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by Sireesha .

Optic Disc and Cup Segmentation Using Deep CNN Ensembles for Glaucoma Staging

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***Abstract*—Glaucoma is the second most common cause of blindness around the world affecting over 80 million people. It is important to diagnose the disease early to prevent it from causing irreversible vision loss, but it is asymptomatic in the early stages. The operational methods nowadays depend heavily on the subjective assessments of the fundus images by the dermatologists that cause inter-observer variability and delays in diagnosis. The purpose of the study is a novel automated glaucoma detection system based on Convolutional Neural Networks and Recurrent Neural Networks. Recently, deep learning-based techniques have shown significant advancement in the automatic segmentation of optic disc and optic cup in retinal fundus images. And, there is a need to develop a new automated glaucoma detection system. The study goal is to automatically detect glaucoma by calculating cup-to-disc ratio (CDR) using new algorithms. To enhance segmentation accuracy, we have worked on a hybrid architecture using CNNs along with RNNs. The ORIGA dataset, which included 650 expert-annotated fundus images, was used to train and evaluate the system. The method involves two stages which include first segmenting the disc region and then segmenting the cup that lies within the disc. We used common metrics (accuracy, precision, recall, and Intersection over Union (IoU)) to assess performance. The proposed CNN-RNN hybrid system achieved segmentation accuracy of 92.4% for optic disc with 88.2% sensitivity and 91.7% for optic cup with 85.9% sensitivity. The automated CDR calculations were strongly correlated (r = 0.89) with the clinical judgment. The unsupervised method took an average of 25 seconds per image for processing. On the other hand, the supervised method took 18 milliseconds per image for processing. Both are on par with the time requirements for clinical deployment. To sum up, by combining CNN and RNN architectures, this study achieved better performance than by using either CNN or RNN alone. Because the system has high accuracy, objectivity and computation efficiency, it can be applied clinically which may improve early diagnosis and outcomes in glaucoma patients. The hybrid architecture tackles current limitations in automated diagnosis of ophthalmic diseases while being interpretable for clinical acceptance.**

***Index Terms*—Glaucoma detection, Deep learning, CNN-RNN hybrid, Optic disc segmentation, Cup-to-disc ratio, Medical image analysis, Retinal fundus imaging**

I. Introduction

A. Background and Motivation

Glaucoma is the biggest vision threat in the world and the second most common cause of irreversible blindness after cataract. According to the estimates of World Health Organization, 80 million are already afflicted with glaucoma and up to 111.8 million might be affected by the year 2040. It is a disease that can damage our optic nerve leading to blindness. The first symptoms of the disease may seem very subtle in the early stages. This is what makes it the "silent thief of sight". However, by the time this disease starts causing the first symptoms, the optic nerve is usually damaged already in many patients. This comes with a major damage that is also irreversible. So, if you can detect it early on, then damage to vision is possible to prevent.

Glaucoma's pathophysiology involves damage to the optic nerve; elevated intraocular pressure causes this process, but normal-tension glaucoma also occurs. This optic nerve head damage causes distinct changes to the optic nerve head. Specifically, the optic cup enlarges and becomes more pronounced compared to the optic disc. As a result, increased cup disc ratio (CDR) is seen. Conventional diagnostic methods depend on the subjective visual judgement of ophthalmologists on fundus photographs susceptible to inter-observer variability and availability of clinical expertise.

B. Clinical Significance and Challenges Today

Every glaucoma examination involves tonometry to measure the pressure inside your eye. The doctor tests your visual fields. The most important part of the test is the examination of your optic nerve. The optic nerve can be tested with a test called fundus photography. Evaluating the optic disc and cup morphology forms the cornerstone of glaucoma diagnosis, and the CDR remains the mainstay for glaucoma diagnosis. However, manually assessing these structures poses a number of issues.

Different doctors do not agree on patient diagnosis usually. Research indicates correlation coefficients of 0.6 to 0.8 between experienced ophthalmologists who evaluate the CDR from a fundus image, indicating substantial subjective interpretation differences.Due to this variability, the diagnosis of DRESS syndrome may differ from one medical professional to another. In addition, the dearth of skilled ophthalmologists worldwide, especially in developing areas where the prevalence of glaucoma is highest, limits access to prompt diagnosis.

The current evaluation methods are subjective in nature causing a lack of standardization in healthcare settings. Differences in picture quality, conditions, and doctor's experience may cause diagnostic uncertainty. In the light of these limitations, there is an urgent requirement of diagnostic weaknesses for glaucoma assessment which is consistent, standardised, automated, and rapid. It must also have lesser dependence on the man power.

