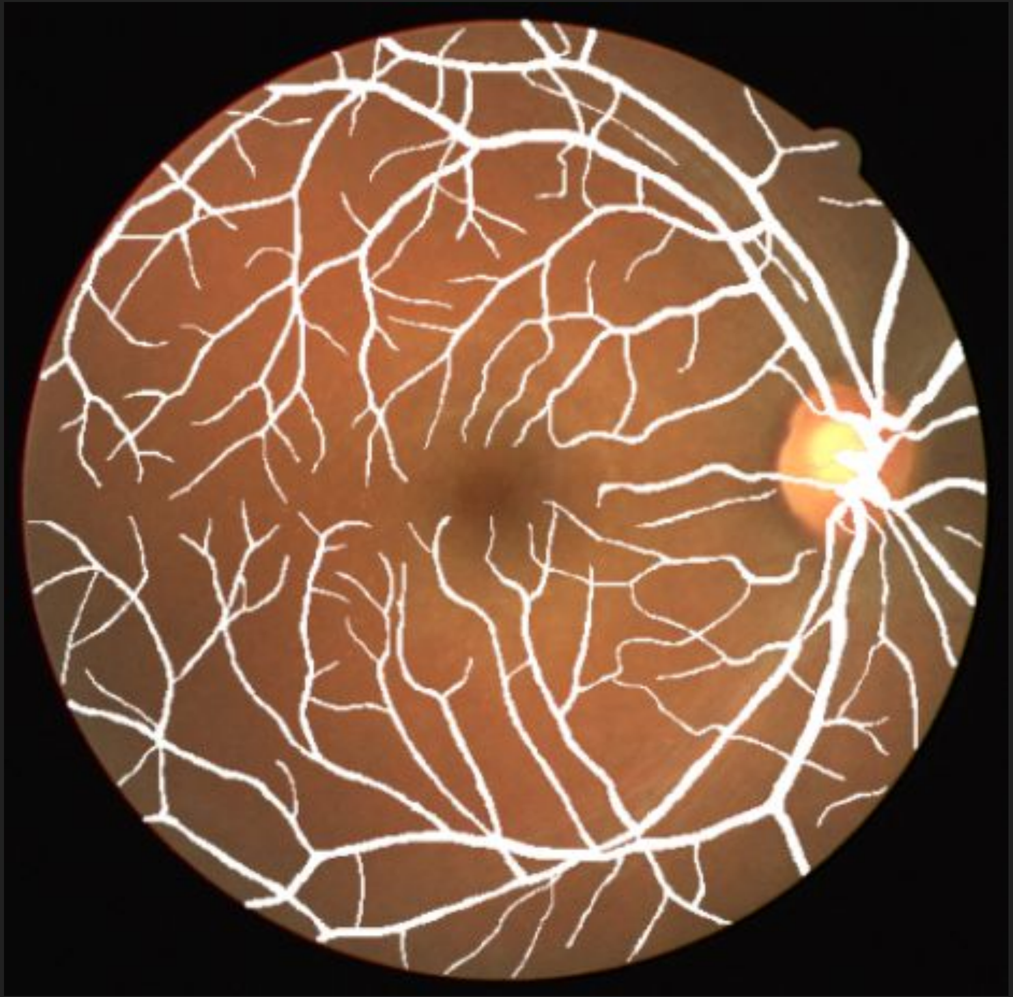
Retinal Vessel Segmentation using U-nets



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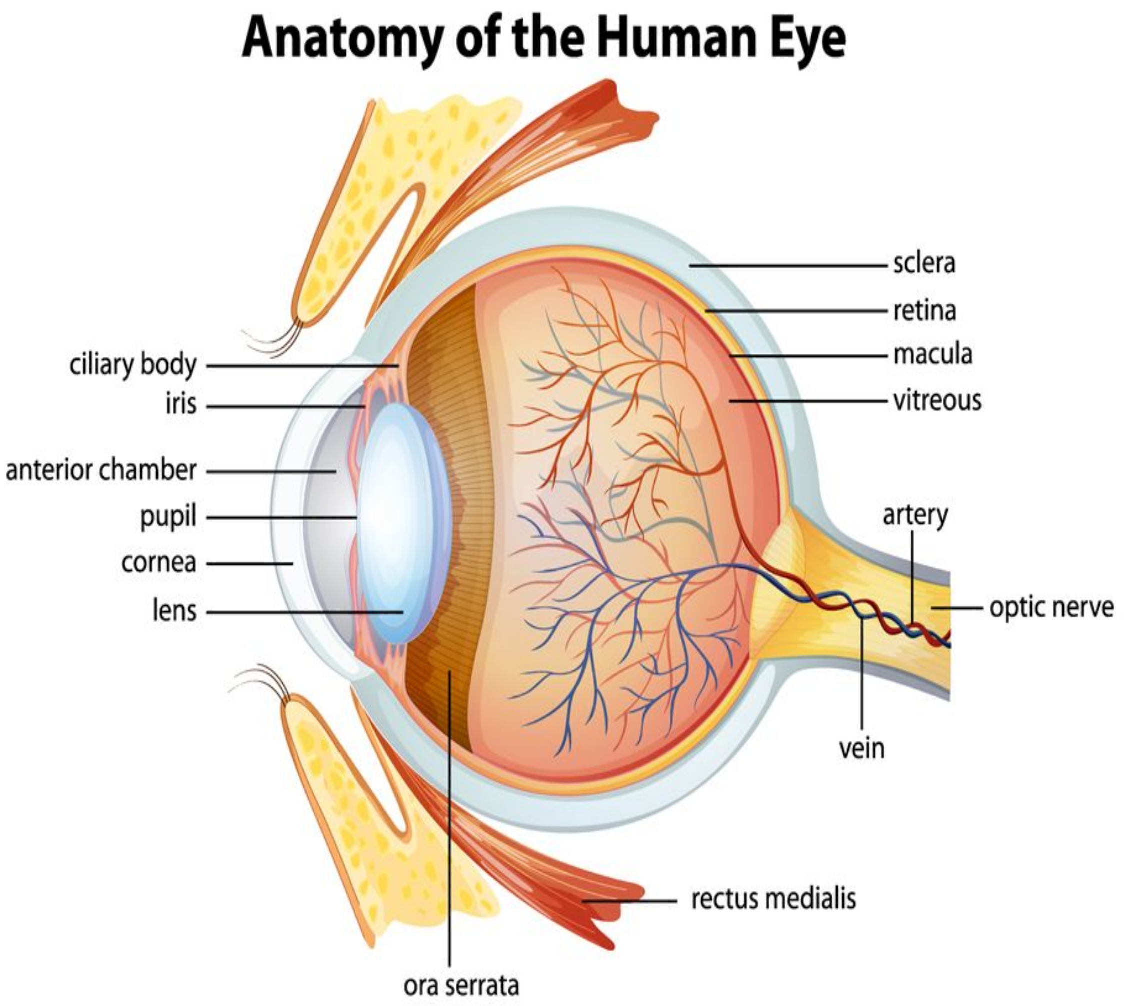


Objectives

- ❑ Retinal vessel Segmentation using U-net
- ❑ Utilizing Various Preprocessing and Postprocessing Techniques.
- ❑ Comparing Various variation of U-net’s Artitecture.
  - ❑ Sequential U-net (Simple)
  - ❑ Residual U-net
  - ❑ Recurrent U-net
  - ❑ R2 U-net (Residual Recurrent Unet)
  - ❑ Simple U-net with Attention)
- ❑ Web Application (Deployment): Creating a user-friendly interface to deploy the developed U-net models for real-world usage in medical field.

