ROBUST OPTIC DISC SEGMENTATION USING XNET ARCHITECTURE

Enhancing automatic segmentation and diagnosis for opthalmic diseases

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INTRODUCTION

Accurate Optic Disc Segmentation: Vital for Opthalmic Disease Diagnostics

Optic disc segmentation is crucial for detecting and monitoring ophthalmic diseases like glaucoma, diabetic retinopathy, and age-related macular degradation.

Variability in pathological features, and poor image quality present challenges to automatic optic disc segmentation.

We present a modified XNet[1] architecture that achieves state-of-the-art on the PALM[2] dataset and demonstrates robustness across other datasets.

OBJECTIVE

Primary Objective: To create a robust optic disc segmentation model using XNet architecture.

Specific Aims:
- Achieve state-of-the-art performance
- Demonstrate robustness
- Create a model using only authentic retinal images without augmentations

METHODOLOGY

Dataset for initial training and testing:
- PALM dataset
- 1144 images and optic disc masks
- Highly imbalanced dataset
- Resized uniformly and normalized

Metrics:
- Dice Coefficient
- IoU

Loss: Weighted Binary Crossentropy

Optimizer: Adam

Models trained and tested on PALM dataset for comparison:
- UNet[3]
- Attention UNet[4]
- SegNet[5]
- XNet

Datasets used to test robustness:
- ORIGA[6]
- REFUGE[7]
- G1020 [8]
- DRISHTI-GS[9]

RESULTS

XNet outperforms all the other models in the combined test set and the test subsets based on image centres.

Notably, XNet's performance on the most underrepresented type of image centre (Optic Disc) is significantly better than other models.

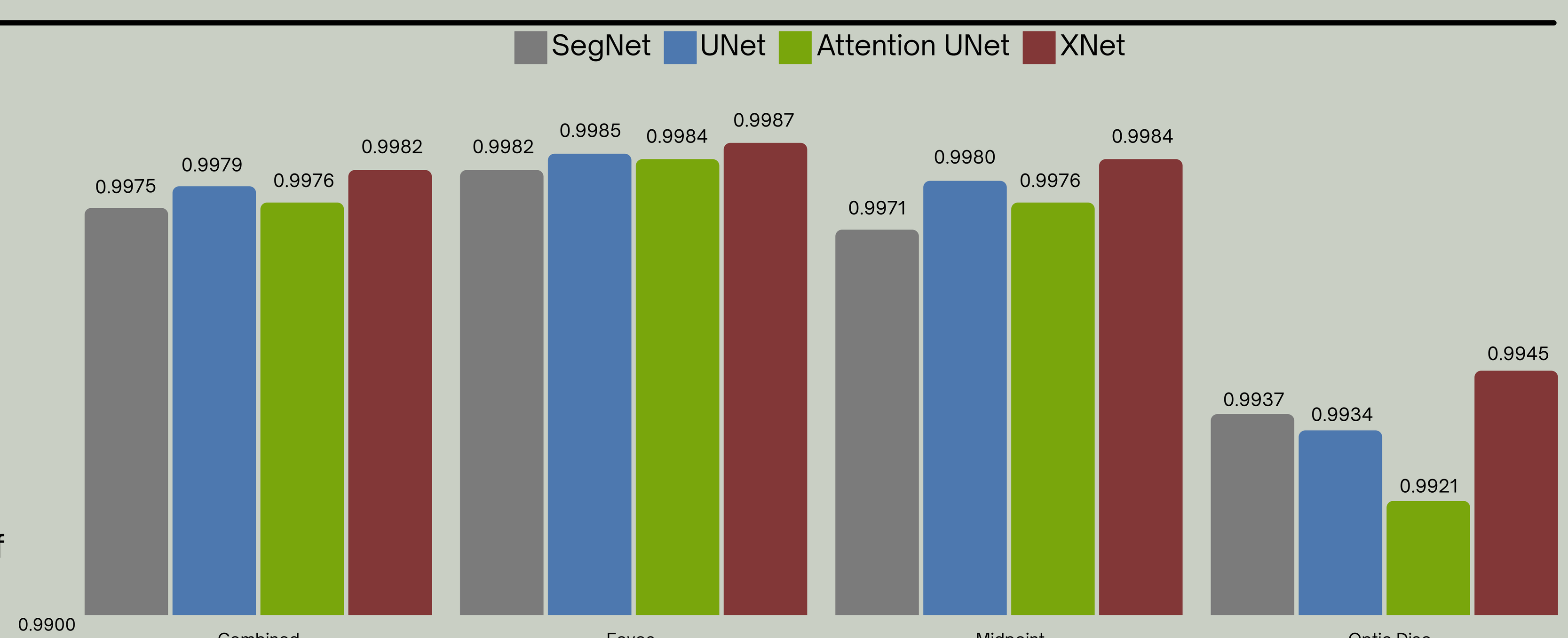


Fig 1: Dice scores of different models on a combined test set, and test sets for each type of image center

XNet defeats state-of-the-art (SOTA) models on the dice coefficients when tested on the REFUGE and DRISHTI-GS datasets.

