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Research Paper

DETECTING GLAUCOMA STAGES USING DEEP LEARNING

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ABSTRACT

Glaucoma is a major cause of irreversible blindness worldwide, often progressing without noticeable symptoms until significant damage has occurred to the optic nerve. Early detection is crucial to prevent vision loss, yet manual screening of retinal fundus images requires expert ophthalmologists and is not always accessible.

This project presents a **Glaucoma Identification System**, an automated deep learning-based solution designed to detect and classify glaucoma severity from retinal fundus images. The system employs an ensemble of **UNet++ segmentation models** with multiple encoder backbones, including ResNet34, InceptionV4, and DenseNet121, enhanced with SCSE attention mechanisms. These models collaboratively segment the optic disc and optic cup regions, enabling precise extraction of structural features.

The segmented outputs are used to compute the **Cup-to-Disc Ratio (CDR)**, a clinically significant indicator for glaucoma assessment. Based on CDR values, the system classifies cases into four stages: Non-Glaucoma, Mild, Moderate, and Severe. The model is trained on publicly available datasets such as REFUGE and ORIGA, using advanced preprocessing techniques and combined loss functions to improve segmentation accuracy.

The complete system is implemented as a **Flask-based web application**, allowing users to upload images and receive real-time diagnostic results along with visualizations and prediction history storage. Experimental results demonstrate high performance, achieving strong Dice scores and pixel accuracy, indicating reliable segmentation and classification.

Overall, the project provides an efficient, scalable, and interpretable solution for automated glaucoma screening, supporting early diagnosis and assisting healthcare professionals in decision-making.

Keywords

Glaucoma Detection, Retinal Fundus Imaging, Optic Disc Segmentation, Optic Cup Segmentation, UNet++, Deep Learning, CNN Ensemble, SCSE Attention, Cup-to-Disc Ratio (CDR), Medical Image Analysis, Computer-Aided Diagnosis, Ophthalmology AI, Image Segmentation, Flask Web Application, Healthcare Automation

I. INTRODUCTION

Agriculture Glaucoma is a progressive eye disease that damages the optic nerve and is one of the leading causes of irreversible blindness worldwide. The disease often develops silently, with no noticeable symptoms in its early stages, making timely diagnosis extremely challenging. As vision loss caused by glaucoma cannot be reversed, early detection and continuous monitoring are essential to prevent severe outcomes and preserve visual function.

Traditional glaucoma diagnosis relies on manual examination of retinal fundus images by skilled ophthalmologists. This process is time-consuming, subjective, and not easily scalable, especially in regions with limited access to medical specialists. With the growing global burden of eye diseases, there is a strong need for automated, reliable, and accessible screening systems that can assist clinicians and enable large-scale early detection.

One of the most important clinical indicators for glaucoma assessment is the **Cup-to-Disc Ratio (CDR)**, which represents the relationship between the optic cup and optic disc in the retina. As glaucoma progresses, the optic cup enlarges relative to the optic disc, leading to an increase in CDR. Accurate segmentation of these regions is therefore critical for effective glaucoma detection and severity classification.

In recent years, deep learning techniques, particularly convolutional neural networks (CNNs), have shown remarkable success in medical image analysis. These approaches enable automated feature extraction and high-precision segmentation, making them suitable for ophthalmic applications. Leveraging these advancements, this project proposes a **Glaucoma Identification System** that uses an ensemble of advanced segmentation models to analyze retinal fundus images.

II. LITERATURE REVIEW

Recent advancements in medical image analysis have significantly improved automated glaucoma detection, particularly through the use of deep learning techniques. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for extracting complex features from retinal fundus images, enabling accurate segmentation and classification of ocular structures.

One of the foundational works in this domain is based on the **UNet++ architecture**, an improved version of the traditional U-Net model. UNet++ introduces nested and dense skip connections that reduce the semantic gap between encoder and decoder features, leading to more precise segmentation results. This architecture has proven particularly effective for medical image segmentation tasks, including optic disc and optic cup detection.

To further enhance performance, researchers have incorporated **attention mechanisms**, such as Spatial and Channel Squeeze and Excitation (SCSE) modules. These modules help the network focus on the most relevant spatial and channel-wise features, improving segmentation accuracy in challenging regions of retinal images.

Another key development in the literature is the use of **ensemble learning techniques**. Instead of relying on a single model, multiple models with different encoder backbones—such as ResNet34, InceptionV4, and DenseNet121—are trained independently and combined to produce more robust predictions. Ensemble strategies like pixel-wise majority voting and softmax probability averaging have been shown to reduce model bias and improve generalization across diverse datasets.

Several publicly available datasets, including **REFUGE, ORIGA, Drishti-GS, and RIM-ONE**, have been widely used to train and evaluate glaucoma detection systems. These datasets provide annotated fundus images with optic disc and cup masks, enabling supervised learning approaches. Studies using these datasets have demonstrated that accurate segmentation of these regions allows reliable computation of the **Cup-to-Disc Ratio (CDR)**, which remains a clinically accepted indicator for glaucoma screening.

III. METHODOLOGY

1. Data Acquisition and Input

The system accepts retinal fundus images from publicly available datasets such as REFUGE and ORIGA. Users can also upload images through the web interface. Each image serves as the input for the automated analysis pipeline.

2. Image Preprocessing

To ensure consistency and improve model performance, each input image undergoes a preprocessing pipeline:

- Resizing images to a fixed resolution (512 × 512 pixels)
- Converting images to RGB format
- Normalizing pixel values to a standard range
- Applying standardization using ImageNet mean and standard deviation
- Enhancing contrast using CLAHE (Contrast Limited Adaptive Histogram Equalization)

These steps help reduce noise, improve image quality, and standardize inputs for the deep learning models.

