Semantic Segmentation on Eye Images for Keratitis Detection

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Goals

- Semantic Segmentation applied to OpenEDS Model, and then evaluated on real-life keratitis dataset
- Create an expressive model that can accurately capture features for pupil, iris, and sclera
- Use extensive augmentation to normalize the datasets against each other to maximize performance on keratitis dataset

Related Works

- Initial approaches used signal processing to identify various parts of the eye, such as the iris [1].
- Learned methods first used boundary detection rather than pixel classification [2].
- Convolutional Networks rose with the prominence of SegNet + Conditional Random Fields [3].
- MobileNet v2 and a UNet + DenseNet architecture used on the OpenEDS dataset, originally for VR/AR gaze tracking. However, competition goal was to minimize parameters while retaining high performance instead of maximizing performance[4, 5].

Dataset

- OpenEDS data consisted of 12759 labeled images from 152 individuals in a standardized 400 x 640
- OpenEDS images come with a labeled iris, pupil, and sclera
- Keratitis dataset gathered from Sankara Nethralaya consisting of 20 images of either bacterial, fungal, or viral keratitis
- Preprocessed keratitis images to be the same size by zero padding top and bottom
- Hand labeled keratitis images for the respective 3 classes with help of Stanford Medical Students
- Input/Output: EDS Image input into model, and predicted mask is output

Methods

- **Baseline Binary:** Binary UNet for sclera detection
- **Baseline Multi Class:** Adapt UNet for multiclass classification for pupil, iris, and sclera
- **UNet + DenseNet:** Use of a UNet architecture connected to a Densenet through densely connected feature maps at multiple resolutions. Expressive loss function consisting of surface loss, categorical cross entropy loss, and dice loss.
- **Data Augmentation Factors:**

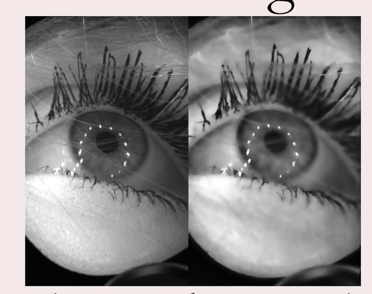

Figure 1: Original OpenEDS Image vs CLAHE Normalized and Bilateral Filtered Images

Geometric Mask Augmentation

- Utilize geometric objects as masks in order for the network to adapt to keratitis-like objects. Geometric masks based off of analyzed keratitis shapes, such as ovals and concentric circles.

Bilateral Filtering

- Utilize bilateral filtering, which is a non-linear, edge-preserving, and noise-reducing filter in order to smooth out images but emphasize edges to better detect boundary points between the iris, pupil, and sclera.

Contrast Limited Adaptive Histogram Equalization (CLAHE)

- Utilize Histogram Equalization in order to mimic similar lighting conditions across the OpenEDS Dataset and keratitis dataset to normalize pixel values across all ranges