It also performs remarkably on the ORIGA and G1020 datasets, thus proving its robustness.

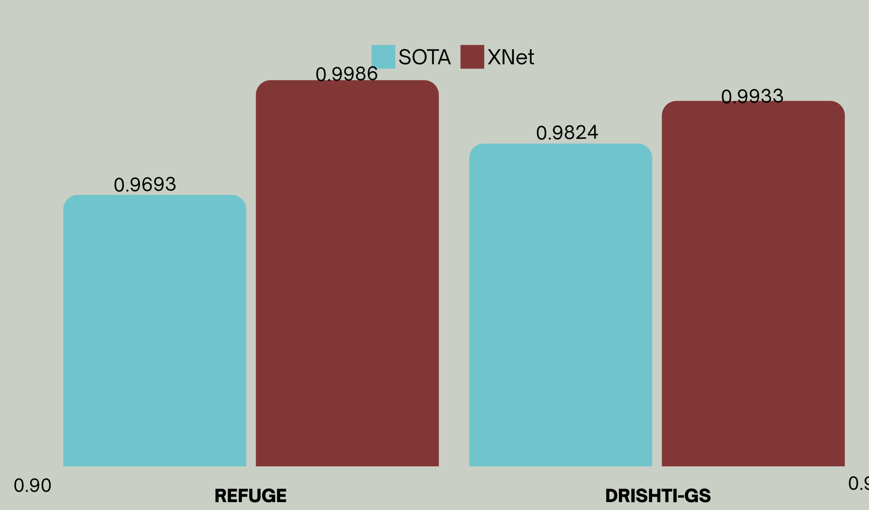


Fig 2. (a) Comparison of Dice coefficient XNet with state-of-the-art on REFUGE and DRISHTI-GS

