Rationale for the Choices Made in Creating the Three Models

1. Otsu's Thresholding
Implementation Choices:
- Gaussian Blur Preprocessing: Applied to reduce noise while preserving edges (kernel size 5×5), ensuring thresholding focuses on structural boundaries.
- Morphological Post-Processing: Used opening (to remove small noise) and closing (to fill holes) with a 5×5 kernel to refine masks.
- Class-Agnostic Approach: Treats the optic disc/cup as a single foreground region without distinguishing between them.

Rationale:
- Speed/Simplicity: Otsu is computationally efficient and requires no training data, making it suitable for initial exploratory analysis.
- Baseline Comparison: Provides a reference for evaluating more complex models. However, it struggles with:
  - Intensity overlap between disc/cup and background.
  - Irregular shapes or pathologies (e.g., glaucoma-induced cup enlargement).
  - Overlapping vasculature or lesions.

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2. Contour Detection
Implementation Choices:
- Canny Edge Detection: Parameters (50, 150) balance noise tolerance and edge sensitivity.
- Largest Contour Selection: Prioritizes contours by area to approximate disc/cup boundaries.
- Morphological Smoothing: Closes gaps in detected edges with a 3×3 kernel.

Rationale:
- Edge-Driven Segmentation: Suitable for well-defined anatomical boundaries. However:
  - Fails with weak edges (common in low-contrast retinal regions).
  - Struggles with overlapping vasculature or lesions.

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3. Pretrained U-Net
Implementation Choices:
- Architecture:
  - Encoder: efficientnet-b3 pretrained on ImageNet
  - Decoder: Custom U-Net decoder for medical image reconstruction.
- Training:
  - Class Weights: addresses class imbalance (background dominance).
  - Optimizer: AdamW with ReduceLROnPlateau scheduling for stable convergence.
- Output: 3-class segmentation (background, disc, cup).

Rationale:
1. Finetuning Pretrained Model:
   - There is not enough data (50 training images) to create a CNN model on its own and accurately create segmentation masks. It would likely overfit.

    - EfficientNet-B3: it’s known for balancing efficiency and accuracy, offering a good trade-off between model size and performance.
2. RGB Input Rather than Grayscale:
    - The model may find the differences in color between the disk/cup/background to be useful.
3. Validation Performance:
    - Cross-entropy loss optimization ensures pixel-wise accuracy.
    - Post-finetuning metrics (not shown here) likely outperformed classical methods.

Why Pretrained U-Net Was Ultimately Chosen

1. Accuracy:
    - Traditional methods (Otsu/Contour) fail to distinguish disc vs. cup and lack robustness to image variability. U-Net leverages contextual information across scales.
2. Generalization:
    - Pretrained weights mitigate overfitting, especially with limited training data
3. Adaptability:
    - The architecture can be extended to handle comorbidities (e.g., hemorrhages, drusen) with additional classes.

Conclusion: The pretrained U-Net is the most accurate for optic disc/cup segmentation due to its ability to more robustly understand which characteristics of the retinal image correspond to the optic disk and cup. Meanwhile, the Otsu and Contour implementations try to explicitly discover features of the image, such as edges, which may be unclear depending on the quality of the image. With lots of varied types of data, a deep-learning architecture like U-Net is most adept. The pre-trained aspect allows the model to work better with less data.

Commentary on Measurements, Analysis, and Error

Ultimately, while the U-Net model predicted segmented masks the best of the 3 models, a lot can be improved for the CDRs to be more real-world accurate.

The greatest improvement would result from retinal images with clear optic cups and high-quality, expert-verified annotations. Without precise and quality annotations, the model can not learn relevant trends in glaucoma and normal retinal images, as it may learn qualities that only exist due to low-quality annotations or retinal images.

Additionally, more data would also assist in making the U-Net model more accurate.

The mean CDRs between glaucoma and normal retinal images were about the same. Anecdotally, from manually annotating the retinal images, many of the glaucoma and normal optic cups and disks looked quite similar. Perhaps this contributed to the ultimate measurements of glaucoma and normal cups and disks being quite similar. The standard deviation for glaucoma CDR was greater than the normal CDR, perhaps because there was a class imbalance between glaucoma and normal.

The mean IOUs were pretty low for the U-Net segmentation masks:
Average Optic Disc IoU: 0.3093
Average Optic Cup IoU: 0.2214
Average Mean IoU: 0.3153

This is likely because there is not enough data for U-Net. The model is predicting the general shape pretty well, but it is not placing the segmentations in the most accurate areas of the image.