Bayes (GNB)

- Assumes pixel intensities follow a Gaussian distribution per class
- Features: RGB values of individual pixels
- Posterior probabilities computed to assign class labels (vessel or background)

Results

Classification Report:

	precision	recall	f1-score	support
0	0.67	0.66	0.66	113484
1	0.67	0.67	0.67	114282
accuracy			0.67	227766
macro avg	0.67	0.67	0.67	227766
weighted avg	0.67	0.67	0.67	227766



SVM

SVM

- Implemented soft-margin SVM using RBF kernel for non-linear classification
- Solved the dual optimization problem using cvxopt quadratic programming
- Handled class imbalance by adjusting sample weights manually
- Identified support vectors from non-zero Lagrange multipliers ($\alpha > 1e-5$)
- Applied Platt scaling (logistic regression) to convert decision scores into probabilities
- Achieved end-to-end training, prediction, and probability output

Results of SVM of two versions

Result of Custom SVM (build from scratch)

Precision	0.22
Recall	0.11
F1 Score	0.14
Accuracy	0.84
AUC	0.60

Result of SVC from Scikit-learn

Precision	0.21
Recall	0.62
F1 Score	0.31
Accuracy	0.65
AUC	0.69

Why did the Custom SVM underperform the Scikit-learn?

Subsampled data (15%) limits model’s ability to generalize, especially on minority class.

No solver optimizations like SMO, kernel caching, or shrinking heuristics used in sklearn.

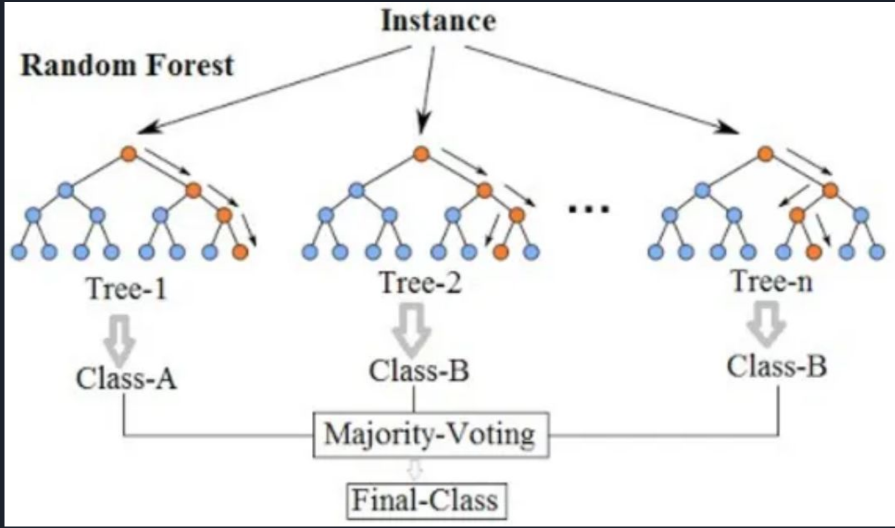
Fixed hyperparameters without tuning (C, γ) reduce classification performance.

Random Forest

Random Forest for Image Segmentation:

Image Segmentation can be regarded as a Classification Problem with RGB value as its feature.

Pro: Suitable for small data set. Resist Overfitting.
Con: Spatial continuity information is lost during training.



Node-Splitting Score

Gini Impurity

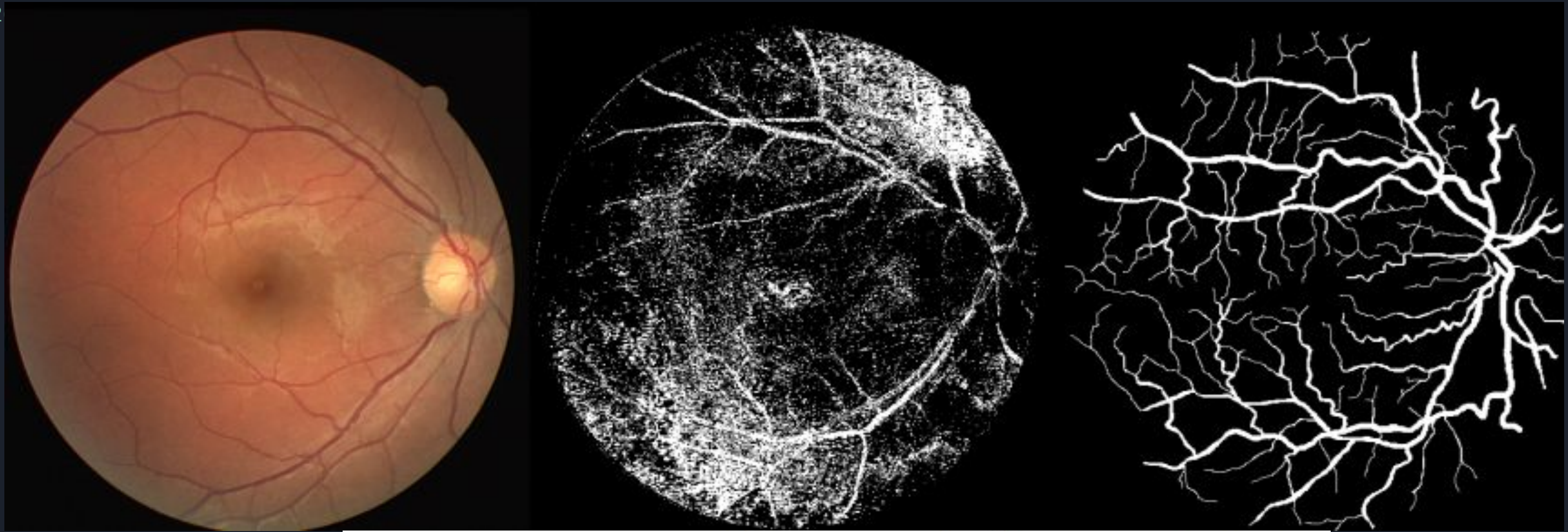
$$G = 1 - \sum_{k=1}^{K} p_k^2$$

where p_k is the proportion of samples of class k in the node.

Information Gain

$$H = -\sum_{k=1}^{K} p_k \log p_k$$

$$\text{Information Gain} = H_{\text{parent}} - \sum_{\text{child}} \frac{N_{\text{child}}}{N_{\text{parent}}} H_{\text{child}}$$



	precision	recall	f1-score	support
background	0.91	0.80	0.85	198755
retinal	0.24	0.44	0.31	29073
accuracy			0.75	227828
weighted average	0.82	0.75	0.78	227828

Conclusions

Conclusions

	K-means	RF	SVM	Naive Bayes
AUC	0.66	0.62	0.60	0.72

The optimized K-means clustering approach yielded notable improvements in sensitivity and AUC compared to the classic K-means variant, even **reaching the level of supervised learning methods**.

This shows that designing the models towards the data has a chance to make the performance of the unsupervised learning model better than that of the supervised learning model.

Thanks!