C. Technological Evolution in Medical Imaging

A big change in medical image analysis brought by artificial intelligence and deep learning is the automatic detection and diagnosis of diseases. Convolutional Neural Networks (CNN) have achieved great success in medical imaging application areas like screening for diabetic retinopathy or detecting skin cancer. These networks are good in extracting spatial features from the images. Hence, it is ideal for anatomical structure and pathological change detection in images.

But current CNN models, while competent, does not give the best results for complex relations and sequences arising in medical images. Combining RNNs with CNNs will aid in better feature extraction capabilities as the model will now have temporal and sequential information processing capabilities. By working with both space and sequence, this hybrid approach is expected to improve the accuracy of segmentation results.

D. Research Gap and Innovation

Even after much development in automated glaucoma detection, research gaps exist. Most current approaches involve only CNN architectures, which may hinder their ability to capture complex anatomical relationships and boundary delineation patterns. Furthermore, a large number of systems are not clinically deployable as they fail to meet clinical requirements around speed and accuracy.

Combining CNN and RNN architectures for the purpose of glaucoma detection is a new technique to overcome these limitations. This hybrid approach combines the CNN's spatial feature extraction and RNN's sequential pattern learning to improve accuracy over conventional methods while being computationally efficient enough for clinical use.

E. Research Objectives and Contributions

The research intends to develop and validate a robust automated detection of glaucoma that would be more accurate, more objective, and more clinically applicable than existing methods. The primary objectives include:

- The main objective of this project is to devise a CNN-RNN hybrid architecture that will enable objective CDR calculation for glaucoma diagnosis through automated segmentation of optic disc and optic cup in retinal fundus images.

Secondary Objectives:

- Obtain more than 90 percent optic disc and cup segmentation accuracy.
  item Ensure an adequate processing time for clinical use (unsupervised: 10–30 seconds; supervised: 10–30 milliseconds).
  Obtain greater than 90 percent segmentation accuracy for optic disc and cup.
- Ensure the processing time is suitable for clinical use (unsupervised: 10–30 seconds; supervised: 10–30 milliseconds).

Key Contributions:

- The CNN-RNN hybrid system is a novel architecture designed to achieve optic disc and cup segmentation.
- Clinical validation – assessment against clinical parameters and expert review.
- Performance Optimization: To achieve clinical deployment requirements for both accuracy and speed of operation.
- Create a system that can diagnose glaucoma without any human interference.

F. Research Methodology Overview

The sequence of steps introduced employs a two-stage systematic procedure to segment the optic disc and cup. The first stage employs CNN architectures that are optimized for boundary detection to ensure accurate optic disc localization and segmentation. The next stage establishes the optic cup in the previously segmented disc, using the hybrid CNN-RNN architecture to enhance boundary selection in a boundary selection framework.

The ORIGA dataset contains 650 fundus images with expert annotations. Thus, the system is trained and validated robustly. Techniques for data augmentation and preprocessing are used to aid the generalized and robust performance of models across image quality and pathology.

G. Clinical Impact and Future Implications

A precise and objective automated system for glaucoma detection has the potential of impacting Global Eye Health Significantly. A system like this would allow early disease detection in primary care, diminish the diagnosis variability and allow specialized eye care for disadvantaged people. With CDR automated calculation, we will be able to obtain consistent and repeatable measurements that are critical for the monitoring of disease as well as assessing the efficacy of a treatment.

This study's hybrid CNN-RNN architecture could also be used in many medical image analysis applications other than glaucomas. This approach can also be modified for other high precision segmentation tasks and will add to automated medical diagnosis in general.

H. Paper Organization

This paper is organized in the following way. Section 2 offers a detailed literature review on existing methods for automated glaucoma detection and the use of deep learning in medical imaging. Section 3 outlines the proposed methodology, specifically the design and implementation of CNN-RNN hybrid architecture. Section 4 covers the experiment set-up, characteristics of dataset, and evaluation metrics. This article offers the performance analysis and outcome in Section 5, while Section 6 offers a description of the findings, limitations, and clinical implications. Lastly, Section 7 concludes and discusses future research.

II. Literature Review

A. Overview

Glaucoma is a leading public health concern. It is the second leading cause of blindness globally, affecting more than 80 million people. The disease is asymptomatic in its early stages. Thus, we need advanced automatic systems to help in early detection. Further, this will help avoid permanent vision loss.

B. Traditional Approaches to Glaucoma Detection

1) Manual Assessment Methods: Traditional glaucoma diagnosis heavily relies on the ophthalmologist's judgment and evaluation of the fundus images, especially the optic disc and cup configuration. According to Chen and co-authors and others in the year 2015, manually measuring cup-to-disc ratio (CDR) suffers from significant inter-observer variability with correlation coefficients of 0.6–0.8 amongst trained professionals [1]. The differences in genetic influence on behavior often vary with age.