3. Optic Disc and Cup Segmentation

The core of the system is based on **UNet++ segmentation models** with SCSE attention modules. Three different encoder backbones are used:

- ResNet34
- InceptionV4
- DenseNet121

Each model independently predicts segmentation masks for three classes:

- Background
- Optic Disc (OD)
- Optic Cup (OC)

An ensemble strategy is applied using **pixel-wise majority voting** and probability averaging to combine predictions from all models, resulting in more robust and accurate segmentation outputs.

4. Feature Extraction (CDR Calculation)

From the segmented masks, the system computes the **Cup-to-Disc Ratio (CDR)**:

- Extract binary masks for optic disc and optic cup
- Identify the largest connected components
- Measure vertical diameters of both structures
- Compute:
  CDR = (Vertical Diameter of Optic Cup) / (Vertical Diameter of Optic Disc)

This metric is a clinically significant indicator used to assess glaucoma severity.

5. Glaucoma Classification

Based on the calculated CDR value, the system classifies glaucoma into four stages:

- Non-Glaucoma
- Mild
- Moderate
- Severe

These thresholds are derived from established clinical standards, enabling interpretable and medically relevant predictions.

6. Visualization and Output Generation

The system generates multiple outputs for better interpretability:

- Segmentation overlay on the original image
- Standalone segmentation mask
- Numerical metrics (CDR, disc area, cup area)
- Confidence score and reliability indicators

This helps users visually verify the model's predictions.

7. System Deployment

The entire pipeline is deployed as a **Flask-based web application**:

- Users upload images through a user-friendly interface
- Backend processes the image using the trained models
- Results are returned in real-time via REST API
- Prediction history is stored in a SQLite database

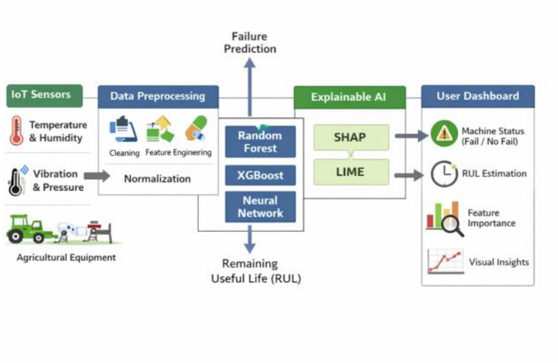
8. Workflow Summary

The overall workflow includes:

1. Image upload
2. Validation and preprocessing

3. Segmentation using ensemble models
4. CDR calculation
5. Severity classification
6. Visualization and result storage

IV. SYSTEM ARCHITECTURE



V. RESULTS & DISCUSSION

1. Segmentation Performance

The system uses three backbone models—ResNet34, InceptionV4, and DenseNet121—within a UNet++ framework. Each model was trained independently and evaluated using standard metrics such as Dice coefficient, pixel accuracy, and Intersection over Union (IoU).

- **ResNet34** achieved a validation Dice score of approximately **0.878** and accuracy of **96.5%**
- **InceptionV4** performed best with a Dice score of around **0.885** and accuracy of **96.8%**
- **DenseNet121** achieved a Dice score of about **0.871** with accuracy near **96.2%**

2. Accuracy of Glaucoma Detection

Using the segmented optic disc and cup regions, the system calculates the Cup-to-Disc Ratio (CDR), which is then used for classification. The results show that:

- The system can effectively distinguish between healthy and glaucomatous cases
- Severity classification (Mild, Moderate, Severe) aligns well with clinical thresholds
- The numerical precision of CDR (up to four decimal places) enhances diagnostic reliability

3. Inference Performance

The system achieves:

- **Processing time:** Approximately **13–15 seconds per image** on CPU
- **Input size:** Standardized to 512 × 512 pixels
- **Output:** Segmentation masks, visual overlays, CDR values, and classification results

4. Advantages of Ensemble Approach

The ensemble strategy provides several benefits:

- **Robustness:** Reduces errors from individual models
- **Consistency:** Produces stable segmentation across varying image qualities
- **Generalization:** Performs well on diverse datasets
- **Smooth Predictions:** Probability averaging improves boundary detection

5. Practical Outcomes

From the implementation perspective:

- The system successfully performs **end-to-end glaucoma screening** from image upload to result generation
- Provides **visual explanations** (segmentation overlays) for better interpretability
- Maintains **prediction history and traceability** through a database

6. Limitations

Despite strong performance, some limitations are observed:

- Accuracy depends on the availability of **fine-tuned model weights**
- **Processing time** is higher on CPU-only systems
- The system is not yet validated for **clinical deployment**
- Assumes a **single optic disc per image**, limiting applicability to complex cases

VI. CONCLUSION

This project presents an effective and automated **Glaucoma Identification System** that leverages deep learning techniques for early detection and severity assessment of glaucoma using retinal fundus images. By integrating advanced segmentation models based on the UNet++ architecture with multiple encoder backbones, the system successfully identifies the optic disc and optic cup regions and computes the clinically significant Cup-to-Disc Ratio (CDR).

The use of an ensemble approach enhances the robustness and accuracy of segmentation, leading to reliable classification of glaucoma into different severity stages—Non-Glaucoma, Mild, Moderate, and Severe. The system not only provides numerical predictions but also generates visual outputs such as segmentation overlays, improving interpretability and trust in the results.

Additionally, the deployment of the model as a Flask-based web application makes the solution practical and accessible, enabling real-time analysis and maintaining prediction history for future reference. This end-to-end implementation demonstrates the feasibility of combining medical image processing, deep learning, and web technologies into a single unified platform.

However, the system is currently intended for research and decision-support purposes and is not yet suitable for direct clinical use. Future improvements such as GPU acceleration, integration of larger datasets, and regulatory validation can further enhance its performance and applicability.

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