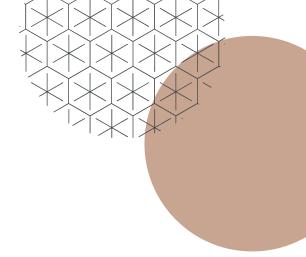
# Retinal Image Segmentation Group 17





### **Problem Statement**

**Primary Goal:** Creating an advanced image segmentation model that can effectively and precisely delineate the network of blood vessels within retinal images.

This segmentation model will play a crucial role in the realm of medical diagnosis by providing a clear and accurate representation of the retinal vasculature. By doing so, it will significantly assist healthcare professionals in detecting and diagnosing a range of retinal conditions, including but not limited to hypertension, diabetic retinopathy, cataracts, glaucoma, and cardiovascular diseases.

## **Dataset Description & EDA**

- In our given dataset we had a total of 28 images with 14 for the left eye and 14 for the right eye.
- All images are circular with black background with the iris clearly visible in the centre and have the same size of 960x999 pixels.
- The mean pixel intensity across all pixels of all images is 54.79 and the standard deviation across the dataset is 73.64. As expected the variation is not significant across the two eyes.
- Color Channel Analysis was performed on the dataset which provided an insight into the color composition of the images.
- Gray-Level Co-occurrence Matrix (GLCM) to gain insights into metrics related to texture analysis, aiding in the identification of underlying patterns and structures within an image.

## **Approaches Explored**

#### KMeans:

- a. In pursuit of enhanced image segmentation accuracy.
- b. Leveraged unsupervised K-means clustering for segmentation.
- c. Applied Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement.
- d. Implemented Median Filtering for noise elimination.
- e. Achieved an accuracy of approximately 40.86%.

#### RandomForest:

- a. Employed a supervised Random-Forest Classifier for segmentation.
- b. Initial preprocessing included CLAHE.
- c. Extracted 7 features per pixel.
- d. Achieved an accuracy of around 68%.

## Final Approach: SVM

SVMs excel in binary and multiclass classification problems and can learn to classify pixels based on features extracted from the image.

SVMs can handle nonlinear relationships between features and classes through the use of kernel functions which is quite beneficial in our case where the relationship between pixel values and class labels are quite complex and nonlinear.

Using a single SVM did not yielded us the desired results which led us to settle on an approach of combining SVM with ensemble learning which involved training multiple SVMs on a subsets of the data and creating a bagged classifier.

Our model was able to predict the probability(p) of whether a pixel corresponds to a blood vessel which we used to assign white color to pixels with p>=0.5 and others as black. This led to a visually interpretable representation of blood vessels.

## Methodology

### Vessel Enhancement:

We aimed to design a SVM that should be able to classify pixels belonging to vessels accurately, to achieve we used the most effective preprocessing method that involved extracting the inverse green channel, enhancing vessel structures for distinct visibility.

### Convolution Operation :

We aimed to enhance feature detection by moving a filter over the image, calculating weighted sums of pixel values. Padding ensures edge pixels are handled smoothly. Convolution iterates through each pixel, considering a local neighborhood defined by the filter size. This enhances feature detection in our model, aiding in blood vessel identification.

• We train a SVM and apply a binary threshold of 0.5, assigning all pixels not associated with vessels to 0 and those belonging to vessels with 255. Ensemble learning from scikit-learn is used to finally make the model more robust.

### Results

Tackling the major challenge faced in our earlier models which was recognizing the thinner blood vessels, we explored the convolution technique which grouped pixels within neighborhoods and compute features for the superpixels.

The application of convolution at different scales improved the model's ability to discern finer blood vessels while maintaining high accuracy.

The final results include an improved precision with an accuracy of 95.28% and an excellent image quality with a Structural Similarity Index Measure of 0.83 and Peak Signal to Noise Ratio of 55.

Metric	Accuracy	Precision	Sensitivity	Specificity	SSIM	PSNR
Value	0.95	0.65	0.51	0.98	0.83	55

## Conclusion

### These were the objectives achieved:

- Inferences drawn from existing research in area.
- EDA on CHASEDB Dataset.
- Comparison of different ML models with wide variety of pre-processing steps.
- Development of a model based on SVM with 95.28% accuracy.

## References

- A threshold based technique to extract retinal blood vessels from fundus images by Jootiprava Dash, Nilamani Bhoi
- Roychowdhury S, Koozekanani DD, Parhi KK. Iterative vessel segmentation of fundus images. IEEE Trans Biomed Eng 2015;62(7):1738e49..
- Segmentation Of retinal blood vessels using scale-space features and k-nearest neighbour classifier by Nancy M Salem and Ashoke K Nandi
- Retinal vessel segmentation using ensemble classifier of Bagged Decision Trees by Fraz MM, et. al.