Datasets

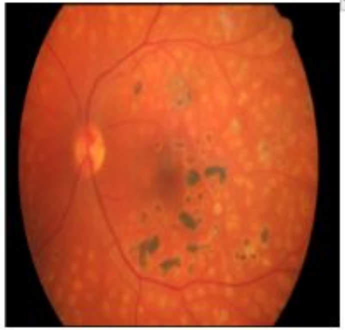
Dataset	Year	Number of Images	Image Size	Description
DRIVE [1]	2004	20	584 * 565 (originally) 576 * 544 (for training)	Digital Retinal Images for Vessel Extraction (DRIVE) dataset.These images are captured from diabetic patients and are commonly used for evaluating algorithms for retinal vessel segmentation.
CHASE [3]	2012	28	999 * 960 (originally) 992 * 960 (for training)	Retinal vessel segmentation challenge (CHASE) dataset. It is curated for vessel segmentation tasks and features images captured from both healthy and diseased eyes.
HRF [2]	2012	45	3304 * 2236 (originally) 1024 * 1024 (for training)	High-Resolution Fundus (HRF) dataset .It is curated for vessel segmentation tasks and features images captured from both healthy and diseased eyes. elopment and evaluation.

Test : Train : Val == 7 : 2 : 1 (Split for all of them)

DRIVE

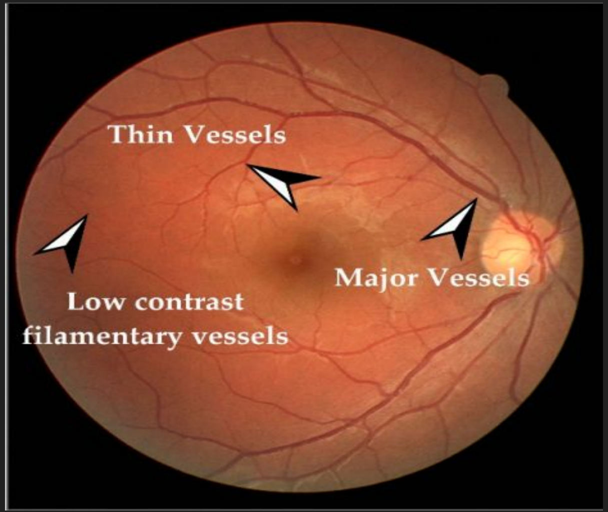
CHASE

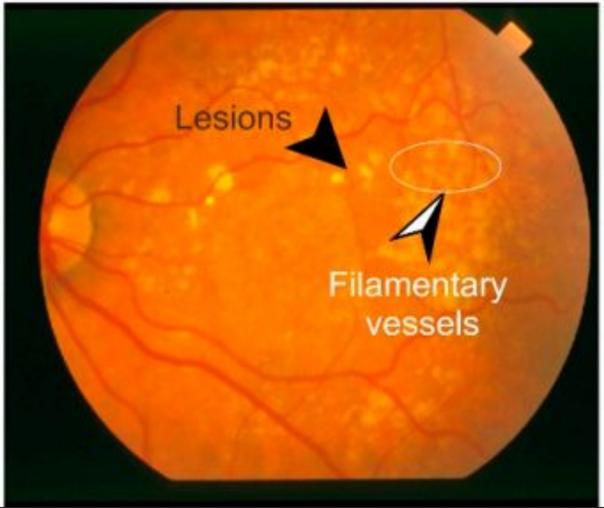
HRF

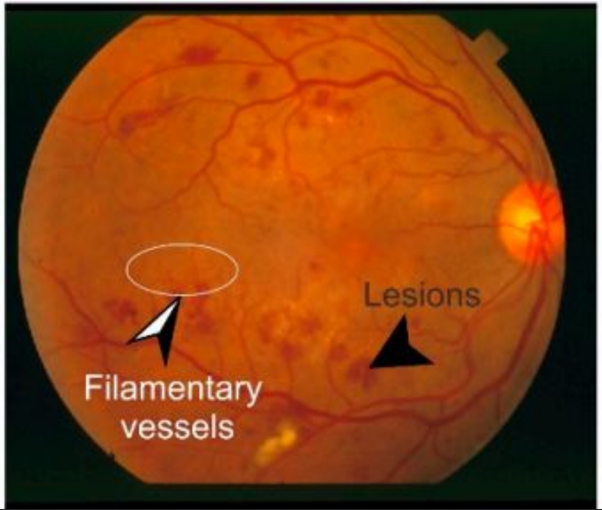


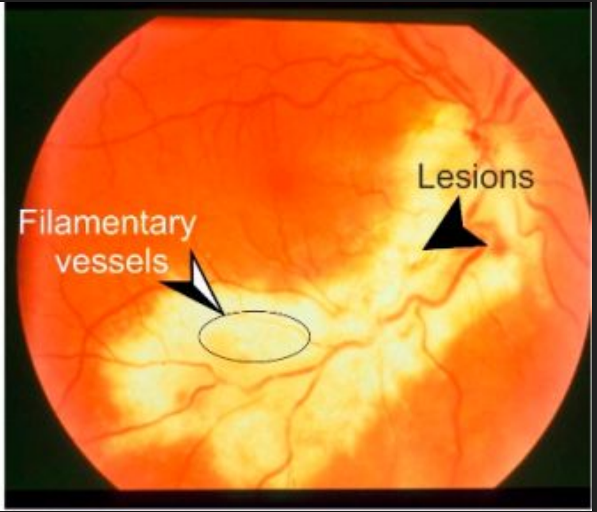
Current Challenges

- different sizes of retina. It makes it difficult for the model to be able to keep track of all size vessels.
- Vessels identification in pathological retinal images faces a tension between accurate vascular structure extraction and false responses near pathologies (such as hard and soft exudates, hemorrhages ,microaneurysms and cotton wool spots) .









