R&D PROJECT

Hemoglobin Level Estimation from Photographic images

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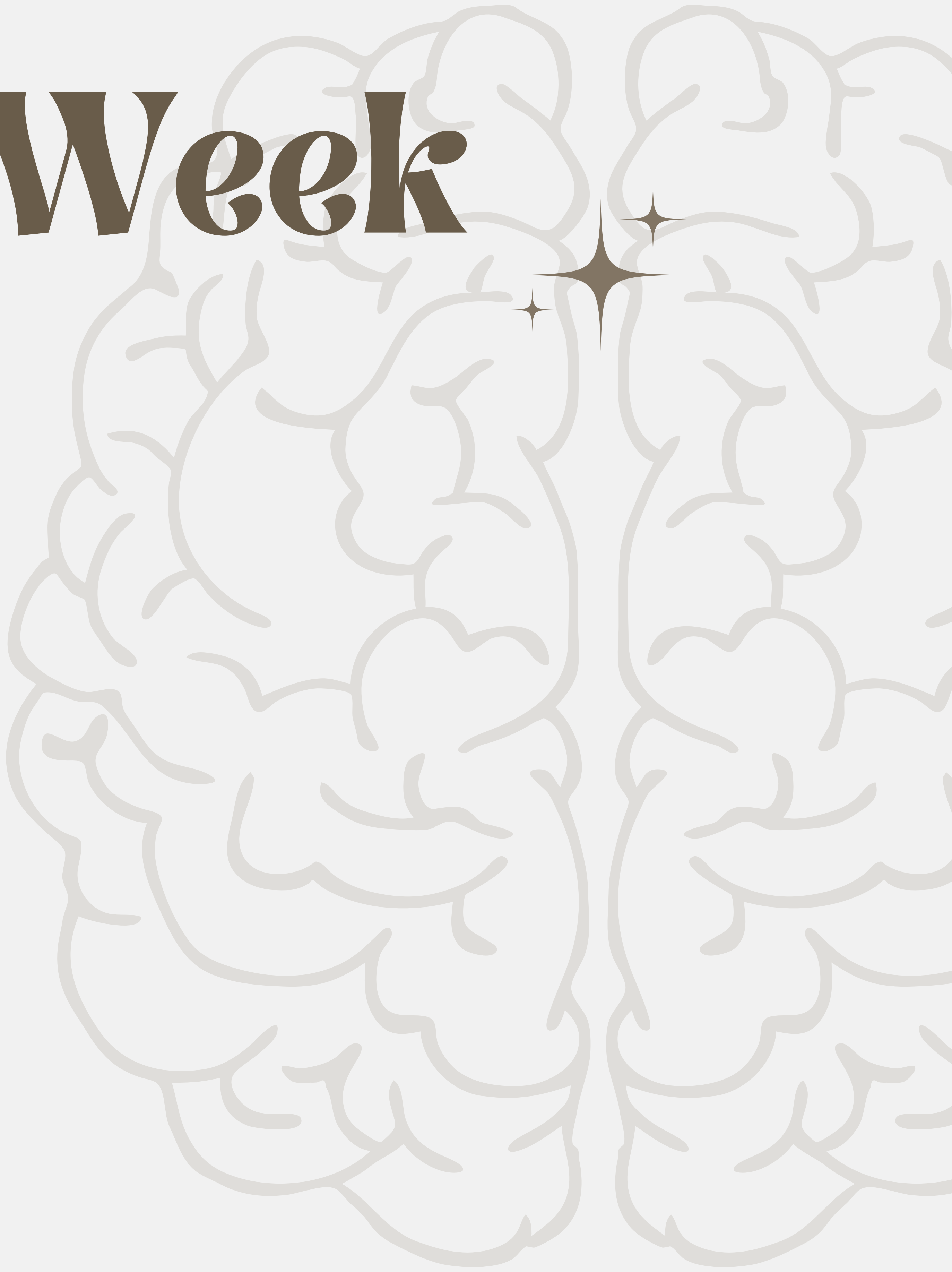
DH 307

Insights from Last Week



- How will you use color palette ?
- What & why F2 score
- Go through citations also
- Think about pipeline.....

Anaemia detection based on sclera and blood vessel colour estimation

OVERVIEW

Objective: To develop a non-invasive method for anaemia detection by analyzing scleral and blood vessel colors from eye images

This is the first study to utilize scleral and blood vessel colors for this purpose

LINK

Why sclera instead of conjunctiva?

- **Absence of melanin in sclera:** Sclera is devoid of melanin, making it less affected by pigmentation variation, in contrast conjunctiva may exhibit pigmentation difference depending on individual skin tone, genetics etc.

- **Higher sensitivity to haemoglobin changes**: Hemoglobin levels are correlated with changes in tissue pallor. The sclera, due to its lighter and more uniform color, provides a clearer and more consistent background for detecting such changes

- **Novelty:**Previous studies had already explored the conjunctiva for anaemia detection, particularly focusing on its pallor. This study aimed to explore the feasibility of using the sclera, a less investigated region

Why scleral blood vessels?

- **Better Contrast with the Background:** The scleral blood vessels are superimposed on the white sclera, whereas conjunctiva being a thin and semi-transparent tissue, has a less uniform background, making vessel detection challenging.

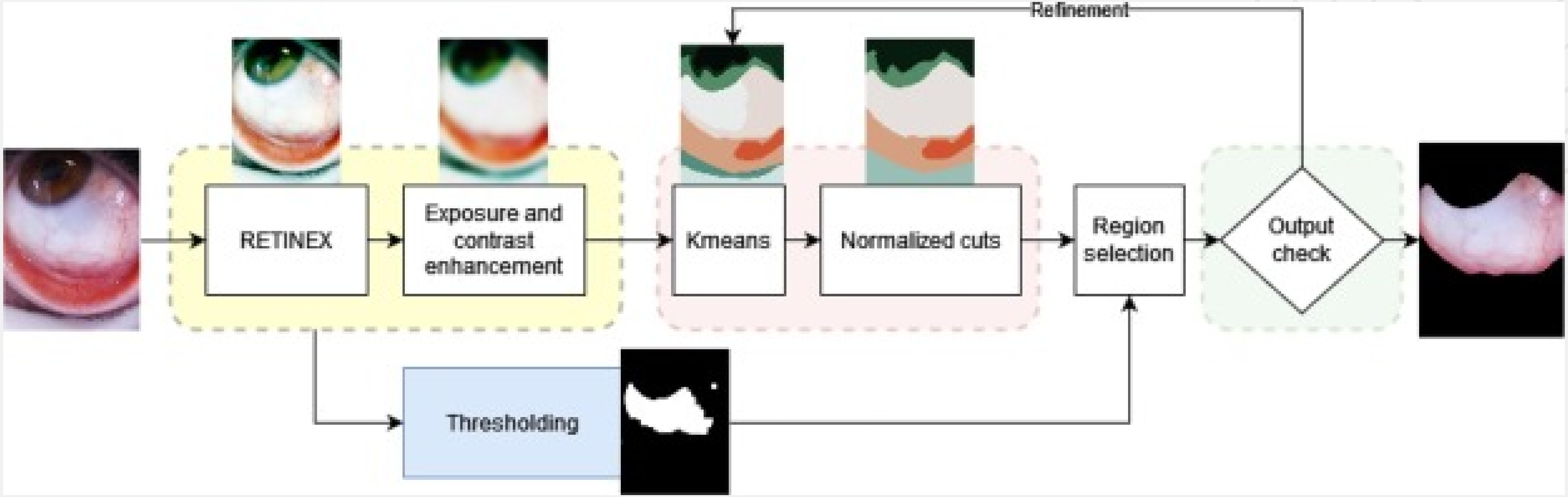
- **Reduced Noise**: Conjunctiva contains a dense and variable network of capillaries, which can make vessel segmentation noisy. Whereas scleral vessels, are typically larger and more prominent.

