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Optic Disc and Cup Segmentation via Enhanced U-Net with Residual and Attention Mechanisms

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RESEARCH HIGHLIGHT

- Optic Disc and Cup Segmentation
- Utilized modified attention-based residual U-Net for retinal image segmentation.
- Conducted comprehensive experiments with diverse datasets.

RESEARCH OBJECTIVES

- Evaluate adaptability of segmentation models to diverse image characteristics.
- Evaluate pretrained models as backbones for U-Net architecture to optimize segmentation tasks.
- Design robust and adaptable segmentation model leveraging Modified Attention Residual U-Net architecture.

INTRODUCTION

- Increased electronic device usage leads to rising eye disorders, requiring accurate detection in retinal images.
- Automated segmentation crucial for early diagnosis of conditions like glaucoma and diabetic retinopathy.
- This study systematically explores pretrained models' suitability for segmentation tasks and designs a robust model for diverse datasets.

MATERIALS

- Three publicly available dataset:

i. Drishti-GS [1],
ii. REFUGE Source-1 [2] and
iii. RIM-ONE-R3 [3].

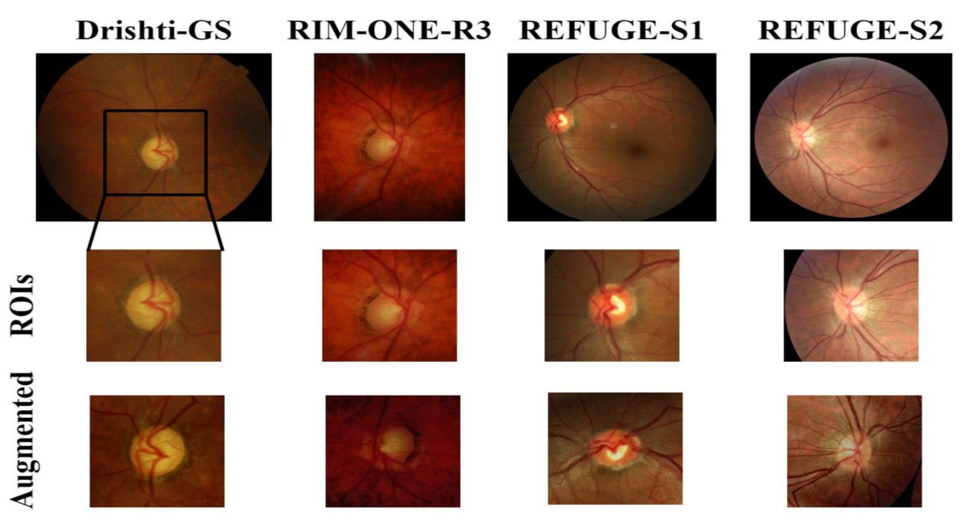

Fig. 1. displays sample images taken from Drishti-GS, RIM-ONE-R3, and REFUGE datasets, highlighting the diversity across four distinct domains encapsulated within the dataset.

METHODS

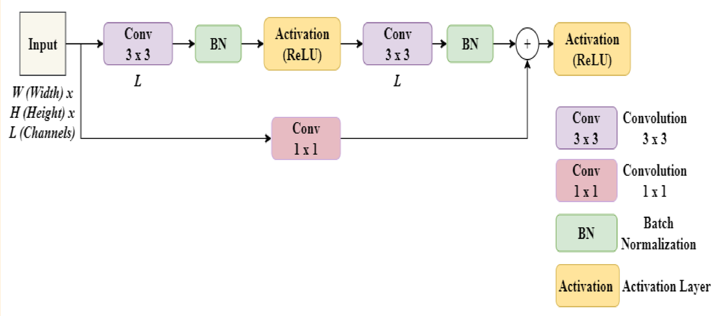

Fig. 2. Residual Connection Block

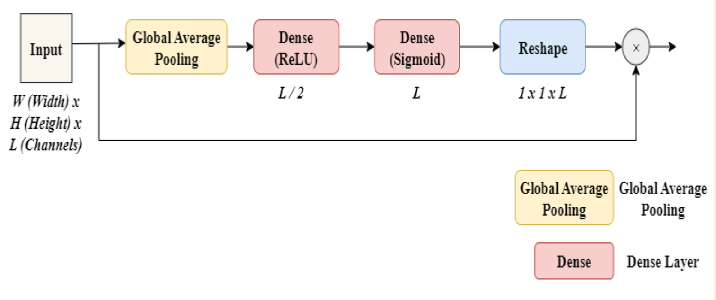

Fig. 3. Channel Attention Block

- **Effective Information Flow:** Facilitates smooth transition of features from low to high levels, ensuring effective learning.
- **Gradient Preservation:** Mitigates vanishing gradient issues, enabling better gradient flow for improved model training.
- **Semantic Feature Enrichment:** Refines attention weights to enhance semantic feature representation.
- **Focus Refinement:** Strategically adjusts focus on vital features, improving segmentation outcomes.