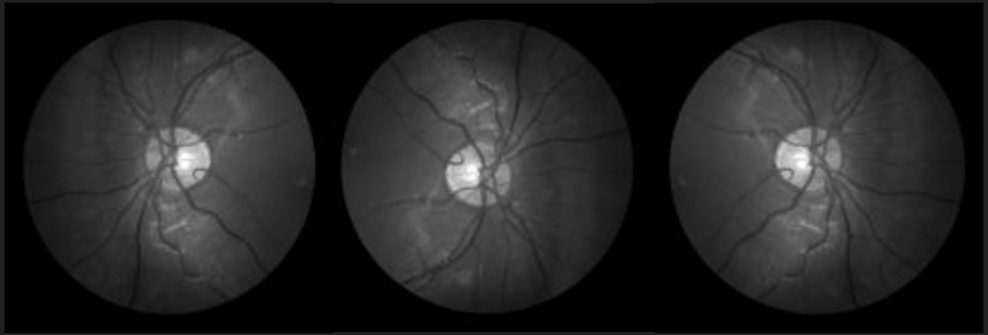
Preprocessing

- Using tf.keras.layers
  - Resizing (all 3 channels)
  - Preprocessing on Green Channel
    - CLAHE
    - Gamma Correction
    - Norm Clip
    - Morphological filter (top hat)
  - Concatenation of Preprocessed image to Original image
  - Multiplication with ROI (calculated by thresholding on Green Channel)
  - Augmentation

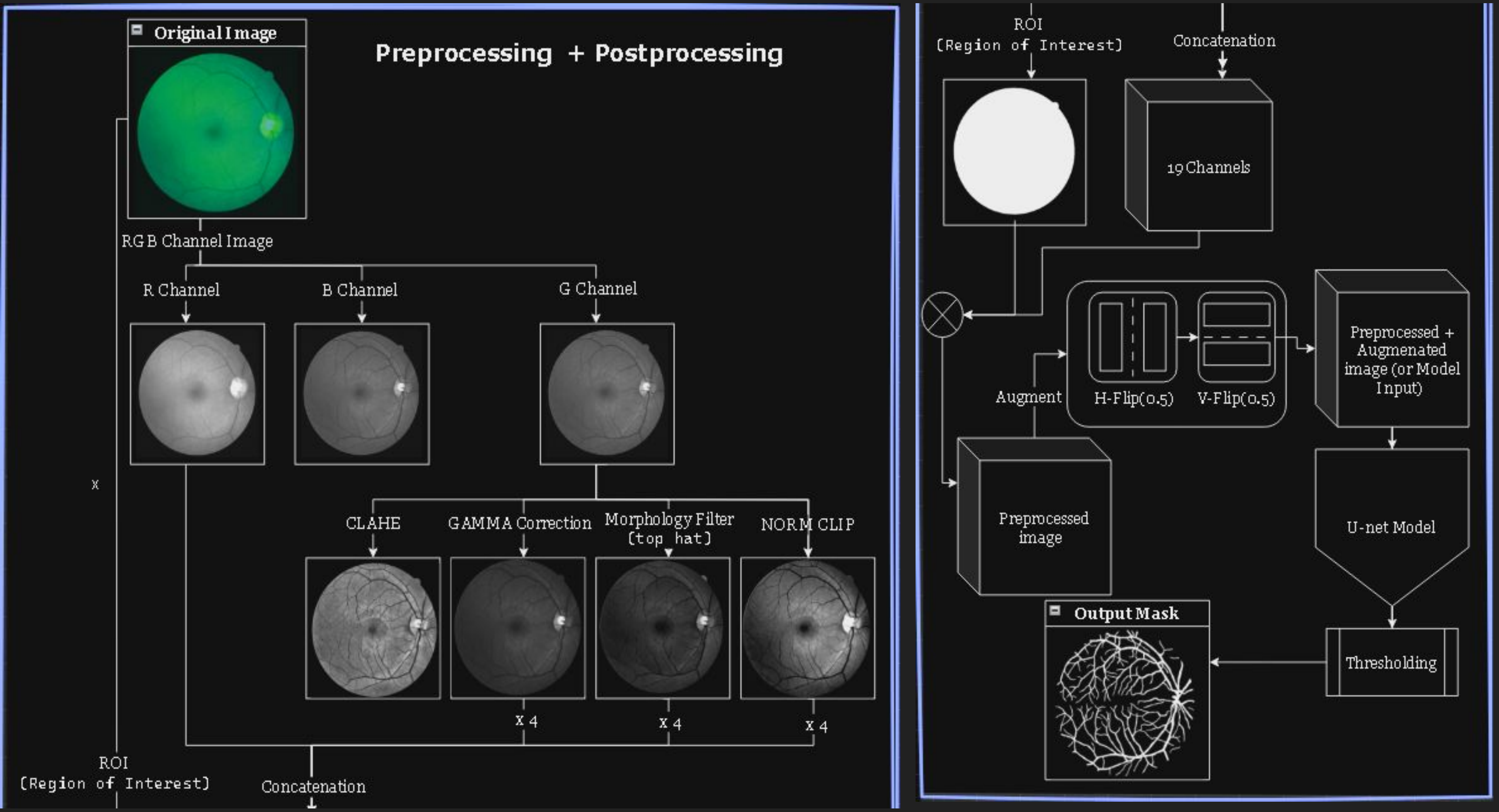
Augmentation

- Using Albumentation library
  - H-Flip (prob = 0.5)
  - V-Flip (prob = 0.5)
  - Same is applied to masks.

Will result in 4 Different Images with equal probability.



Augmented images



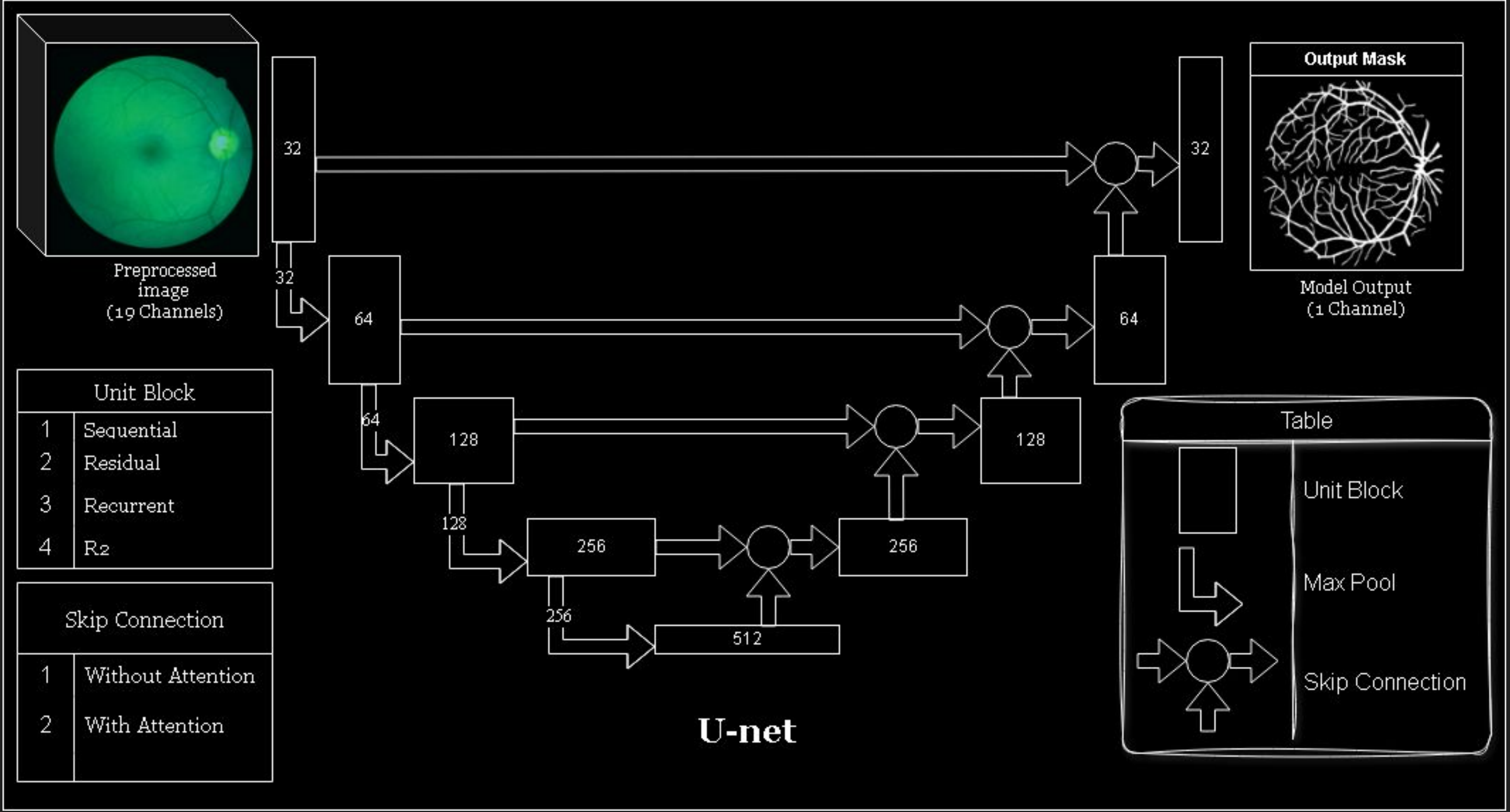
Preprocessing + Postprocessing
Original Image
RGB Channel Image
R Channel
B Channel
G Channel
CLAHE
GAMMA Correction
Morphology Filter
(top hat)
NORM CLIP
x 4
x 4
x 4
x
ROI
(Region of Interest)
Concatenation
ROI
(Region of Interest)
Concatenation
19 Channels
Augment
H-Flip(0.5)
V-Flip(0.5)
Preprocessed + Augmenated image (or Model Input)
Preprocessed image
U-net Model
Output Mask
Thresholding