- **Novelty:** Prior research has largely focused on the pallor of the conjunctiva

Pipeline of this Research Paper:

1. Sclera Segmentation Algorithm
2. Vessel Detection
3. Feature Extraction
4. Classification

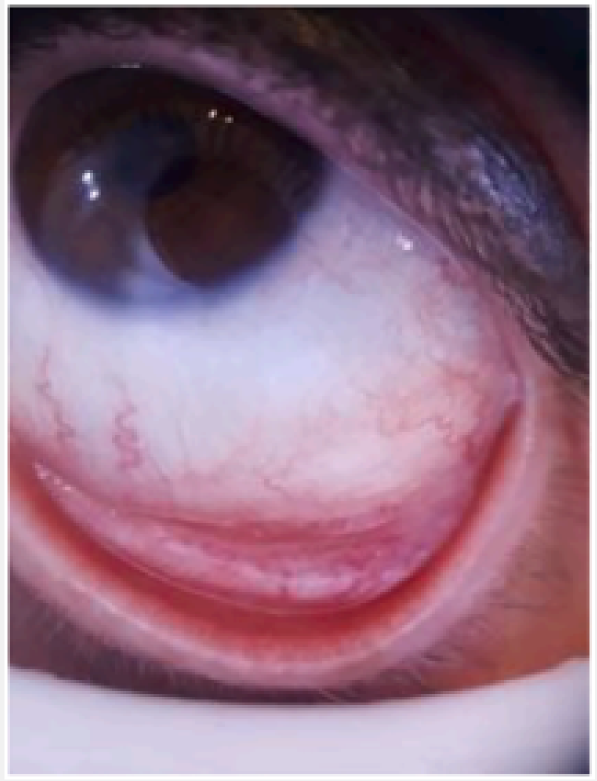
1. Sclera Segmentation Algorithm



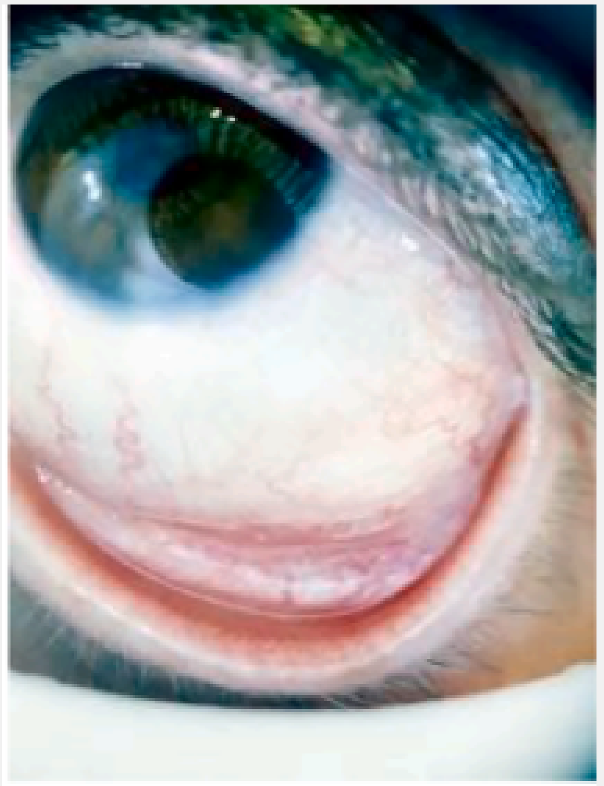
1. Sclera Segmentation Algorithm

1.1 RETINEX :

- Due to the ocular bulb shape and direction of light, peripheral portions of the sclera are usually darker than the centre
- So to avoid error during k-means clustering, Multi-Scale Retinex with Color Restoration (MSRCR) is applied
  - It equalizes the lighting across the image
  - ensures consistent intensity across whole image



Original Image

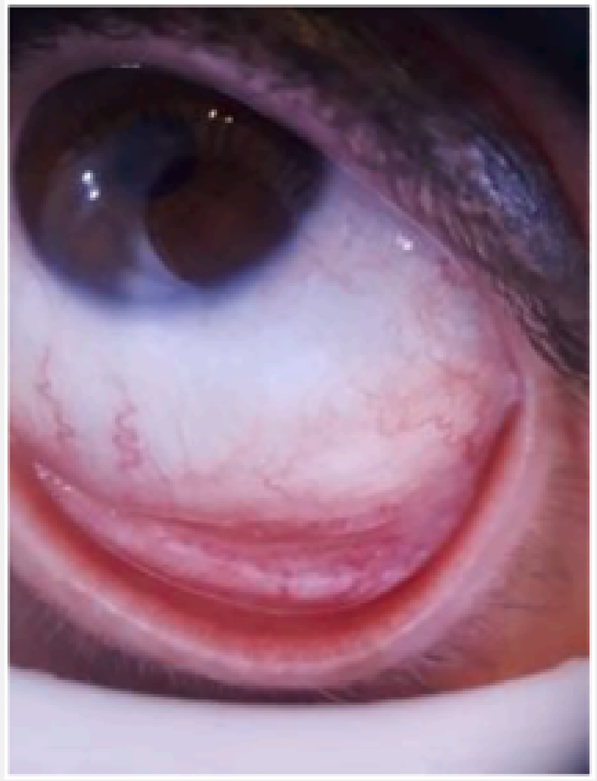


Retinex Filtered Image

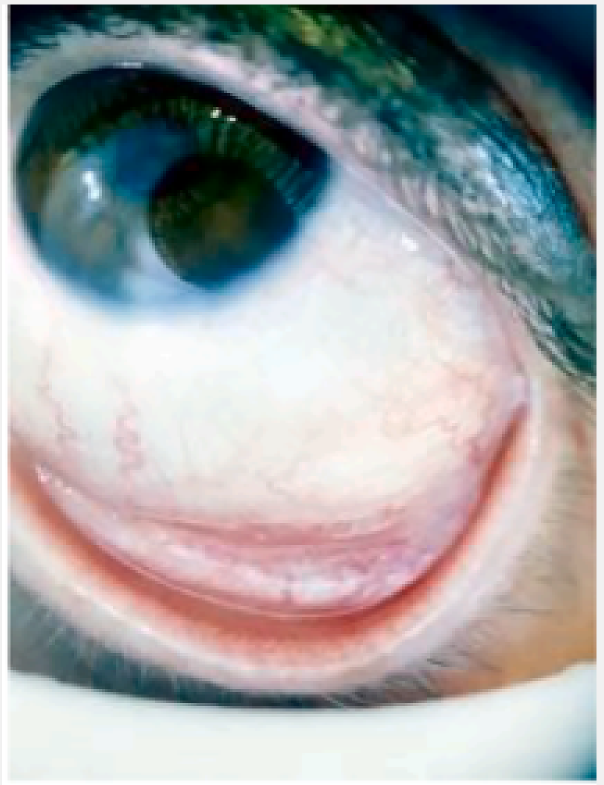
1. Sclera Segmentation Algorithm

1.2 Exposure and Contrast Enhancement :

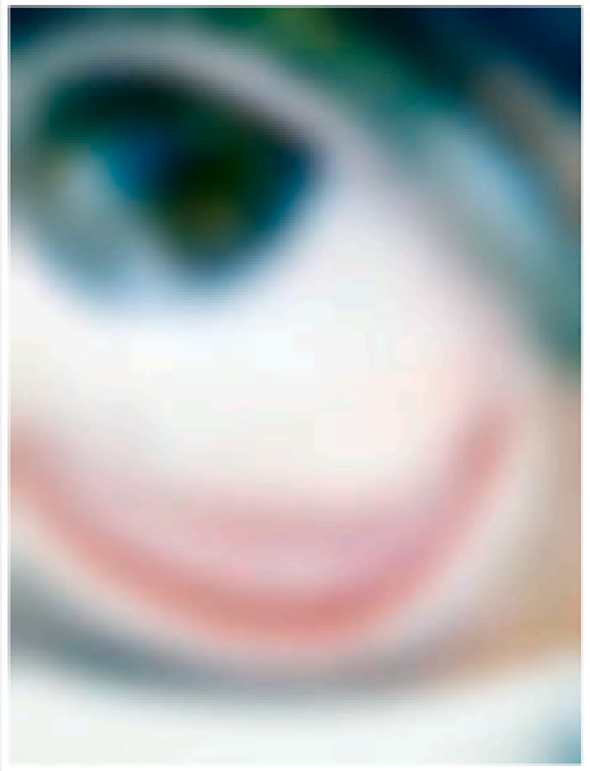
- Since the blood vessels in the sclera are red as the conjunctiva, they were clustered as a part of conjunctiva. This is called as ‘vessel noise’.
- It is removed by applying Gaussian blur to the retinex filtered image.
- The smoothing effect of the Gaussian Blur Filter reduces the sharpness of edges in the image, this effect is counteracted by subsequent contrast and sharpening manipulation



Original Image



Retinex Filtered Image



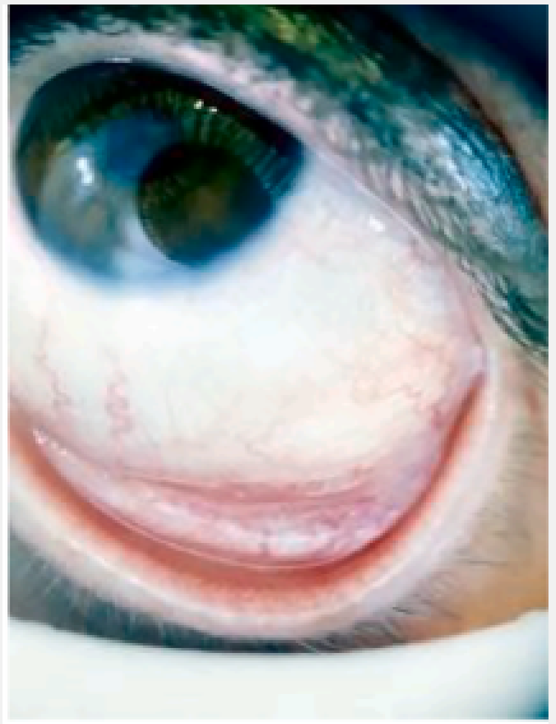
Blurred Image

Final Image

1. Sclera Segmentation Algorithm

2.1 Thresholding :

- It is the initial identification of the scleral region based on pixel intensity and color
- Input for thresholding is retinex filtered image.
- Global Thresholding method is applied to separate the sclera based on intensity levels.
  - Pixels above a certain intensity threshold to the sclera and below to background
- Applying fixed threshold can fail due to variations in scleral brightness across images, so dynamic thresholding was applied
  - If the initial mask contains fewer pixels than a predefined percentage of the total image (e.g., 5%), the threshold is lowered incrementally