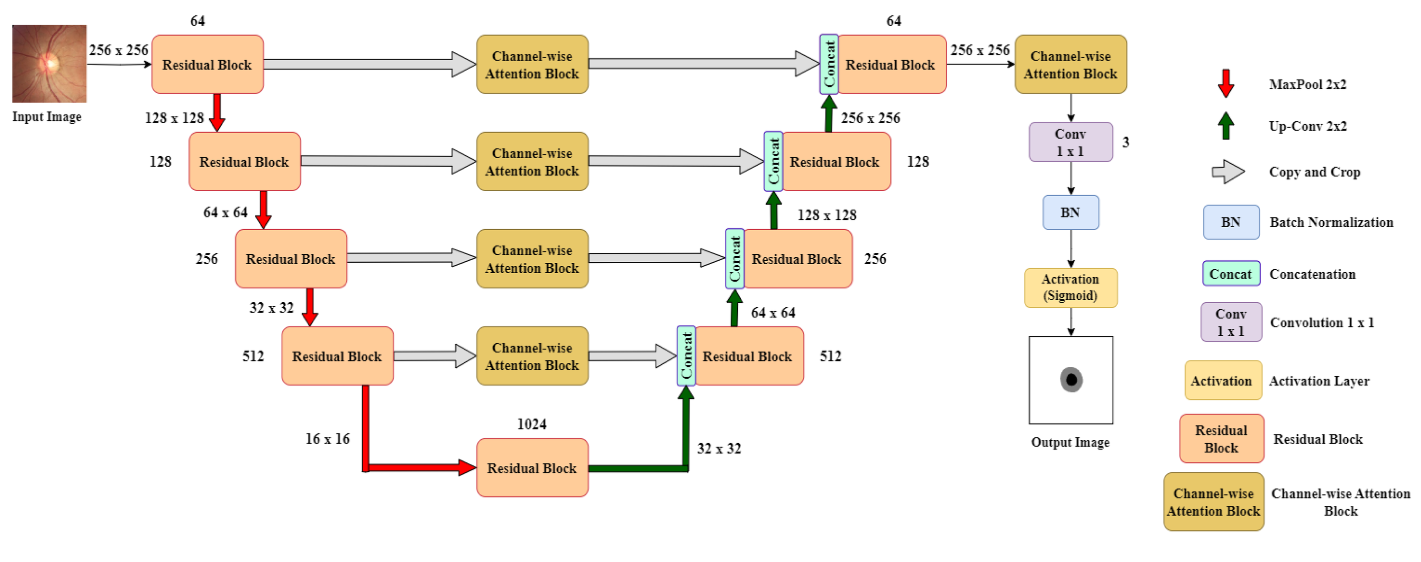

Fig. 4. Attention Residual U-net

- **Hierarchical Feature Extraction:** The integration of residual connections and attention mechanisms enables hierarchical feature extraction, capturing both low-level and high-level features effectively during downsampling.
- **Dynamic Feature Recalibration:** Channel-wise attention enhances discriminative power by dynamically recalibrating attention, focusing on informative channels and suppressing less relevant ones.
- **Integration of Spatial and Channel-wise Information:** Concatenating downsampling outputs with channel-wise attention during upsampling effectively integrates spatial and channel-wise information, enriching semantic features for accurate segmentation.

RESULTS

Table I
Segmentation outcomes (%) of the model on three datasets, presented in terms of Intersection over Union (IoU) and Dice Coefficient (DC) metrics.

Datasets	Optic Cup		Optic Disc	
	IoU	DC	IoU	DC
RIM-ONE-R3	83.52	91.02	92.45	96.08
REFUGE	88.88	94.11	95.26	97.57
Drishti-GS	90.56	95.05	96.23	98.07

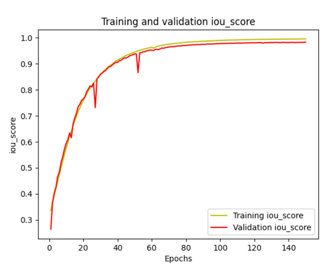

Fig. 5. Training and validation IoU curve

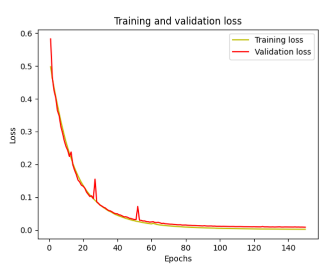

Fig. 6. Training and validation Loss curve

- Figures 5 and 6 show the IoU and loss curves for the validation dataset, respectively, closely matching the training curves. This alignment indicates the model's robust training and its capacity to generalize effectively to new data.
- Figure 7 displays segmentation results on representative images from different domains, showcasing the model's impressive ability to accurately delineate object boundaries in line with ground truth contours.

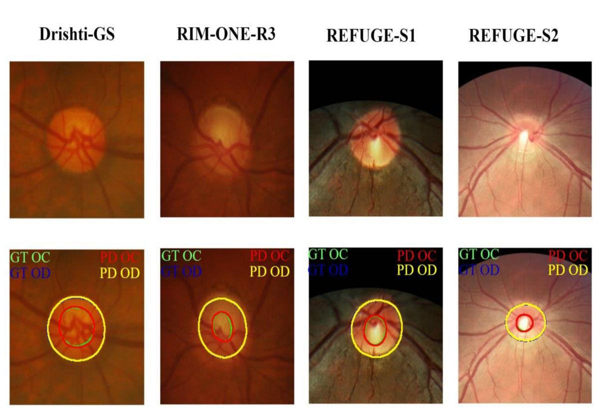

Fig. 7. Contour representations of ground truth (GT) and predictions (PD) for Optic Cup (OC) and Optic Disc (OD) across each dataset. GT of OC is depicted in green, PD of OC in red, GT of OD in blue, and PD of OD in yellow.

CONCLUSIONS

- Introduces significant segmentation improvements for optic disc (OD) and optic cup (OC) in retinal disease detection.
- Utilizes modified U-Net architecture with channel-wise attention and residual mechanisms.
- Achieves remarkable Intersection over Union (IoU) and Dice Coefficient (DC) scores: 87.77% IoU, 93.48% DC for OC, and 95.09% IoU, 97.48% DC for OD.
- Future work: Improve model adaptability for consistent segmentation across diverse retinal image datasets.

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