Models

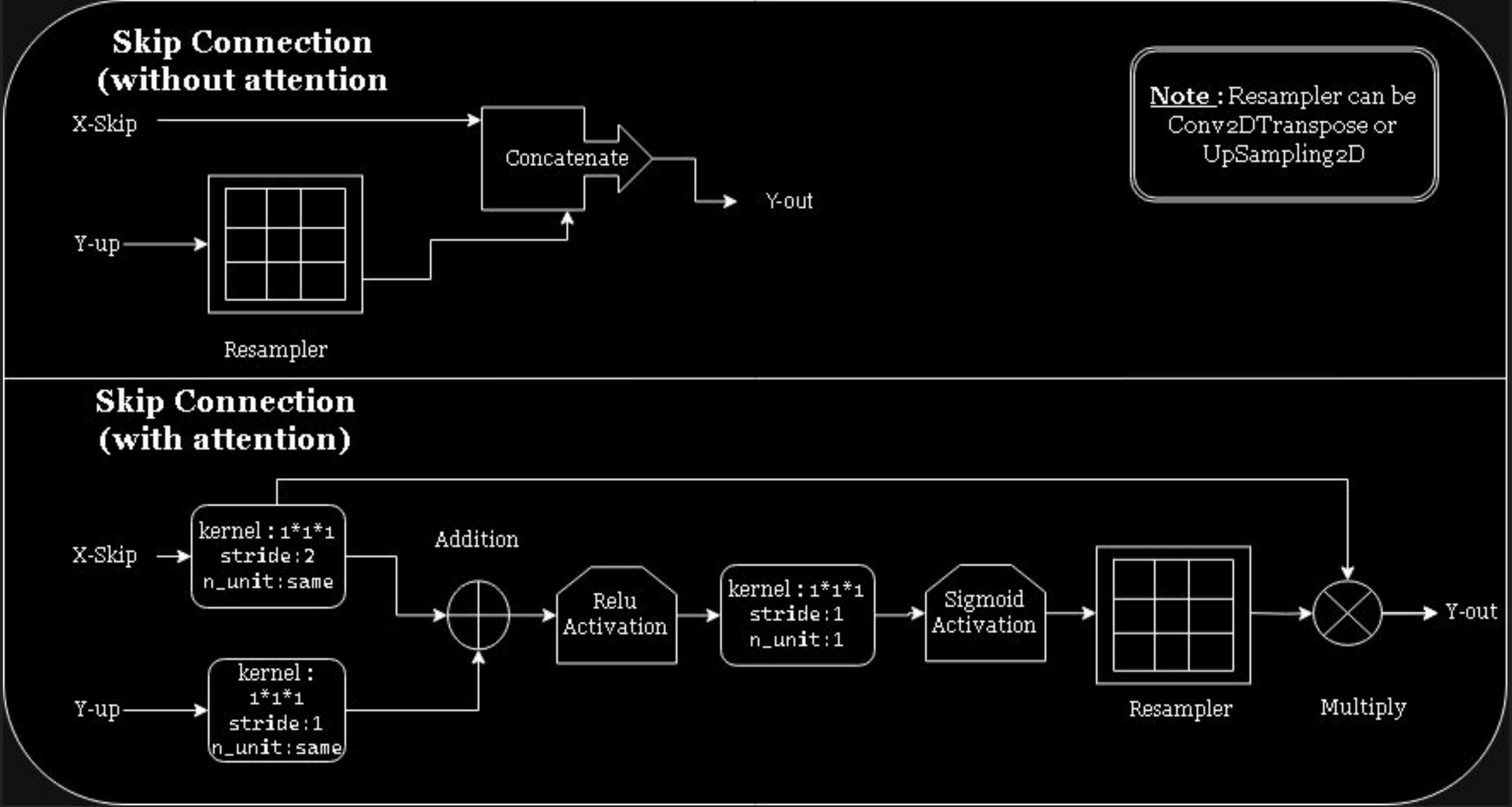
- Various Unet Models Compared (build)
  - Sequential U-net (Simple) : The basic implementation of UNet
  - Residual U-net : The residual U-Net incorporates residual connections, inspired by the ResNet architecture.
  - Recurrent U-net : The recurrent UNet introduces recurrent connections,by incorporating recurrent units, such as LSTM or GRU cells.
  - R2 U-net (Residual Recurrent Unet) : This variation represents a fusion of the residual and recurrent architectures
  - Simple U-net with Attention : Soft Attention mechanisms are employed instead of traditional skip connections that enable dynamically focus on relevant regions of the input image,