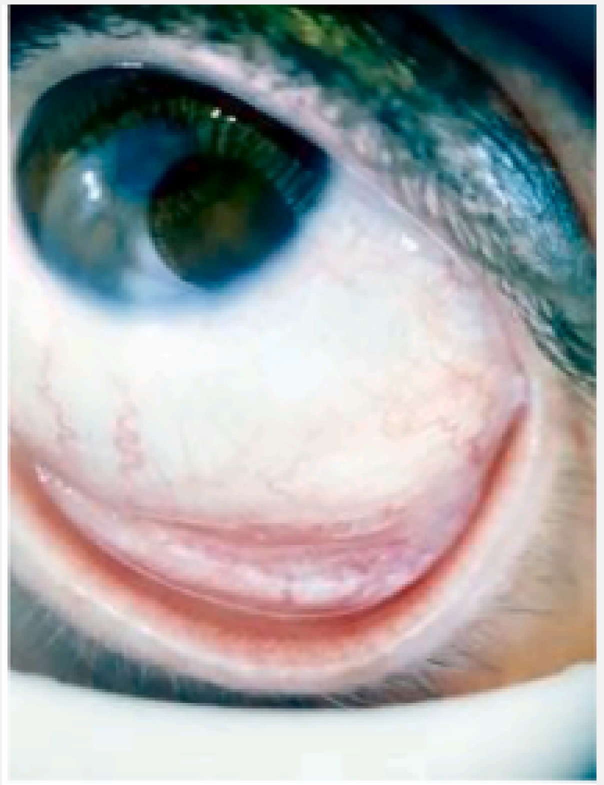
Retinex Filtered Image

Global Thresholded image

1. Sclera Segmentation Algorithm

2.2 Morphological Operations :

- Thresholding can leave small gaps or include noise. Morphological operations are applied to refine the binary mask
    - **Opening**: removes the noise
    - **Closing**: fills the gap made by removing the noise



Retinex Filtered

Thresholded Image

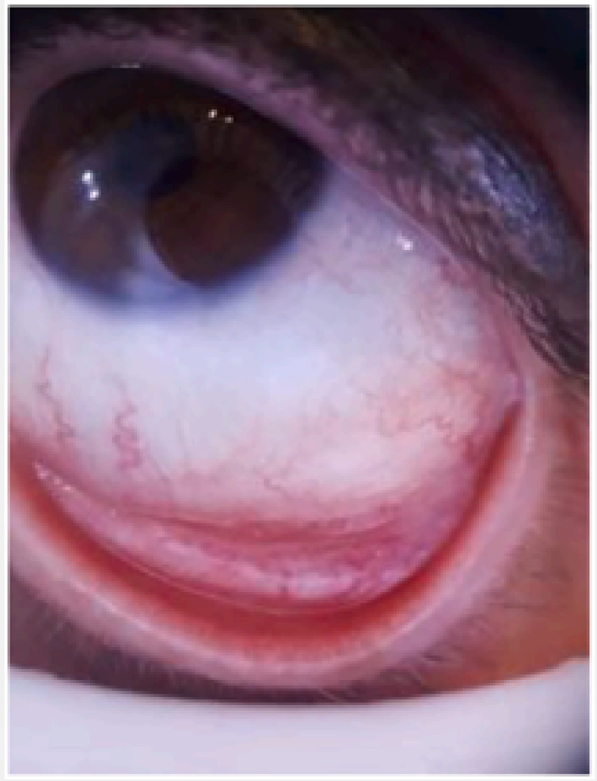
Opening

Closing

1. Sclera Segmentation Algorithm

3. K-Means & Ncuts :

- Each pixel is represented in a 5-dimensional feature space
  - x,y: Spatial coordinates of the pixel
  - R,G,B: Intensity values from the RGB color space
- Pixels are grouped into k clusters based on their similarity in the 5D feature space
- Kmeans lacks the ability to capture global relationship within image.
- K-means clusters are used as input to **Ncut**, which refines the segmentation globally
- Ncut interprets the segmentation task as a graph partitioning problem



Original Image

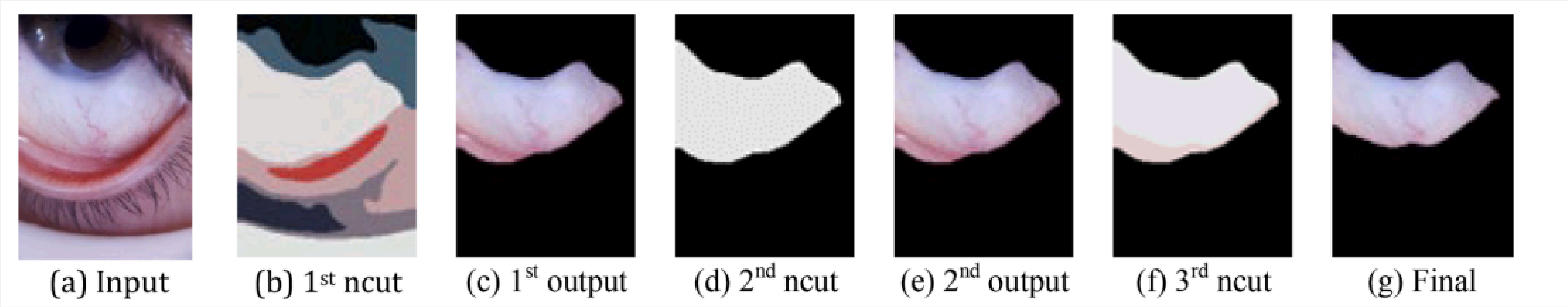
K-means

Ncuts refinement

1. Sclera Segmentation Algorithm

4. Improving Precision:

- Sometimes cluster belonging to conjunctiva is also included in the final mask.
- To manage these cases, colour of the selected region is evaluated.Segmentation is rejected if the standard deviation of the alpha channel is greater than a fixed threshold or L, a* and b* are out of the 25th – 75th percentile range.
- If the segmentation is rejected, Ncut on the current segmentation is applied again to cut out the incorrectly included clusters



Refinement Process

1.Sclera Segmentation Algorithm Results

To evaluate the performance of the algorithm for sclera segmentation, all 218 pictures from the dataset were manually segmented

Scleral segmentation algorithm performance scores.

	Precision	Recall	F1	Accuracy	Jaccard
Average	88.53	82.53	84.10	73.58	94.2
Std dev	13.29	12.10	9.39	12.58	4.25

Precision:proportion of correctly identified sclera pixels to all pixels predicted as sclera

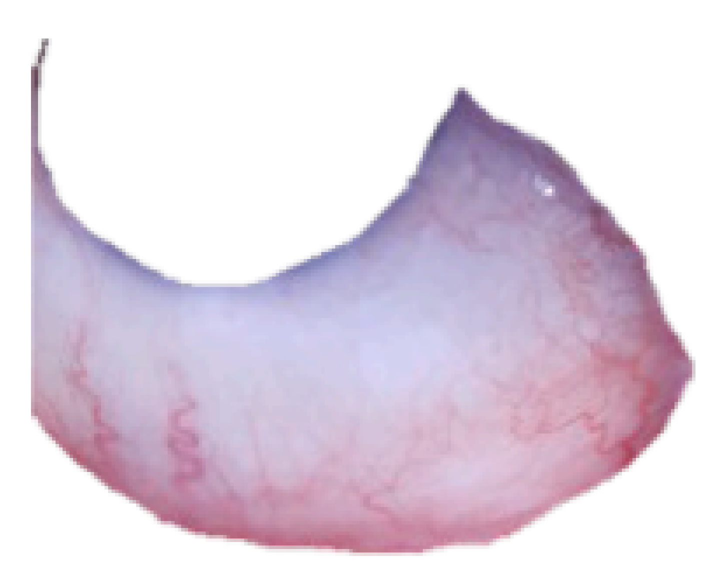
Recall:proportion of correctly identified sclera pixels to all actual sclera pixels in the ground truth

Jaccard Index : measure of similarity between the predicted sclera region and the ground truth.