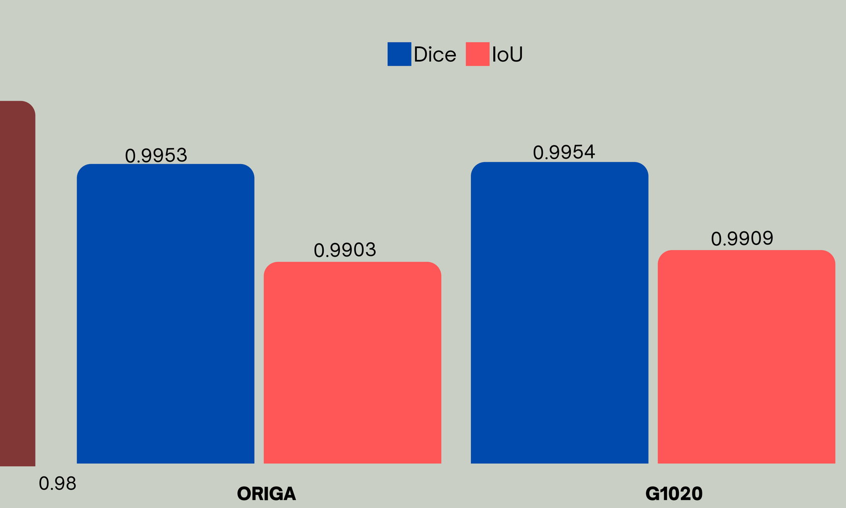


Fig 2.(b) Dice and IoU scores of XNet on ORIGA and G1020 datasets

MODEL ARCHITECTURE

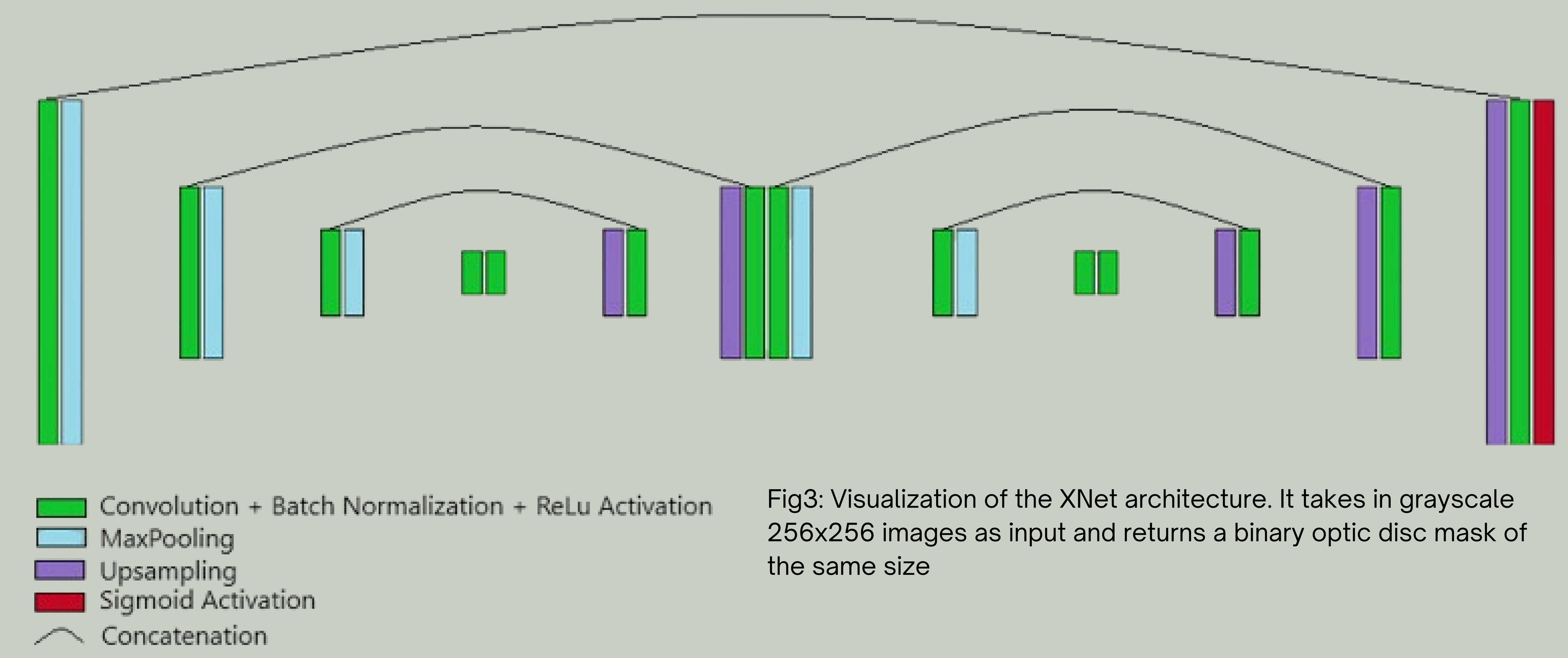
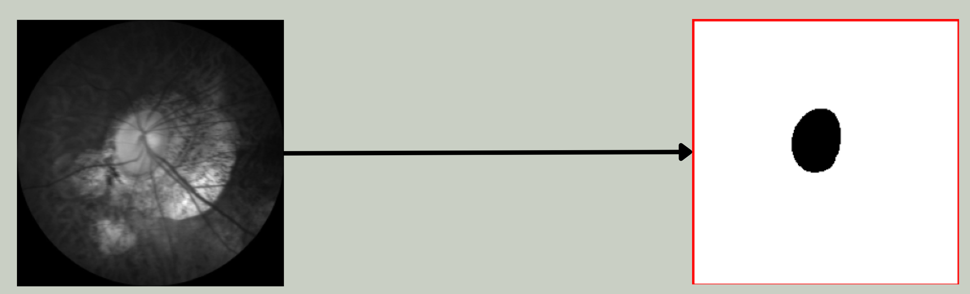
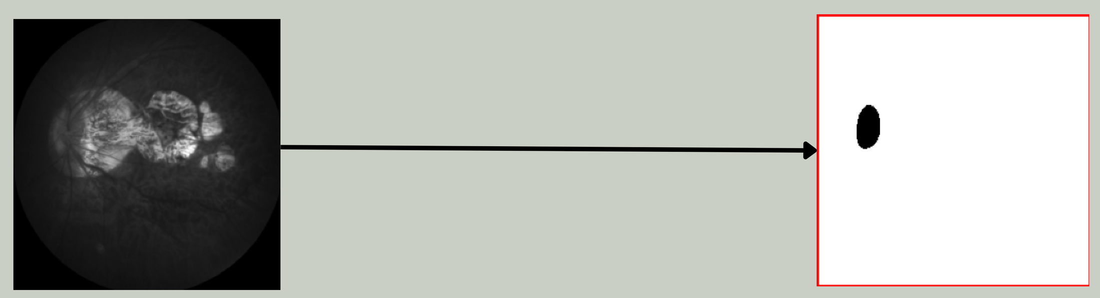