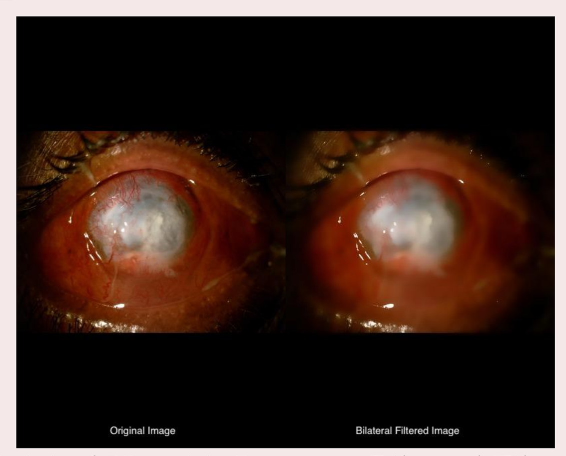

Figure 2: Original Keratitis Image vs Bilateral Filtered Image

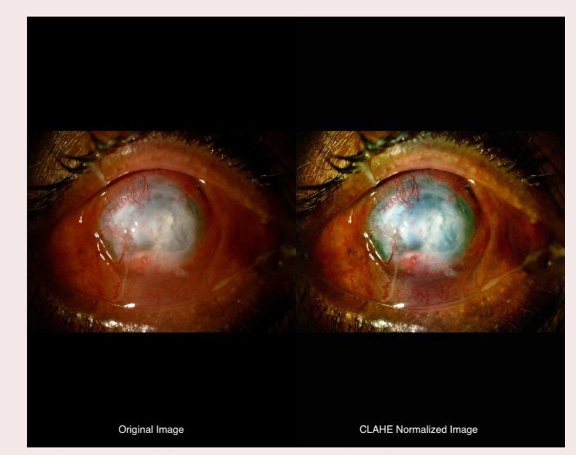

Figure 3: Original Keratitis Image vs CLAHE Normalized Image

Results

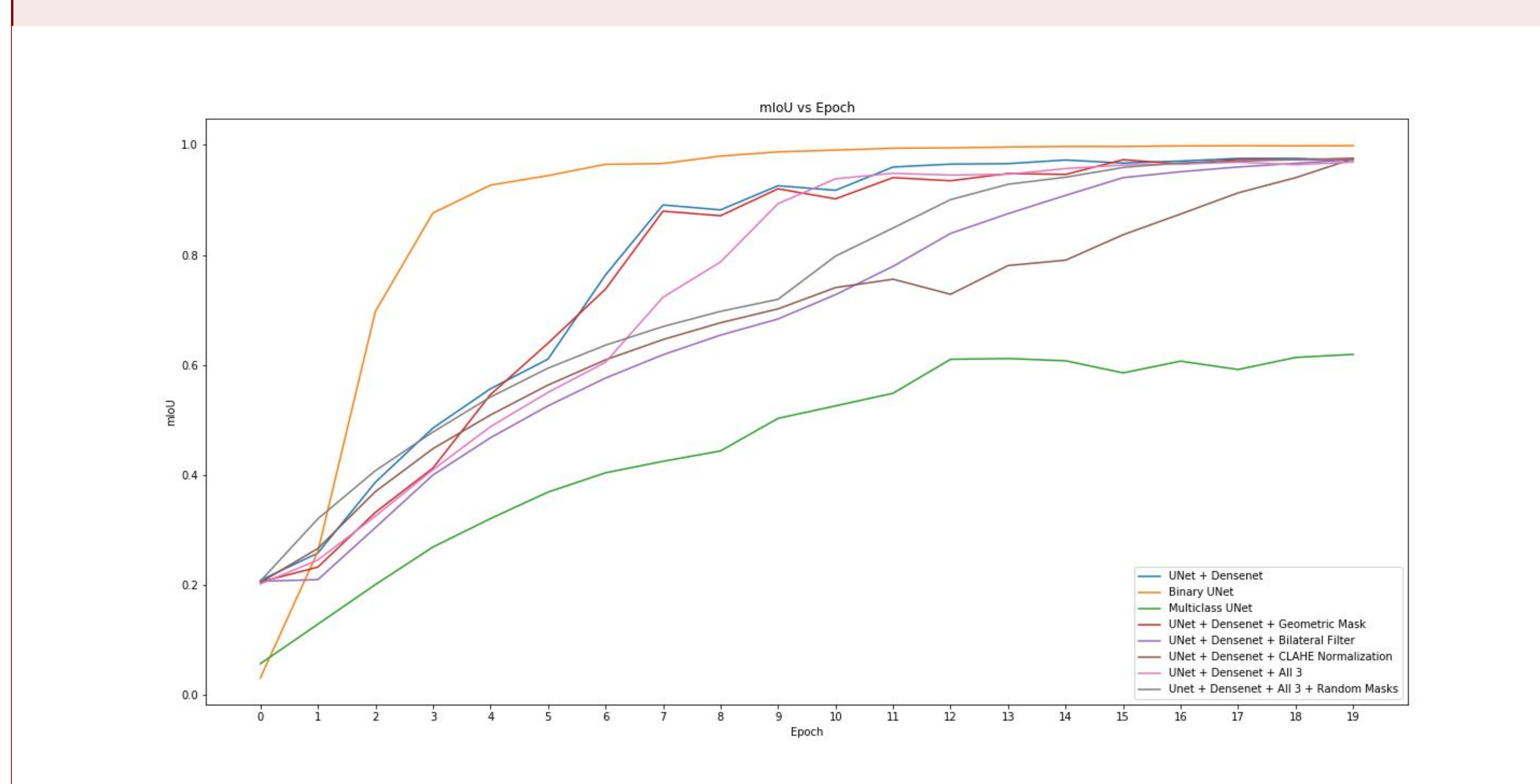

Figure 4: mIoU vs Epoch for Multiple Experiments

- Model architecture complexity reflects direct increase in mIoU.
- Geometric Masking helps the model improve the most, but bilateral filtering and CLAHE normalization do not provide increase our mIoU as much.
- Linear Combination of data augmentation techniques seems to fare slightly better than original UNet + DenseNet
- Random Mask Injection lowers mIoU which makes sense there are significant modifications to training data

Model Results

Model Name	mIoU (EDS)	mIoU (Keratitis)
Baseline (Multi Class)	0.6190	0.3451
UNet + DenseNet	0.9722	0.3847
UNet + DenseNet (GM)	**0.9755**	0.4256
UNet + DenseNet (BF)	0.9733	0.4034
UNet + DenseNet (CLAHE)	0.9747	0.4125
UNet + DenseNet (All 3)	0.9730	0.4491
UNet + DenseNet (All 3 + Random)	0.9674	**0.4729**

Discussion

- UNet Baseline is not expressive enough to capture that multiple modalities and edge cases, but more expressive loss functions and architectures help improve it.
- Geometric Mask Augmentation alone provides the most significant increase. Mask augmentation now used widely in many generative modeling tasks, and transfers well to vision and segmentation tasks.
- Increased data augmentation on training set improves keratitis detection task.

Future Work

- Continue to gather data to improve keratitis predictions
- Utilize CRFs in image processing pipeline for increased pattern recognitions
- Incorporate outlined keratitis prediction

References

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4. Van Thong Huynh, Soo-Hyung Kim, Guee-Sang Lee, and Hyung-Jeong Yang. Eye semantic segmentation with a lightweight model. In *2019 IEEE/CVF International Conference on Computer Vision Workshop*. IEEE, 2019.
5. Aayush K. Chaudhary, Rakshit Kothari, Manoj Acharya, Shusil Dangi, Nitinraj Nair, Reynold Bailey, Christopher Kanan, Gabriel Diaz, and Jeff B. Pelz. Ritnet: Real-time semantic segmentation of the eye for gaze tracking, 2019.