EPA (Elegant Persian Algorithms)

Development of an AI Model for Glaucoma Detection through Segmentation

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INTRODUCTION AND MOTIVATION

Overview:

Glaucoma is a critical ophthalmic condition that, if not diagnosed and treated early, can lead to irreversible blindness. It is one of the primary causes of blindness in developed countries. Accurate segmentation of structures related to glaucoma, such as the optic disc and optic cup, is essential for early detection and monitoring. Traditional methods of detecting glaucoma involve measuring intraocular pressure (IOP); however, the Cup-to-Disc Ratio (CDR) has proven to be a more precise indicator. Automating the segmentation of these structures can significantly enhance the accuracy and efficiency of glaucoma diagnosis.

Motivation:

Early diagnosis is crucial to prevent permanent optic nerve damage. Manual segmentation of the optic disc and cup is time-intensive, requiring skilled professionals and about eight minutes per eye [2]. Automated segmentation can expedite mass screenings and offer vital support in regions with limited access to specialists. Moreover, the clinical significance of this project lies in its potential to transform glaucoma screening practices. Automated segmentation of the optic disc and cup enables rapid and accurate assessment of CDR, which is a critical parameter in glaucoma diagnosis. This approach can enhance early detection, allowing for timely interventions and potentially preventing vision loss in many patients [1][2].

DATA COLLECTION

Datasets:

For this project, we are utilizing the RIM-ONE DL, ORIGA, REFUGE, and G1020 datasets. These datasets provide comprehensive retinal image data, including both glaucomatous and healthy cases, and are annotated with ground truth segmentation masks for the optic disc (OD) and optic cup (OC).

These images were sourced from various hospitals and institutions:

- **RIM-ONE DL:**

Hospital Universitario de Canarias (HUC), Hospital Universitario Miguel Servet (HUMS), and Hospital Clínico Universitario San Carlos (HCSC) [3].

- **Sources:** Images from three Spanish hospitals.
- **Characteristics:** High-resolution retinal images annotated with OD and OC masks.
- **Openness to Additional Datasets:** Considering integration of datasets like Drishti-GS for improved performance.

- **ORIGA, REFUGE, and G1020:**

datasets: These datasets provide additional diversity and volume, which are crucial for improving the model's performance and robustness.

Data Characteristics:

The images in these datasets are high-resolution retinal fundus images, annotated with ground truth segmentation masks for the OD and OC. The diversity in the datasets ensures robustness and generalizability of the trained model [3].

Openness to Additional Datasets:

We remain open to exploring various datasets that can enhance our model's accuracy and robustness. Publicly available datasets such as Drishti-GS and others could be integrated to increase the volume and variability of training data [4].

IMAGE VISUALIZATION

The initial step in the data preparation involves visualizing the retinal fundus images to identify the optic disc and optic cup regions. This process helps in understanding the dataset better and preparing for subsequent preprocessing steps.

Visualization Techniques

Visualization involves displaying the retinal images alongside their corresponding segmentation masks. This step helps in verifying the quality and consistency of the annotations. Tools such as matplotlib in Python can be used for this purpose. By examining the images, we can identify common patterns and variations in the appearance of the optic disc and cup, which are critical for effective model training [5].

Preprocessing Insights

During visualization, preprocessing needs such as resizing, normalization, and augmentation are identified. Preprocessing ensures that the images are uniform in size and intensity, which is important for the neural network to learn effectively. Common preprocessing steps include:

01

Resizing

Adjusting the image dimensions to a fixed size (e.g., 256x256 pixels).

02

Normalization

Process of adjusting the pixel values in an image to a common scale. This is a crucial step in the preprocessing pipeline to ensure that the model can learn effectively and make accurate predictions.
Min-Max Normalization: This technique rescales the pixel values to a range between 0 and 1 or -1 and 1

03

Augmentation

Applying transformations such as rotation, flipping, and cropping to artificially increase the dataset size and variability [6].

SEGMENTATION AND CLASSIFICATION OF GLAUCOMA USING U-NET WITH DEEP LEARNING MODEL

Key Points:

- U-Net for Optic Cup Segmentation: U-Net effectively segments the optic cup from retinal fundus images.
- DenseNet-201 for Feature Extraction: A pre-trained DenseNet-201 model is used to extract relevant features from retinal images.
- DCNN for Classification: A deep convolutional neural network (DCNN) classifies glaucoma based on segmented OD and OC features.
- Importance of Segmentation: Accurate OD and OC segmentation is crucial for calculating the cup-to-disc ratio (CDR), an important glaucoma indicator.
- Performance: The model, combining U-Net and DCNN, outperforms other deep learning models like VGG-19 and ResNet-152v2 in accuracy and precision. [15]

OPTIC DISC AND OPTIC CUP SEGMENTATION FOR GLAUCOMA DETECTION FROM BLURRED RETINAL IMAGES USING IMPROVED MASK-RCNN

Key Points:

- Improved Mask R-CNN: Utilizes an enhanced Mask R-CNN framework with a DenseNet-77 backbone for segmenting OD and OC from blurred retinal images.
- Data Preprocessing and Augmentation: Artificial blurriness is added to training samples to improve robustness against real-world blur.
- DenseNet-77 Backbone: Effective for feature extraction, aiding in the accurate localization and segmentation of OD and OC regions.
- Evaluation and Results: Tested on the ORIGA dataset, achieving high precision (0.965), recall (0.963), F-measure (0.97), and IoU (0.972), even under challenging conditions.
- Conclusion: The method offers robust performance for early glaucoma detection, even with blurred images, making it suitable for clinical use.[16]

BUILDING THE INITIAL U-NET MODEL

The U-Net architecture is selected for its proficiency in biomedical image segmentation, even with limited data. The initial model comprises a contracting path that captures the context and a symmetric expanding path that allows precise localization. This structure is particularly effective for segmenting the optic disc and cup in retinal images.