Model's Parameter

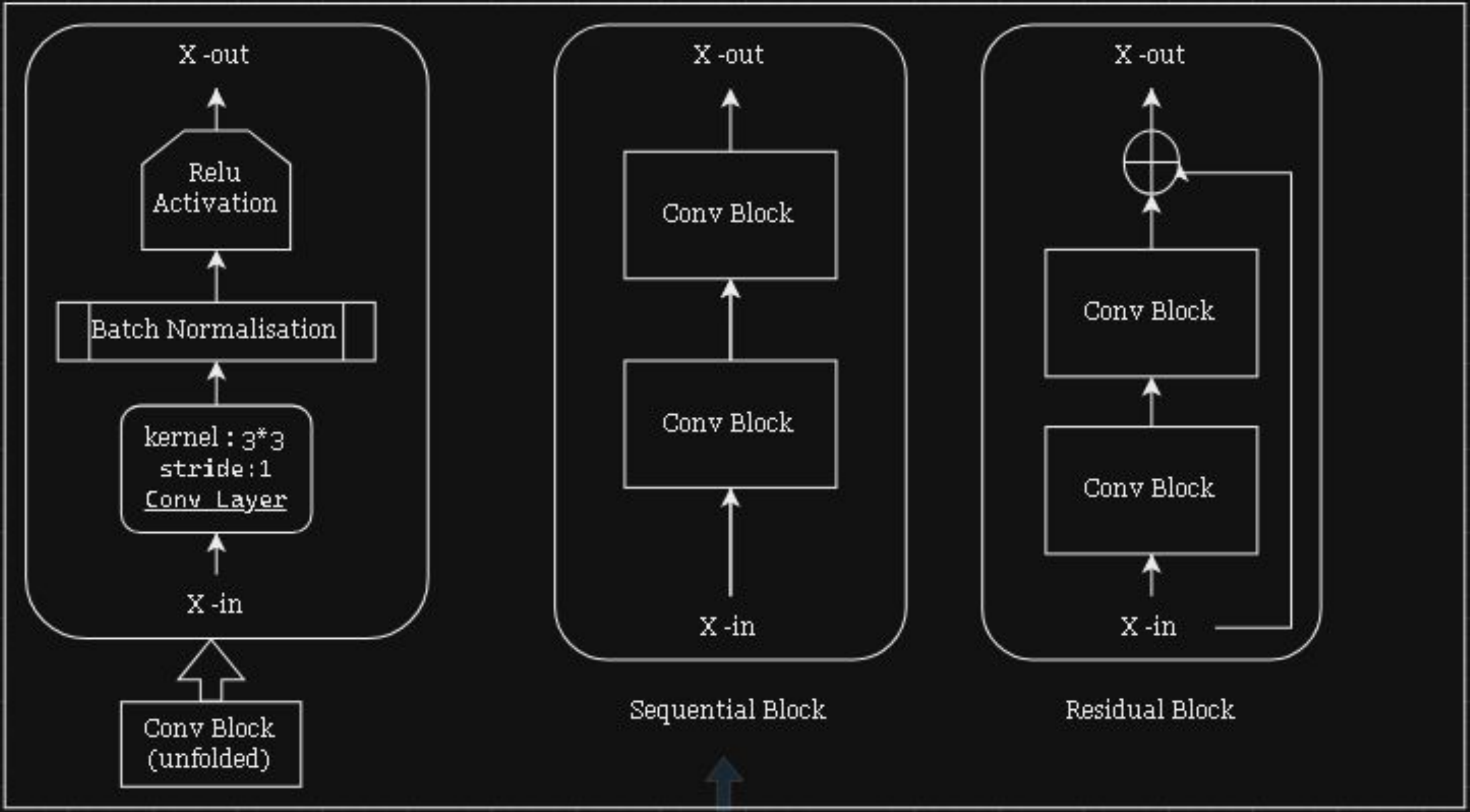
- U-net's Parameters:
  - Level = 4
  - Start units = 32
  - Scale = 2
  - Dilation rate = 1
  - n_channels (input) = 19
- General Parameters:
  - Optimizer = Adam (lr = 0.005)
  - Epochs = 150
  - Batch Size = 2
- Callbacks
  - Checkpoint (for best Weights)
  - ReduceLROnPlateau (0.6,5)
- Loss
  - Jaccard loss
- Metrics :
  - Specificity & Sensitivity
  - IOU
  - AUC
  - Accuracy & Fscore (B= 1)



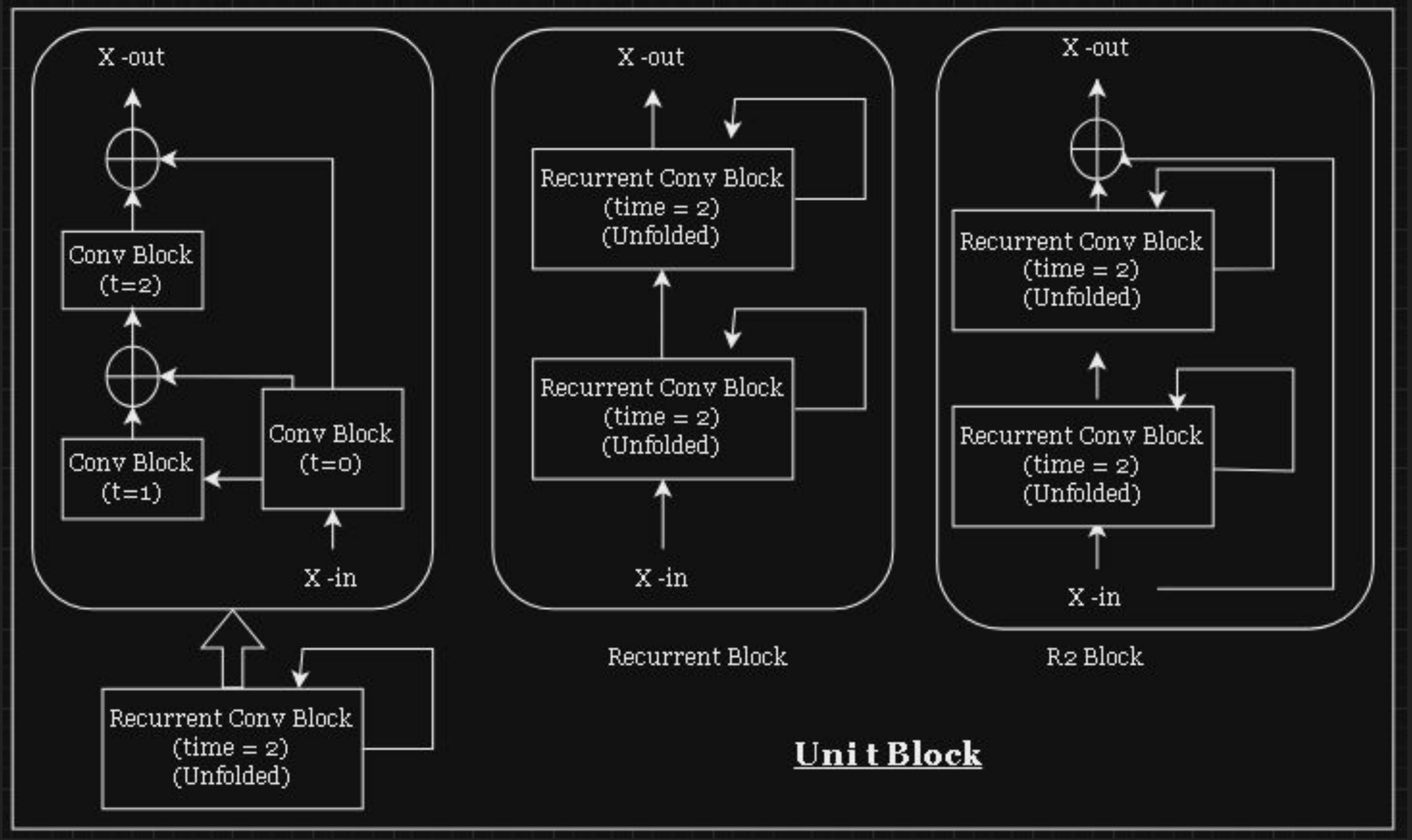
Basic U-net Architecture



Skip Connection (with and without attention)