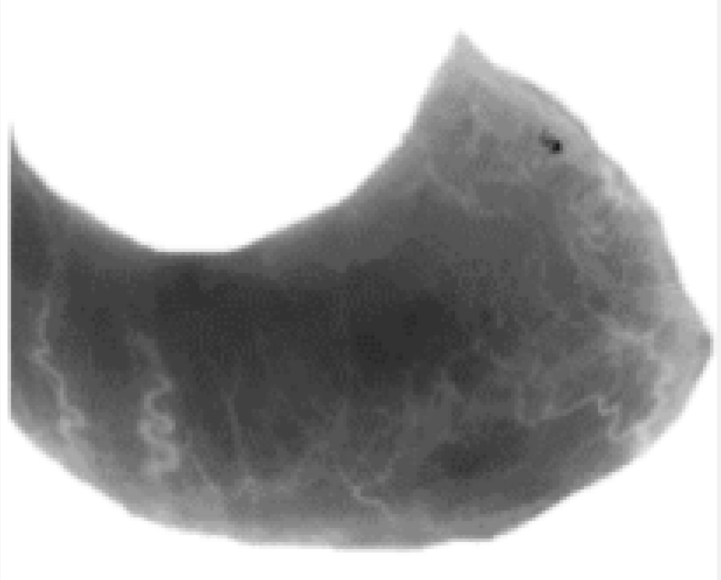
2. Vessel Detection

1. Weighted Line Detection:

- Channel selection:
  - The green channel of the image is selected because it typically offers the highest contrast between blood vessels (dark regions) and the surrounding tissue (light regions)
  - The green channel is inverted to make the vessels appear brighter against a darker background
- Sliding Window:
  - A sliding window of size W is used to scan the entire image. Each window focuses on a small region around a pixel p.
  - The average intensity within this window is calculated



Original Image

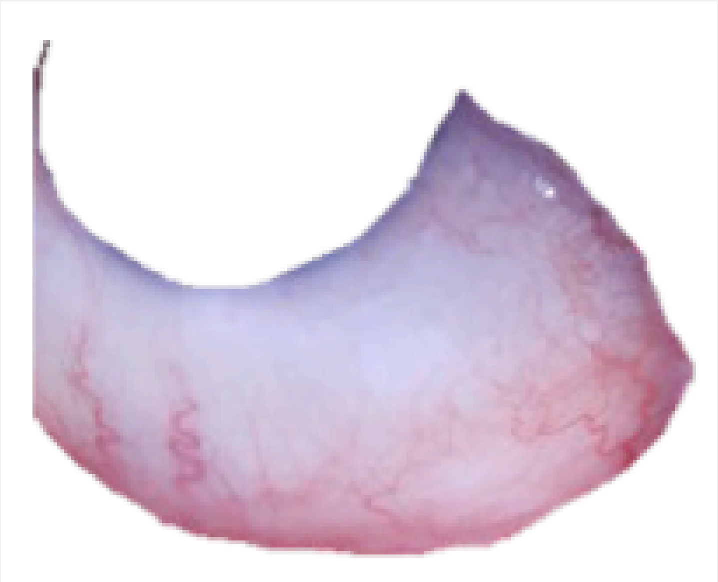


Inverted Green Channel

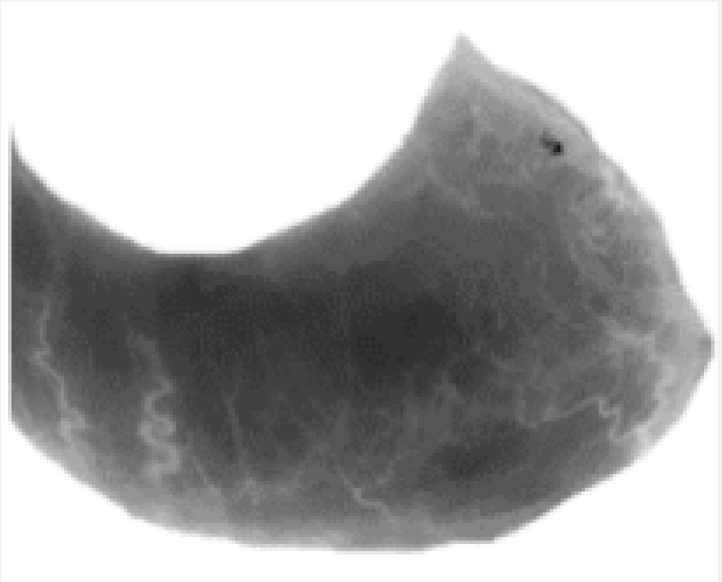
2. Vessel Detection

1. Weighted Line Detection:

- Line Detection Mask:
  - Twelve Boolean masks, representing lines at different angles (e.g., 0°, 15°, ..., 165°), are applied within the window
  - For each mask, the intensity values of the pixels that match the line orientation are summed
  - These intensities are weighted inversely proportional to their distance from the center pixel pp
- The mask with the highest weighted sum is identified as the "winning line," representing the dominant linear structure in the current window



Original Image



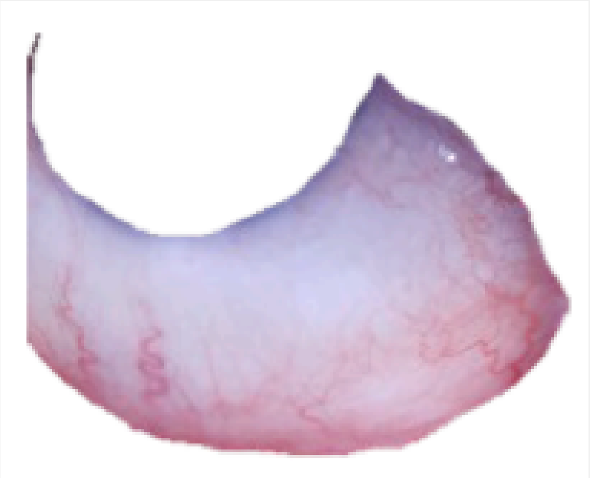
Inverted Green Channel

Line Detection Result

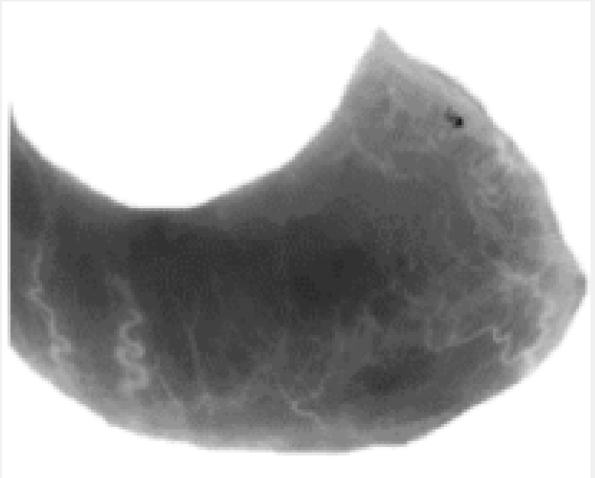
2. Vessel Detection

2. Vessel Centrelines:

- There are various isolated segments , especially in the thinner vessel region
- This problem is solved by using a hidden Markov model (HMM) to trace the central lines of the vessels, so it includes the thin vessels that were previously excluded and combines the results of the line detection with those of the HMM



Original Image



Inverted Green Channel

Line Detection Result

Centreline result

Union

The vessel detection mask itself is not colored, but it serves as a filter or mask to isolate the vessel regions in the original colored sclera image.

3. Feature Extraction

- RGB Features:
  - Compute the average intensity for the Red, Green, and Blue channels within the segmented regions.
- CIELAB Color Space:
  - L*: Lightness (brightness of the region).
  - a*: Green-to-red color range.
  - b*: Blue-to-yellow color range.
- HSL Color Space:
  - Hue (H): Dominant color.
  - Saturation (S): Intensity of color.
  - Lightness (L): Overall brightness.
- Erythema Index (EI):
  - $EI = R - G$
  - Indicates redness, relevant for vascular analysis.

4. Results:

- After many experiments ,only 2 features El, and a* is used as they have good correlation with haemoglobin concentration levels.
- In anemia detection, false negatives (failing to detect anemia when it is present) are more harmful than false positives.
- **F2** prioritizes recall to ensure that most anemic patients are correctly identified
- **F1** provides a balanced view of precision and recall

Best result for each classification algorithm on the sclerae validation set.

Features	Algorithm	Parameters	Precision	Recall	F1	F2
EI, a*	Nearest Neighbour	K = 7, uniform weights	87.0	78.0	79.8	78.4
EI, a*	Random Forest	estimators = 20, max features = auto, Gini criterion	78.0	73.0	72.5	72.4
EI, a*	Adaboost	Estimators = 40	83.0	73.0	74.7	73.2
EI, a*	Polynomial SVM	C = 20, degree = 3, gamma = auto	74.6	90.1	80.1	86.4

4. Results:

Best result for each classification algorithm on the vessels validation set.