Initial Model Configuration

Input Size:	256x256 pixels
Convolutional Filters:	64 filters in the initial layer, doubling after each pooling operation
Pooling Size:	2x2
Activation Function:	ReLU

Loss Function: Dice loss, which directly optimizes the overlap between predicted and actual segmentation masks [8].

EVALUATION METRICS AND LOSS FUNCTION

Metrics

Dice Coefficient:

Measures the overlap between the predicted segmentation mask and the ground truth. It is calculated as

$$\text{Dice}=2\times \mid A\cap B \mid \quad \mid A \mid + \mid B \mid \text{Dice}= \mid \text{A} \mid + \mid \text{B} \mid 2\times \mid \text{A}\cap \text{B} \mid ,$$

where AA and BB are the predicted and ground truth masks, respectively.

Intersection over Union (IoU):

Evaluates the ratio of the intersection and union of the predicted and actual segmentation masks. It is calculated as

$$\text{IoU}= \mid A\cap B \mid \quad \mid A\cup B \mid \text{IoU}= \mid \text{A}\cup \text{B} \mid \quad \mid \text{A}\cap \text{B} \mid .$$

Loss Function:

The Dice loss function will be employed, as it directly optimizes the overlap between the predicted and actual segmentation masks, thereby improving the model's accuracy in identifying the optic disc and cup [8].

OPTIMIZING AND FINALIZING THE U-NET MODEL

Image Preprocessing

Effective preprocessing techniques include:

- **Image Resizing:** Standardizing the input size to 256x256 pixels ensures uniformity.
- **Normalization:** Scaling pixel values to a range of [0, 1] helps in faster and more stable convergence.
- **Data Augmentation:** Applying random rotations, flips, and shifts increases dataset variability, which helps in generalizing the model better [9].

Model Optimization

To improve the model's performance:

01

Learning Rate Adjustment

Using learning rate schedules or adaptive learning rates (e.g., Adam optimizer) can help in achieving faster convergence.

02

Regularization Techniques

Applying dropout and batch normalization to prevent overfitting and improve generalization.

03

Advanced Architectures

Exploring modifications like attention mechanisms to focus on important regions in the image [10].

OPTIMIZING AND FINALIZING THE U-NET MODEL

Algorithm Selection

For this project, we selected the U-Net architecture as our primary algorithm for several reasons:

Proven Effectiveness

The U-Net architecture has consistently demonstrated high proficiency in biomedical image segmentation tasks, making it an ideal choice for segmenting the optic disc and cup in retinal images [7].

Extensive Validation

Numerous studies and articles, including those cited in this report, have validated the U-Net model's performance in similar applications, highlighting its robustness and accuracy [7][8].

Symmetric Design

The U-Net's unique structure, comprising a contracting path that captures context and an expanding path that ensures precise localization, is particularly effective for the detailed segmentation required in glaucoma detection.

The U-Net's balance between capturing broad contextual information and maintaining high spatial accuracy aligns well with our project's requirements. Therefore, it was chosen over other architectures like CNN and AFNN, which, although potentially effective, do not have the same level of validation in the specific context of retinal image segmentation [7][11].

REALISTIC CONSTRAINTS AND MEASURES

Constraints:

Medical image datasets often have limited training samples compared to traditional image datasets. For example, the Drishiti-GS dataset for glaucoma has only 0.1K samples, whereas natural image datasets like MS-Coco contain 330K training images. This disparity can lead to inferior performances and overfitting in domain generalization tasks [12].

Measures:

Data Augmentation:

Techniques such as rotation, flipping, and scaling to artificially increase the size of the training dataset.

Transfer Learning:

Utilizing pre-trained models on related datasets to improve performance on the glaucoma dataset.

Public Data Collection:

Sourcing additional data from publicly available medical image databases to expand the training set [13].

FUTURE WORK

Enhancing Model Robustness

Future work will focus on enhancing the model's robustness and generalizability through:

Cross-Dataset Evaluation:

Testing the model on different datasets to ensure its applicability across various demographic groups and imaging conditions.

Integration with Clinical Workflows:

Developing user-friendly interfaces and integrating the model with existing clinical systems to facilitate its adoption by healthcare professionals.

Advanced Techniques

Exploring advanced techniques such as:

3D Segmentation:

Extending the model to handle 3D retinal scans for more comprehensive analysis.

Ensemble Methods:

Combining multiple models to improve segmentation accuracy and robustness.

Explainability:

Implementing methods to make the model's predictions more interpretable to clinicians [14].

CONCLUSION

This project aims to develop an AI-based segmentation model capable of accurately detecting and segmenting the optic disc and optic cup in retinal images for glaucoma screening.
By leveraging deep learning techniques, particularly the U-Net architecture, the model aims to facilitate early diagnosis and monitoring of glaucoma, thereby potentially preventing irreversible vision loss in affected individuals.

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