Simple & Residual Unit Block



Recurrent & R2 (Residual Recurrent) Unit Block

Model Results

Dataset	Model	Split	Accuracy	Auc	FScore	Iou	Loss(jaccard)	Sensitivity	Specificity
DRIVE	Simple Unet	train	0.959481	0.913883	0.827087	0.705446	0.294554	0.8078	0.98019
		val	0.961587	0.918631	0.823483	0.699934	0.300066	0.817227	0.979247
		test	0.957424	0.921806	0.824812	0.701958	0.298042	0.830396	0.974732
	Residual Unet	train	0.962111	0.916503	0.837091	0.720011	0.279989	0.810432	0.982829
		val	0.96136	0.915785	0.822299	0.698224	0.301776	0.813958	0.979473
		test	0.959719	0.920714	0.831877	0.712222	0.287778	0.824055	0.978313
	Recurrent Unet	train	0.961697	0.922209	0.839318	0.72326	0.27674	0.831561	0.979469
		val	0.96185	0.921255	0.827599	0.7059	0.2941	0.832459	0.977797
		test	0.959712	0.928341	0.835572	0.717652	0.282348	0.846951	0.97509
	R2 Unet	train	0.958344	0.912549	0.820413	0.695856	0.304144	0.793454	0.980795
		val	0.960604	0.919286	0.818806	0.693201	0.306799	0.812987	0.9786
		test	0.957358	0.912579	0.817612	0.691798	0.308202	0.795469	0.97929
	Attention Unet	train	0.960194	0.922131	0.83223	0.712872	0.287128	0.823327	0.978785
		val	0.959762	0.92513	0.820138	0.695114	0.304886	0.834996	0.975079
		test	0.957974	0.926009	0.827	0.705154	0.294846	0.833548	0.974791

Dataset	Model	Split	Accuracy	Auc	FScore	Iou	Loss(jaccard)	Sensitivity	Specificity
HRF	Simple Unet	train	0.965476	0.918251	0.843967	0.730866	0.270766	0.819779	0.984365
		val	0.964884	0.918319	0.812865	0.685831	0.31001	0.828345	0.978159
		test	0.969487	0.922706	0.863558	0.760394	0.245855	0.828028	0.988253
	Residual Unet	train	0.96683	0.932126	0.854492	0.746746	0.255017	0.854502	0.981457
		val	0.965626	0.929639	0.820757	0.697458	0.299498	0.851128	0.976816
		test	0.970383	0.935383	0.871037	0.77188	0.233123	0.859679	0.984965
	Recurrent Unet	train	0.966945	0.927531	0.854096	0.746107	0.255534	0.847883	0.98246
		val	0.966407	0.926022	0.824373	0.702536	0.295487	0.844963	0.978749
		test	0.970646	0.929896	0.870763	0.771474	0.233612	0.849815	0.986569
	R2 Unet	train	0.967624	0.934227	0.859424	0.754195	0.247401	0.866896	0.980806
		val	0.965531	0.93163	0.823706	0.701625	0.29631	0.864816	0.975579
		test	0.970792	0.935092	0.873505	0.775693	0.228721	0.86664	0.984522
	Attention Unet	train	0.966239	0.93187	0.852629	0.743877	0.257857	0.855849	0.980642
		val	0.96457	0.92897	0.814722	0.688927	0.304912	0.853003	0.97484
		test	0.969865	0.933594	0.868763	0.768333	0.236623	0.856954	0.984745

Dataset	Model	Split	Accuracy	Auc	FScore	Iou	Loss(jaccard)	Sensitivity	Specificity
CHASE	Simple Unet	train	0.974525	0.907107	0.808292	0.678875	0.319206	0.792083	0.987898
		val	0.969245	0.883633	0.76767	0.624773	0.375227	0.743987	0.985701
		test	0.967318	0.901233	0.772169	0.62979	0.378193	0.790044	0.981263
	Residual Unet	train	0.978849	0.927341	0.842813	0.728852	0.268962	0.838501	0.989135
		val	0.973513	0.911931	0.807688	0.678453	0.321547	0.809435	0.985641
		test	0.970217	0.917022	0.7955	0.661046	0.346201	0.827041	0.981562
	Recurrent U-net	train	0.977607	0.927883	0.835386	0.717845	0.280212	0.839469	0.987749
		val	0.972952	0.918759	0.806985	0.677529	0.322471	0.823394	0.983983
		test	0.970402	0.923721	0.799996	0.667405	0.341507	0.840018	0.980983
	R2 U-net	train	0.976944	0.915241	0.826328	0.704611	0.293228	0.81055	0.989086
		val	0.972026	0.905324	0.795998	0.66197	0.33803	0.793499	0.985205
		test	0.970127	0.913673	0.792834	0.657264	0.349629	0.817794	0.982069
	Attention U-net	train	0.973691	0.9163	0.806055	0.675787	0.321605	0.80938	0.985625
		val	0.968049	0.907286	0.773627	0.631742	0.368258	0.79406	0.980856
		test	0.965343	0.913679	0.767091	0.622952	0.384757	0.815263	0.977321