Features	Algorithm	Parameters	Precision	Recall	F1	F2
EI, a*	Nearest Neighbour	K = 7, uniform weights	92.0	77.0	82.6	78.9
EI, a*	Random Forest	estimators = 20, max features = log2, Gini criterion	69.0	72.0	70.0	71.1
EI, a*	Adaboost	Estimators = 2	72.0	72.0	70.3	71.0
EI, a*	Polynomial SVM	C = 60, degree = 4, gamma = auto	57.6	95	71.4	83.8

Proposed plan of action

- **Exploratory Data Analysis**

- **Image Pre-processing:**
    - Resize : to make each image of same width and height
    - Normalize: for steady training (convergence)
    - Augment: to increase the dataset if required for deep learning models

- **Region of Interest extraction:**
    - Conjunctiva/Sclera/Nail/Tongue region
        - Segmentation model U-Net or Mask R-CNN
    - Color Palette
        - Contour Detection
        - Template Matching

Proposed plan of action

- **Color Calibration:**
  - Use the color palette to normalize the color space of image
  - How??

- **Feature extraction:**
  - RGB
  - HSV
  - LAB

- **EDA on Features:**
  - Correlation

Proposed plan of action

- **Model Development:**
  - Baseline Models
    - Random Forest
    - SVM
    - XGBoost
  - Deep Learning Models
    - Custom CNN
    - Transfer Learning

- **Model Evaluation:**
  - MAE
  - MSE
  - RMSE

Semantic segmentation of palpebral conjunctiva for anemia detection

OVERVIEW

Objective: Segmentation of Region of Interest for analysis or feature extraction

Five deep learning models (UNet, UNet++, FCN, PSPNet, LinkNet) were compared for their effectiveness in segmenting palpebral conjunctiva

LinkNet architecture performed best

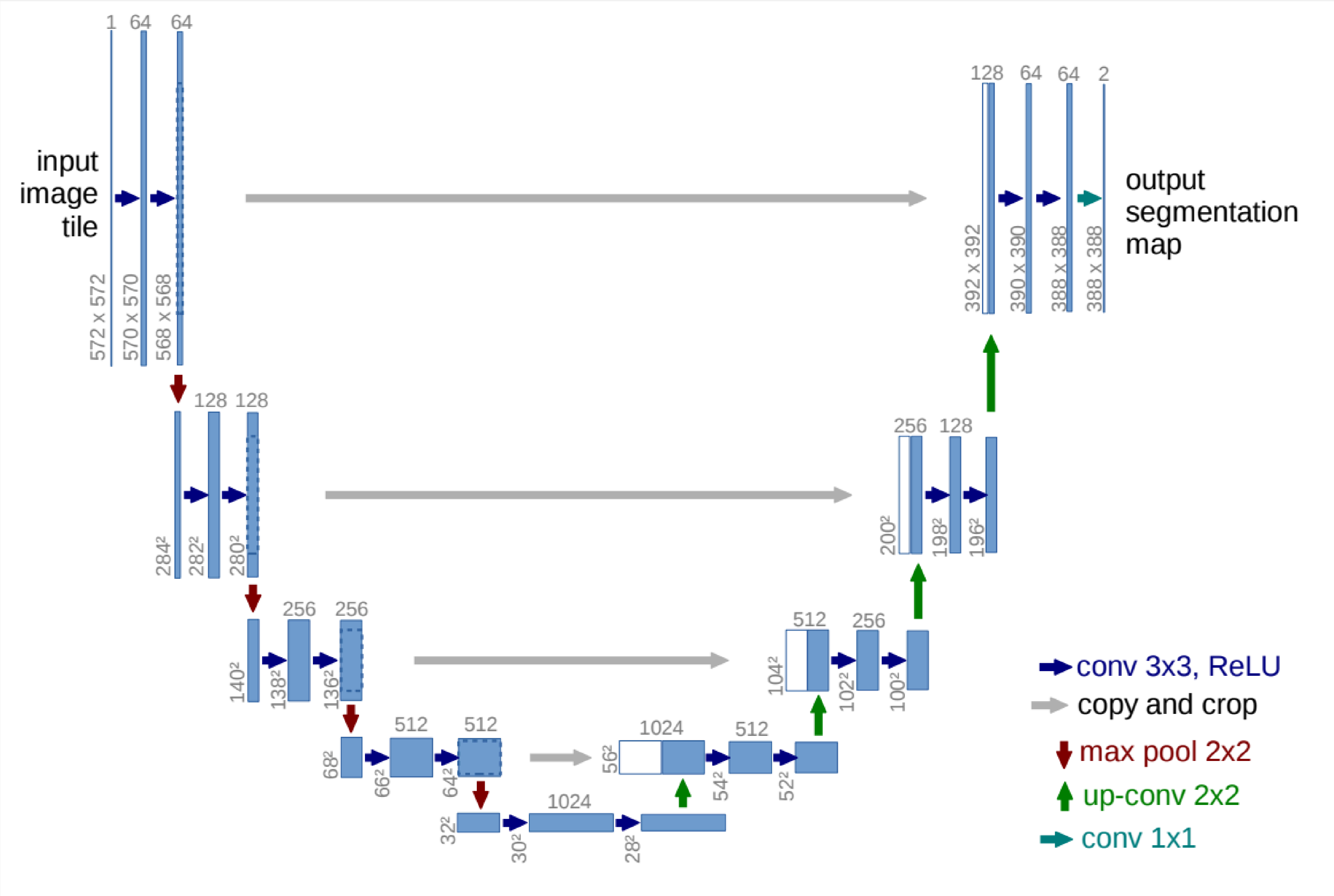
LINK

Pipeline for this Research Paper

1. UNet
2. UNet++
3. FCN
4. PSPNet
5. LinkNet

1.U Net

Consists of an encoder-decoder structure with skip connections for preserving spatial information



Result:

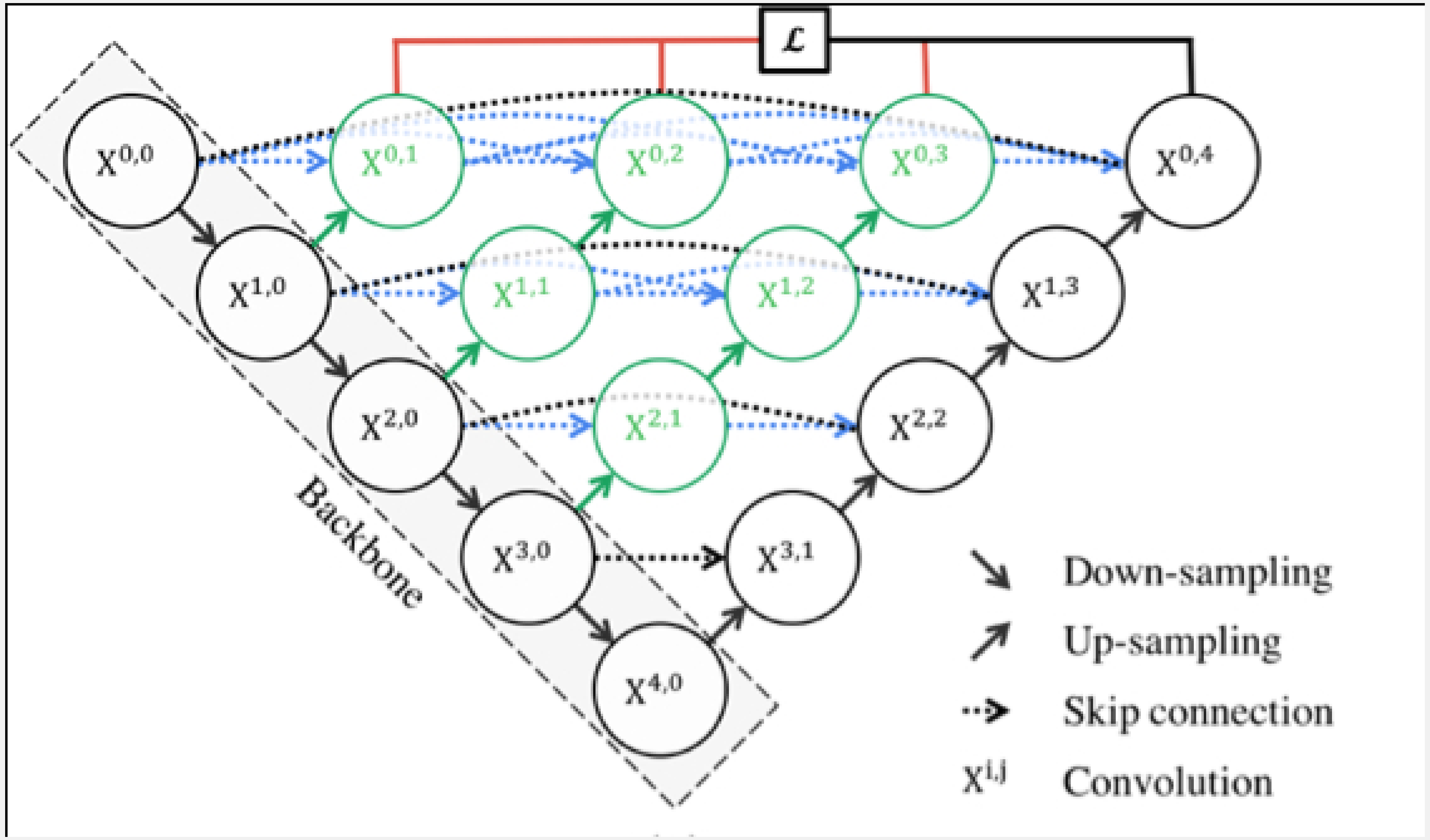
Accuracy: 94.12%

IoU: 90.05%

Dice: 93.76%

2. U Net ++

An enhanced version of UNet with dense nested skip connections



Result:

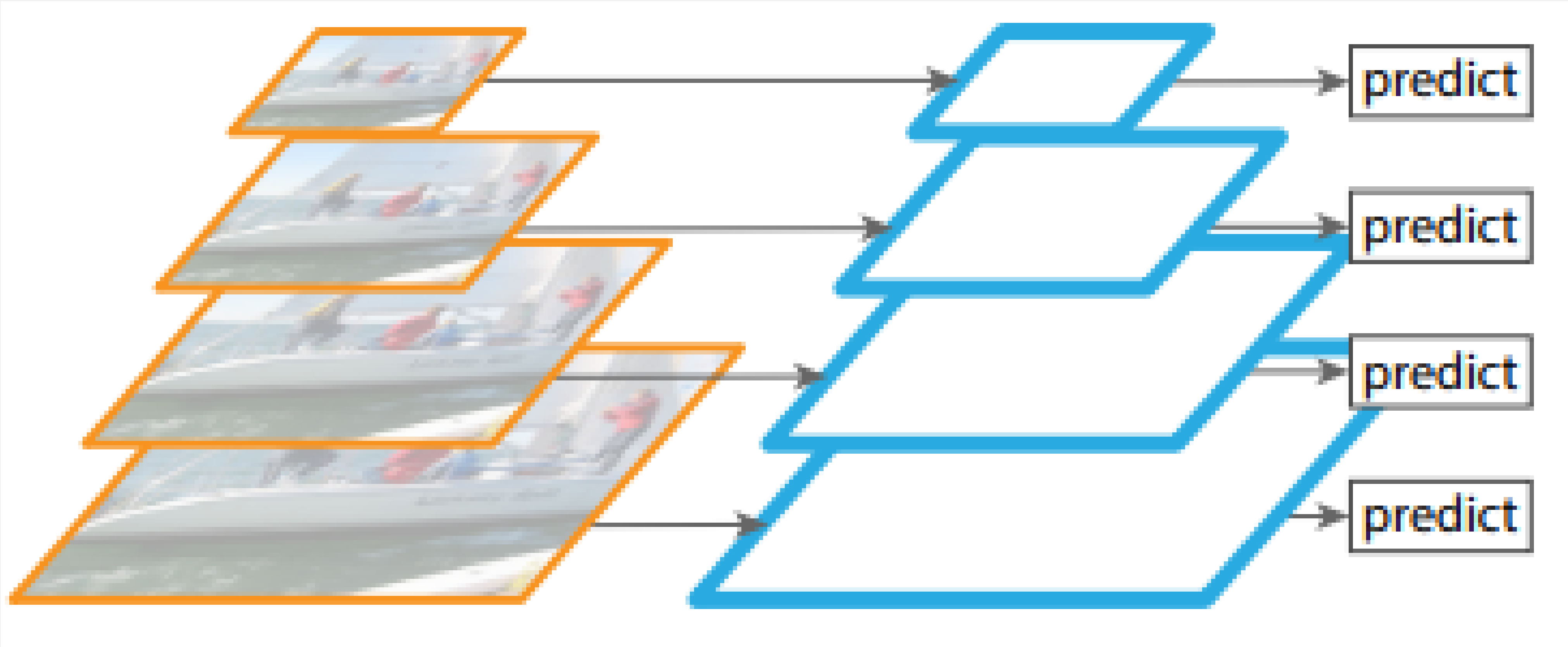
Accuracy: 94.15%

IoU: 90.12%

Dice: 93.79%

3. Feature Pyramid Network

Utilizes a top-down and bottom-up approach to combine low- and high-level features for robust segmentation



Result:

Accuracy: 93.34%

IoU: 89.95%

Dice: 92.34%

4. Pyramid Scene Parsing Network (PSPNet)

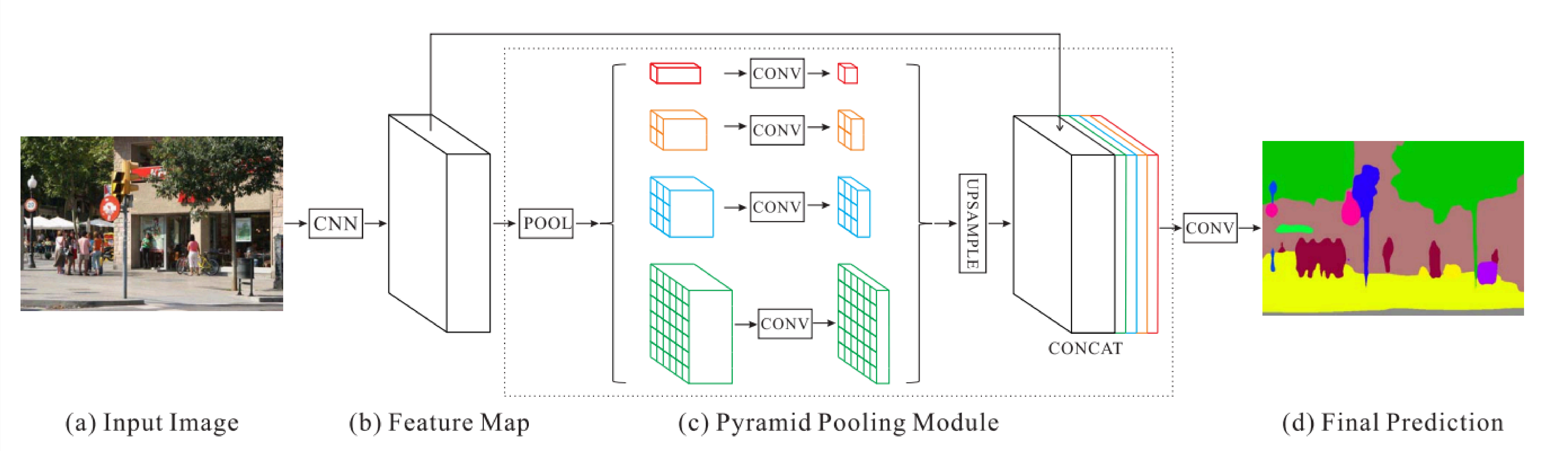
Uses pyramid pooling to capture both local and global image features

Result:

Accuracy: 91.85%

IoU: 87.52%

Dice: 92.31%

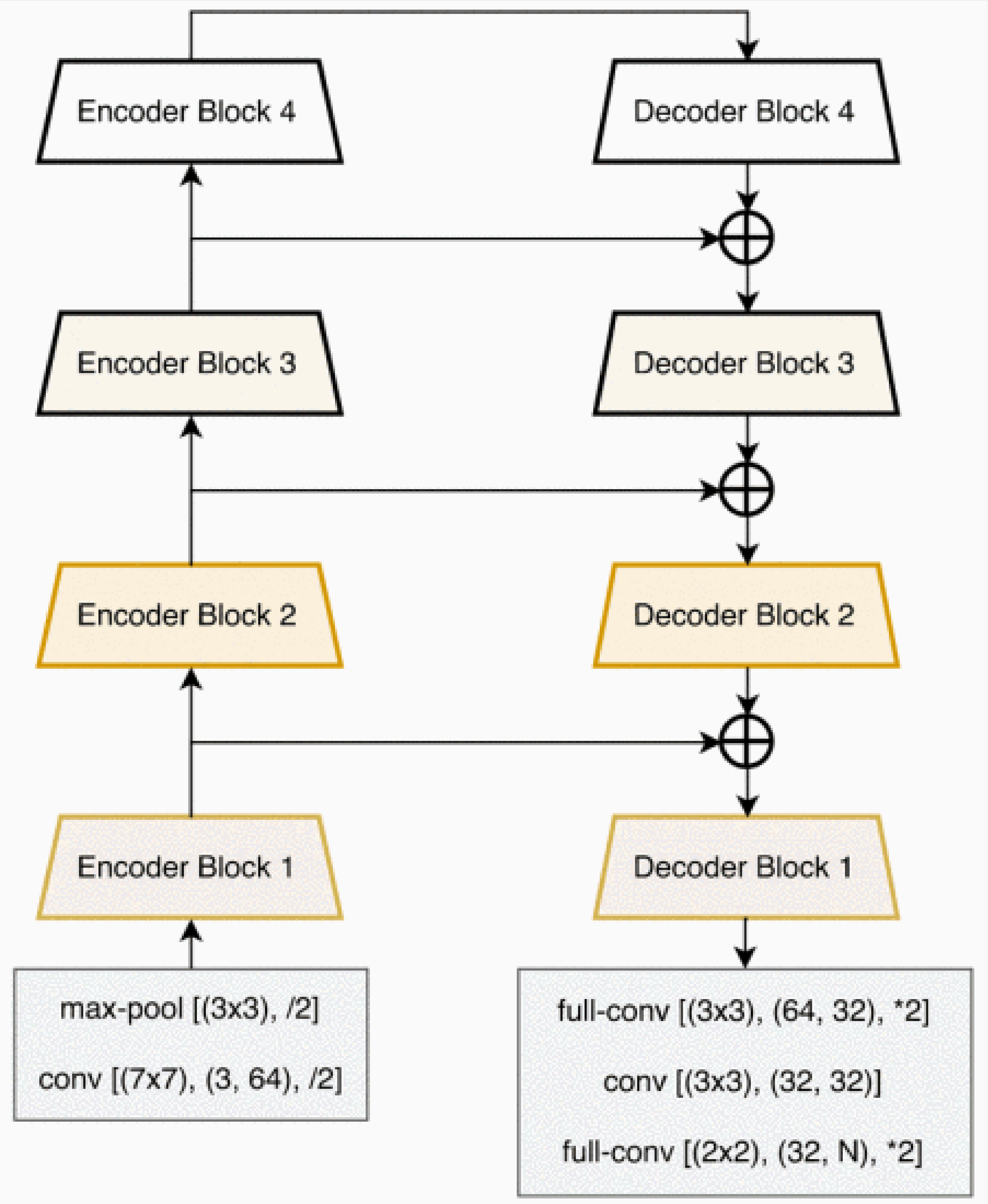


5. LinkNet

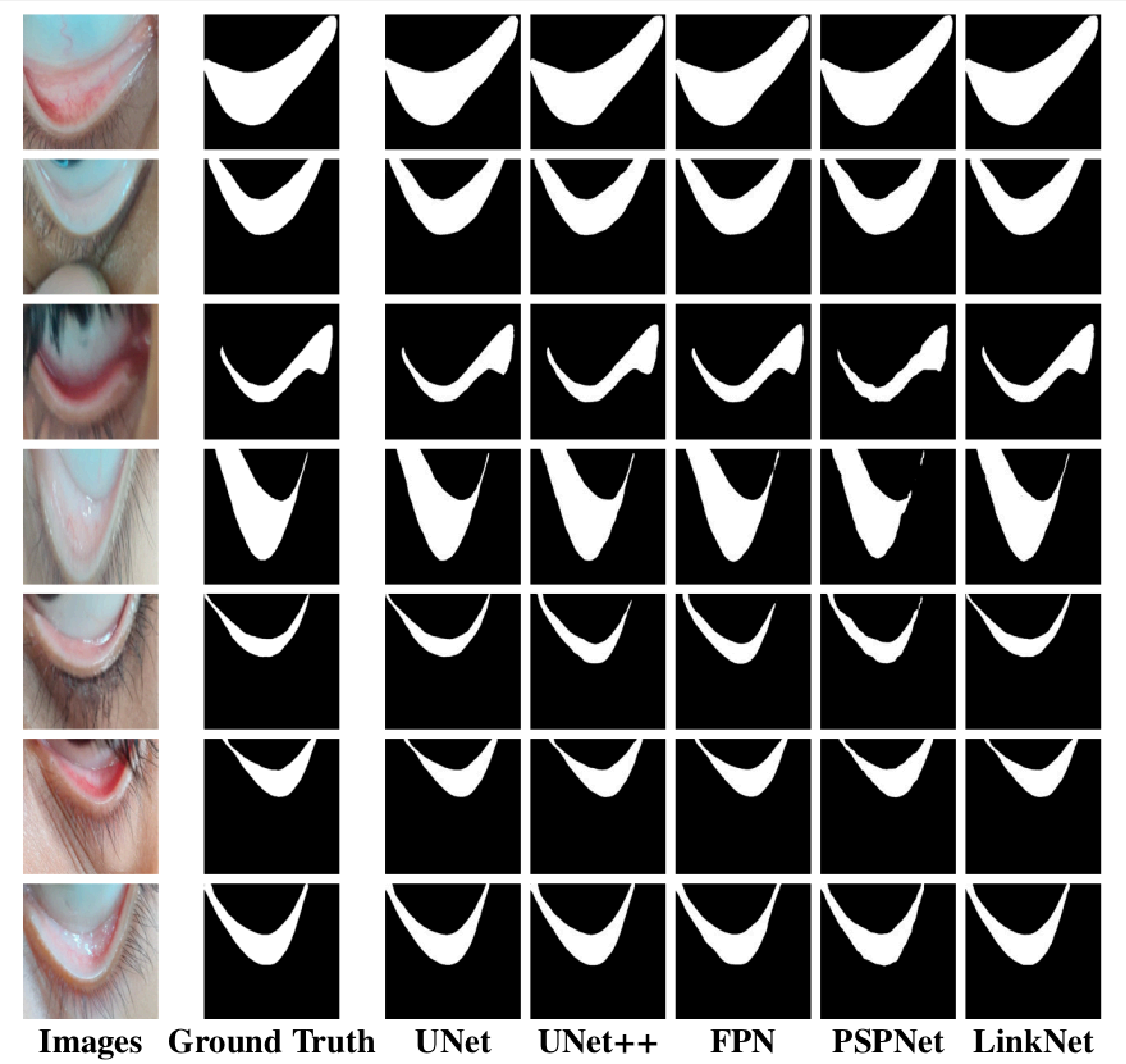
Employs an encoder-decoder structure like UNet but focuses on efficient residual connections and feature addition

Result:

Accuracy: 94.17%
IoU: 90.14%
Dice: 93.87%



Result:



Application of ensemble models approach in anemia detection using images of the palpable palm

OVERVIEW

Objective: To develop an accurate, efficient, and cost-effective model for anemia detection using ensemble machine learning techniques