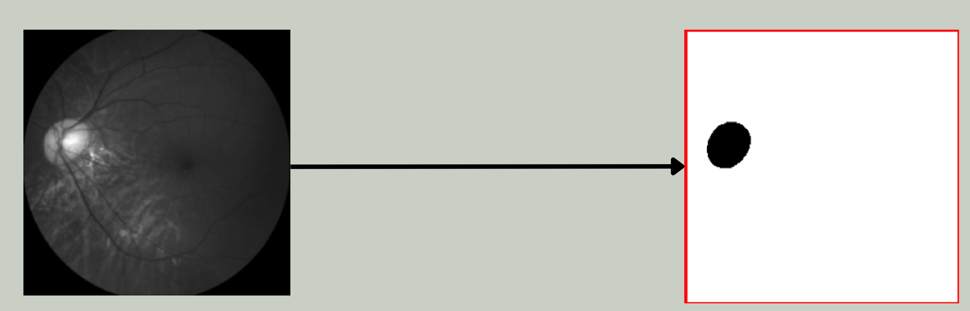
Fig3: Visualization of the XNet architecture. It takes in grayscale 256x256 images as input and returns a binary optic disc mask of the same size



(a)



(c)



(b)

Fig 4: Predictions of the XNet model on
(a) Optic disc centred image (b) Midpoint of fovea and optic disc centred image (c) Fovea centred image

CONCLUSION

In this study, we adapted XNet for binary segmentation tasks and trained and tested it on the PALM dataset to segment optic discs from retinal images. Our model not only outperforms existing, widely used segmentation architectures but also demonstrates exceptional robustness across unseen datasets (REFUGE, ORIGA, DRISHTI, G1020).

The impact of our findings extends to the development of more reliable automated diagnostic tools for ophthalmic conditions such as glaucoma. Furthermore, the adaptability of Xnet suggests potential applications in segmenting other anatomical structures beyond the optic disc.

For future work, we propose exploring the application of our model to segment retinal vessels and optic cups. Additionally, validation on larger, more balanced, and diverse datasets is recommended to further solidify its generalizability and clinical utility.

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REFERENCES

1. J. Bullock, C. Cuesta-Lazaro, and A. Quera-Bofarull, "XNeT: A Convolutional Neural network (CNN) implementation for medical x-ray image segmentation suitable for small datasets," Journal of Medical Imaging, p. 69, Mar. 2019, doi: 10.1117/12.2512451. Available: https://doi.org/10.1117/12.2512451
2. 1.H. Fang, F. Li, J. Wu, et al., "Open Fundus Photograph Dataset with Pathologic Myopia Recognition and Anatomical Structure Annotation," Sci. Data, vol. 11, no. 1, p. 99, Jan. 2024, doi: 10.1038/s41597-024-02911-2.
3. 1.Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Deep Learning for Biological Image Segmentation. In N. Navab, J. Hornegger, W. M. Wells, & A. F. Frangi (Eds.), Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015 (pp. 234-241).
4. 1.O. Oktay, J. Schlemper, L. Folgoc, et al., "Attention U-Net: Learning Where to Look for the Pancreas," arXiv preprint arXiv:1804.03999, Apr. 2018. [Online]. Available: https://doi.org/10.48550/arXiv.1804.03999.
5. V. Badrinarayanan, A. Kendall, and R. Cipolla, "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation," arXiv preprint arXiv:1511.00561, Nov. 2015, revised Oct. 2016. [Online]. Available: https://doi.org/10.48550/arXiv.1511.00561
6. Z. Zhang et al., "ORIGA(-light): An Online Retinal Fundus Image Database for Glaucoma Analysis and Research," in Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2010, pp. 3065-3068, doi: 10.1109/IEMBS.2010.5626137.
7. J. Orlando et al., "REFUGE Challenge: A Unified Framework for Evaluating Automated Methods for Glaucoma Assessment from Fundus Photographs," Medical Image Analysis, vol. 59, p. 101570, 2019, doi: 10.1016/j.media.2019.101570
8. M. N. Bajwa, G. A. P. Singh, W. Neumeier, M. I. Malik, A. Dengel, and S. Ahmed, "G1020: A Benchmark Retinal Fundus Image Dataset for Computer-Aided Glaucoma Detection," arXiv preprint arXiv:2006.09158, 2020. [Online]. Available: https://arxiv.org/abs/2006.09158. doi: 10.48550/arXiv.2006.09158
9. J. Sivaswamy, S. R. Krishnadas, G. Datt Joshi, M. Jain and A. U. Syed Tabish, "Drishti-GS: Retinal image dataset for optic nerve head(ONH) segmentation," 2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI), Beijing, China, 2014, pp. 53-56, doi: 10.1109/ISBI.2014.6867807.