Result Analysis

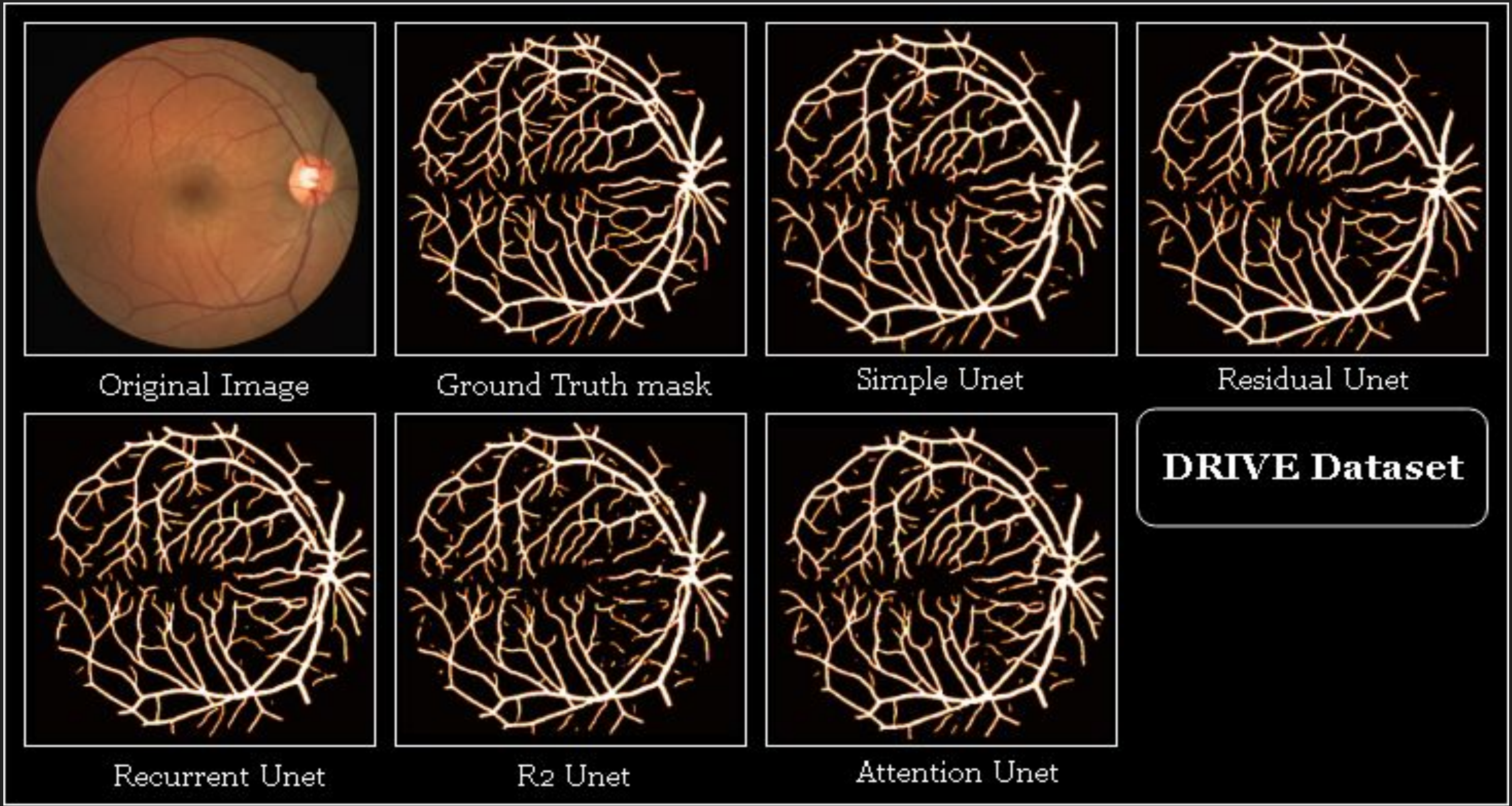
- Talking about the DRIVE and CHASE data, Recurrent U-net outperforming other models on testing data. Followed by Residual U-net which is also performing better then rest models.
- On HRF dataset (high quality image datasets) the R2 U-net outperformed other models , followed by a tough fight between Residual and Recurrent U-net.

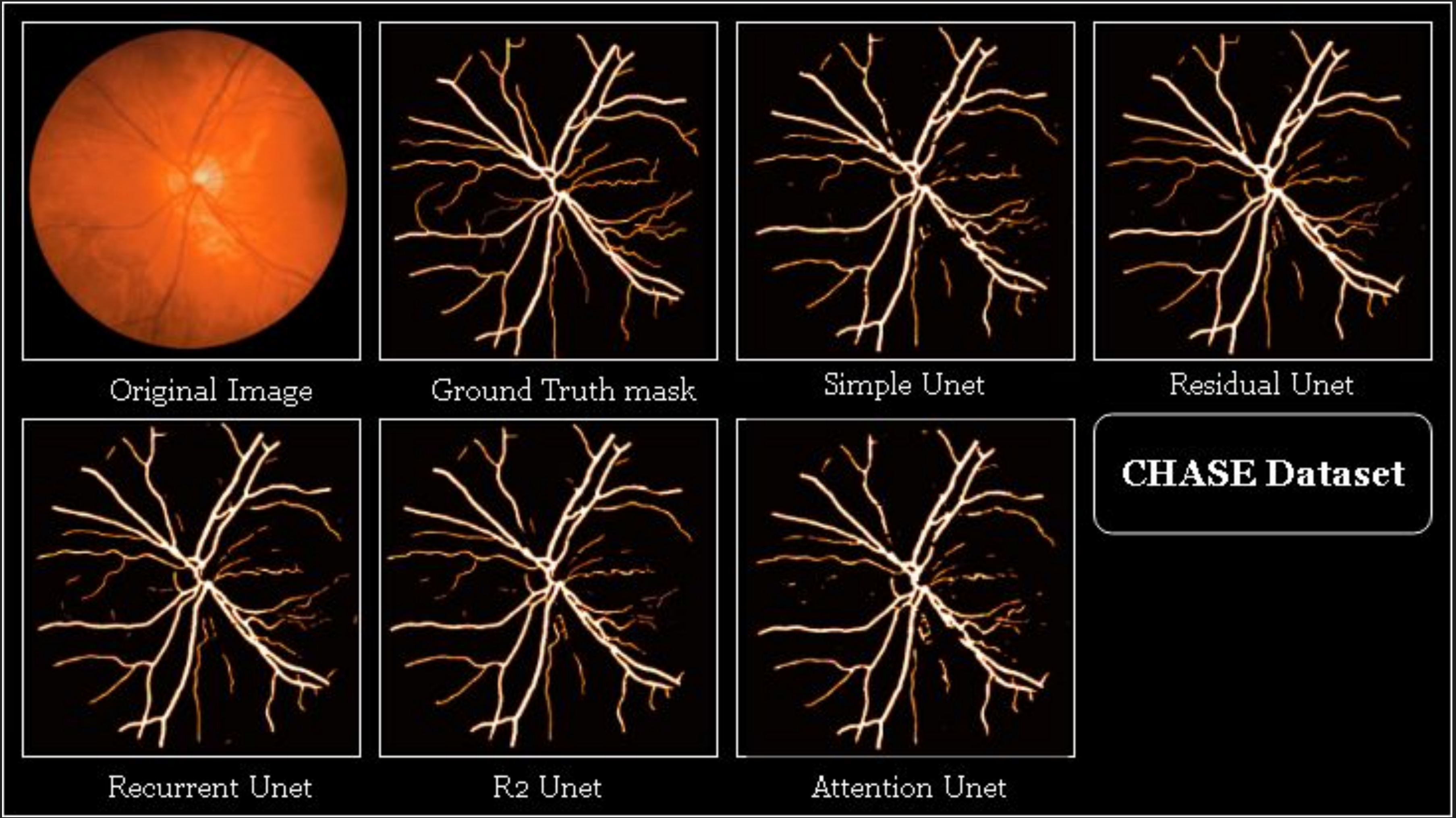
- The Sequence for model performance considerin metrics values previous on test data is:
  - DRIVE: Recurrent > Residual > Attention > Simple > R2 Unet
  - CHASE: Recurrent > Residual > R2 > Simple> Attention U-net
  - HRF: R2 > Recurrent > Residual > Attention > Simple U-net