Dataset: Palm Images

LINK

Pipeline

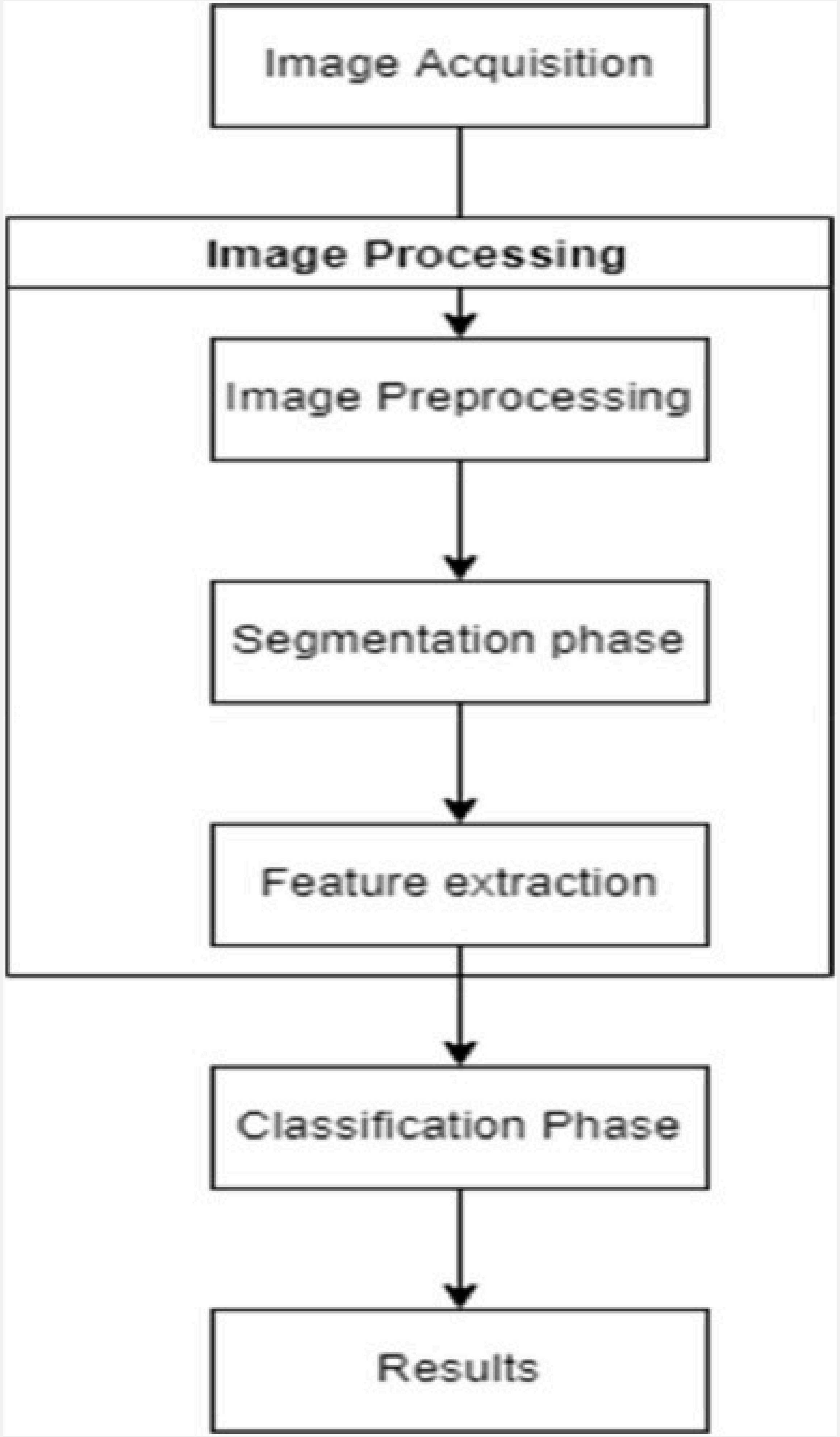
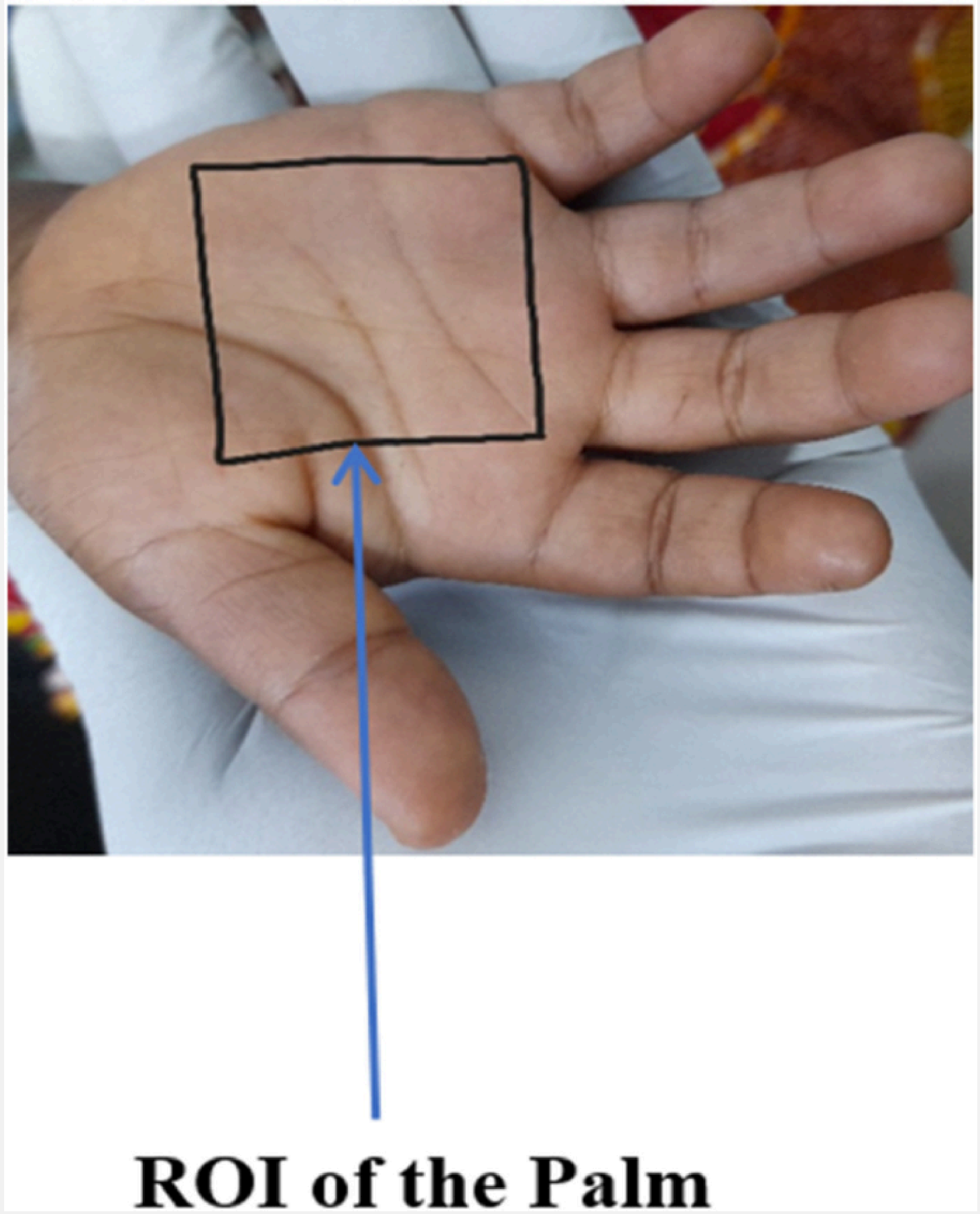


Image Acquisition
Image Processing
Image Preprocessing
Segmentation phase
Feature extraction
Classification Phase
Results


ROI of the Palm

Segmentation Phase

- **Conversion to Grayscale**
  - Grayscale simplifies the image by reducing it to a single channel
- **Noise Removal Using Median Filter**
- **Image Enhancement**
  - To improve the visual quality of the grayscale image
- **Region of Interest (ROI) Extraction**
  - Conversion from RGB to YCbCr
    - This color space separates luminance (Y) from chrominance (Cb and Cr)
    - This transformation makes it easier to identify skin regions
  - Thresholding
    - To separate the object (palm) from the background
    - A binary image is created where pixels within a specific range of YCbCr values (matching skin tone) are set to 1 while other pixels are set to 0
- **Binary to RGB conversion**

Feature Extraction

- **RGB features are extracted**
    - Matlab is utilized for feature extraction

Table 1. Samples of the converted palm images into components of the RGB values.

Image ID	Red (R)	Green (G)	Blue (B)	Status
Image 001	39.03780	34.134139	26.82800	anemic
Image 002	37.01250	33.848009	29.13950	anemic
Image 003	43.87580	30.547063	25.57720	anemic
Image 004	40.80080	32.910173	26.28900	anemic
Image 005	45.47100	31.396006	23.13300	anemic

Results:

Table2. Evaluation metrics for individual machine learning models.

Classifiers	Evaluation Metrices%				
	Accuracy	Specificity	Precision	Sensitivity	F1 Score
Random Forest	99.53%	100%	100%	99.22%	99.61%
SVM	81.80%	82.62	84.24%	87.49%	80.72%
Naïve Bayes	78.16%	79.19%	73.09%	77.45%	74.13%
ANN	74.45%	76.47%	92.71%	78.14%	75.83%
Decision Tree	99.20%	100%	100%	98.71%	99.35%

Random Forest recorded the highest accuracy

Results:

Stacking recorded the highest accuracy

Table 3. Evaluation metrics for ensemble models.

S/N	Ensemble method		Accuracy	Specificity	Precision	Recall/Sensitivity	F1 Score
			Evaluation metrics				
1	Bagging	NB	79.75%	59.68%	70.18%	76.02%	72.99%
		SVM	80.48%	86.75%	82.94%	22.14%	77.17%
		ANN	78.56%	75.79%	79.56%	81.36%	83.36%
		DT	79.24%	100%	100%	60.81%	75.63%
2	Boosting		74.67%	71.39%	86.07%	73.20%	79.11%
3	Voting	RF+SVM+ANN	82.46%	88.00%	94.14%	80.16%	86.59%
		RF+DT+NB	99.22%	100%	100%	98.71%	99.35%
		SVM+NB+RF	83.16%	80.50%	87.76%	84.78%	86.24%
		ANN+SVM+NB+DT+RF	87.30%	90.09%	94.40%	86%	90.01%
		SVM+ANN+NB	82%	87.67%	81.90%	78.22%	87.89%
4	Stacking	NB+RF	99.98%	100%	100%	100%	100%
		RF+NB+SVM	99.53%	100%	100%	99.22%	99.61%
		NB+RF+SVM+ANN	99.30%	100%	100%	98.84%	99.42%
		ANN+DT+RF+SVM+NB	99.98%	100%	100%	100%	100%
		SVM+NB+ANN	82.12%	83.99%	89.35%	88.22%	89.23%

Future Research

RECOMMENDATION FOR NEXT RESEARCH

- Segmentation Models in Detail
- Color palette Research Paper

R&D PROJECT

Thank you

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