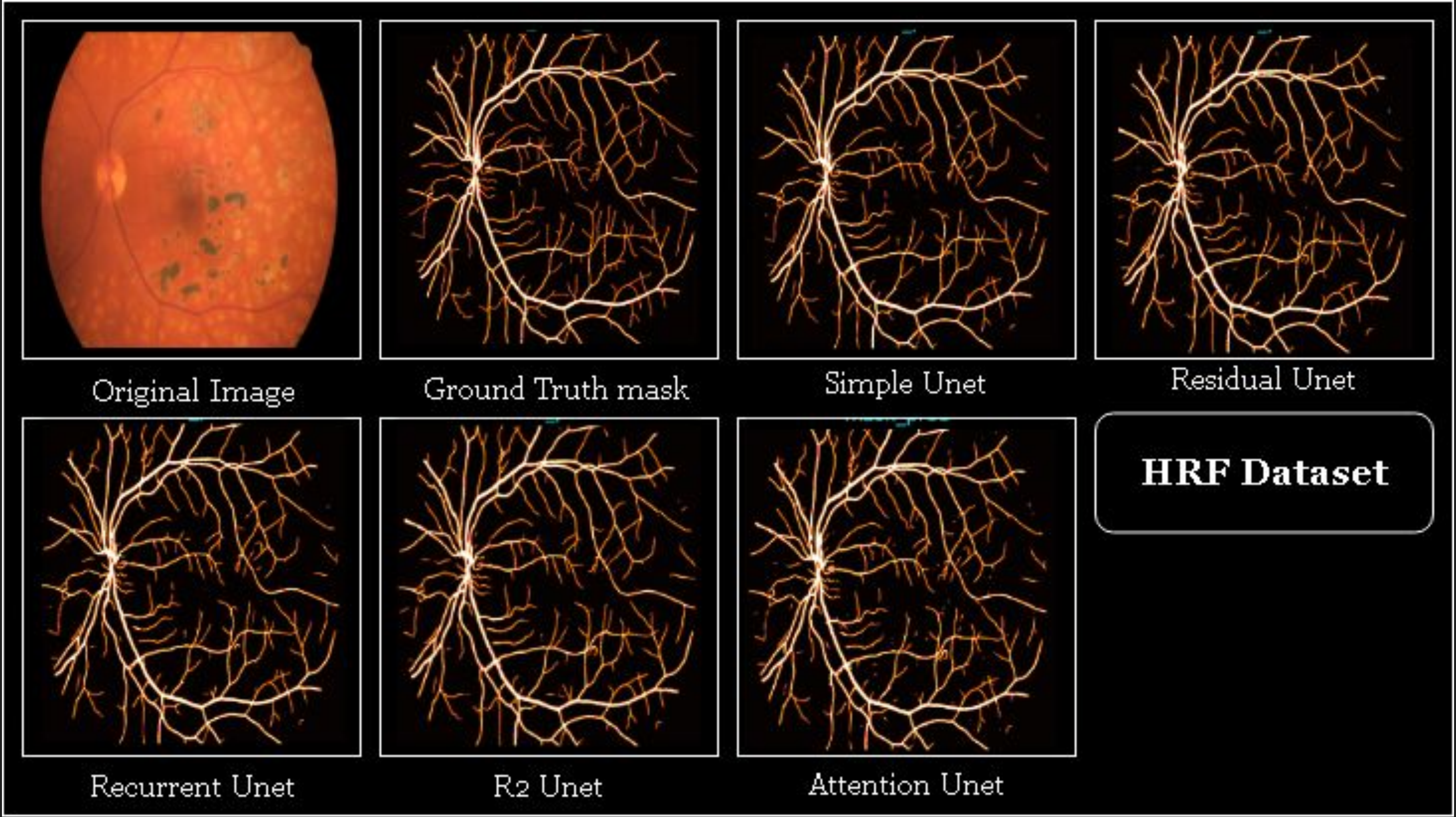
Note : The image size is also reduced from DRIVE -> CHASE -> HRF dataset.

- Some more analysis we construct , for the fundus image vessel segmentation task ,R2 U-net tends to perform well as we increase the image size.and the Recurrent U-net generally performs slightly better than Residual U-net.(maybe because the number of parameters follow the same trend)

Model’s Performance




Original Image
Ground Truth mask
Simple Unet
Residual Unet
Recurrent Unet
R2 Unet
Attention Unet
CHASE Dataset


Original Image
Ground Truth mask
Simple Unet
Residual Unet
Recurrent Unet
R2 Unet
Attention Unet
HRF Dataset

Future Outlook

- ❑ Explore various additional preprocessing techniques to improve vessel segmentation accuracy.
- ❑ Investigate concurrent preprocessing methods applied to the same image to optimize segmentation.
- ❑ Experiment with alternative deep learning models such as DeepLab, SegNet, and architectures incorporating GANs and FPNs.
- ❑ Deploy the developed model into a practical application for real-world usage.
- ❑ Extend focus beyond vessel segmentation to tackle other retinal eye segmentation challenges, including identifying arteries, veins, optic disc, optic nerve, lesions, and hemorrhages.
- ❑ Web Server Deployment: Deploying final models on web servers for easy access by stakeholders.
- ❑ Research Paper References: Incorporating a wider range of research papers for informed methodology.
- ❑ Comparative Analysis: Comparing results with existing research for validation and improvement insights.

Conclusion

- The Recurrent U-net consistently outperformed other models on the DRIVE and CHASE datasets, exhibiting superior segmentation accuracy.
- Conversely, the R2 U-net demonstrated superior performance on the HRF dataset, closely followed by the Recurrent and Residual U-net models.
- Through comprehensive evaluation of key metrics including Sensitivity, IOU, AUC, and F-score, a performance sequence on test data for each dataset was determined.
- Analysis indicated that as the image size increased, the performance of the R2 U-net improved significantly for fundus image vessel segmentation tasks.
- The Recurrent U-net exhibited slightly better performance compared to the Residual U-net, potentially due to similar trends in the number of parameters.
- The project contributes to understanding the effectiveness of different models for retinal vessel segmentation tasks, aiding future research and clinical applications.
- Insights into dataset-specific performance highlight the importance of tailoring model selection based on dataset characteristics.
- Understanding the impact of image size and model architecture on segmentation performance informs future model development efforts and optimization strategies for retinal image analysis tasks.

References

- Datasets :
  - [1] Reference: Staal, J., Abramoff, M. D., Niemeijer, M., Viergever, M. A., & van Ginneken, B. (2004). Ridge-based vessel segmentation in color images of the retina. IEEE Transactions on Medical Imaging, 23(4), 501-509
  - [2] Reference: Budai, A., Bock, R., Maier, A., Hornegger, J., & Michelson, G. (2013). Robust vessel segmentation in fundus images. International Journal of Biomedical Imaging, 2013, Article ID 154860.
  - [13] Reference: Fraz, M. M., Remagnino, P., Hoppe, A., Uyyanonvara, B., Rudnicka, A. R., Owen, C. G., & Barman, S. A. (2012). An ensemble classification-based approach applied to retinal blood vessel segmentation. IEEE Transactions on Biomedical Engineering, 59(9), 2538-2548.

- Research Papers:
  - [4] Ronneberger, O., Fischer, P. and Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. In *Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18* (pp. 234-241). Springer International Publishing..
  - [5]Almotiri, J., Elleithy, K. and Elleithy, A., 2018. Retinal vessels segmentation techniques and algorithms: a survey. *Applied Sciences*, *8*(2), p.155.