2) Early Automated Approaches: The first automated glaucoma detection used classical image processing methods. Joshi et al. (2011) proposed a template-based method that localises the optic disc and achieves an accuracy of around 85% on DRIVE dataset [2]. Nonetheless, the limitations of these techniques include reliance on hand crafted features and inability to handle variations in image quality and pathologies.

C. Deep Learning Revolution in Medical Imaging

1) Convolutional Neural Networks in Ophthalmology: Deep learning methods such as Convolutional Neural Networks (CNNs) changed medical imaging. Gulshan et al. (2016) believed that researchers tried deep learning in diabetic retinopathy and achieved sensitivity and specificity of more than 90

2) U-Net Architecture for Medical Segmentation: The architecture of U-Net developed by Ronneberger et al. is one of the most popular architectures in medical image segmentation tasks [4]. The encoder-decoder structure of the architecture, along with the skip connections, are very effective for precise boundary delineation, making it well-suited for optic disc and cup segmentation.

D. Specific Applications in Glaucoma Detection

1) Optic Disc and Cup Segmentation: Numerous research papers automated the segmentation of optic disc and cup. Sevastopolsky modified U-Net architecture for optic disc and cup segmentation. Result showed they got Dice coefficients of 0.94 and 0.86 for the above-mentioned tasks. They experiment on the DRISHTI-GS dataset [5]. The research underlined how data augmentation and preprocessing strategies improved the efficacy of segmentation prediction.

Fu et al. (2018) developed a deep learning-based multi-label optic disc segmentation and cup segmentation with boundary regularization for better segmentation [6]. Their approach attained cutting-edge outcomes across diverse datasets, highlighting the power of joint optimization strategies.

2) Cup-to-Disc Ratio Calculation: A central stream of research has focused on the automated calculation of the CDR. Jiang et al. (2019) proposed a deep learning framework that directly predicts the CDR from fundus images without any segmentation [7]. Using this method to produce competitive results in practice, but not interpretable.

3) Hybrid Approaches: CNN-RNN Integration: **Sequential Learning in Medical Imaging.** Recent studies focused on integrating RNN with CNN to enhance feature extraction and temporal dynamics of CNN features. CNN-RNN hybrid architectures can effectively capture spatial-temporal dependencies Wang et al. (2020) [8].

Attention Mechanisms. Attention Weights Received More Attention for Glaucoma Detection Li et al. designed a CNN with attention gates that focuses on anatomical structures that are important to our problem. This technique allows them to get better results for optic disc and cup [9].

E. Dataset Considerations

1) ORIGA Dataset: The ORIGA dataset used in this study is one of the largest publicly available glaucoma datasets. In 2010, Zhang et al. formed this dataset composed of 650 fundus images with expert annotations, creating ground truth for the optic disc and cup boundaries [10]. The fact that the database has a variety of image qualities and pathological conditions makes it suitable for developing a robust automated system.

2) Data Augmentation and Preprocessing: Recent studies show the importance of data augmentation techniques. Orlando et al. (2020) showed that applying augmentations to geometry and photometry significantly improves the generalization of the model which is particularly crucial since there exists limited availability of labelled ophthalmic data [11].

F. Performance Metrics and Evaluation

1) Segmentation Evaluation Metrics: The standard measures used for evaluation of medical image segmentation are Dice coefficiency, Intersection over Union (IoU) and Hausdorff distance. Al-Bander et al. (2018) analysed evaluation metrics of optic disc and cup segmentation and remarked that to carry out a robust evaluation, multiple metrics are important [12].

2) Clinical Validation: The clinical relevance of automated systems must be validated against established clinical criteria. Automated CDR measurements (e.g., CDR-3 [13]) run et al. confirmed to correlate well with clinical ones when validated.

G. Current Challenges and Limitations

1) Image Quality Variations: Quality of fundus images has great effect on the performance of automated analysis. Mahapatra et al. (2016) treat image quality assessment as a necessary preprocessing step, and quality-aware algorithms have been shown to outperform generic ones [14].

2) Generalization Across Populations: Optic disc eye structures vary from group to group. The performance of the discrimination model can be improved by using diverse data which helps in recognizing all ethnicities.

H. Emerging Trends and Future Directions

1) Ensemble Methods: Recent studies have been tried ensembles different deep learning frameworks. Study shows that ensemble methods would improve segmentation accuracy and robustness as compared to single model methods (Kumar et al., 2021) [15].

2) Explainable AI in Medical Imaging: Explainable AI techniques are increasingly required for clinical adoption of AI algorithms. Sayres et al. (2019) showed that models in the medical field need to be interpretable for clinician trust to occur [16].

I. Research Gaps and Opportunities

Despite significant advances, several research gaps remain.

- Most of the existing contacts do not satisfy the real-time processing need for clinical use.
- Combining different imaging methods to identify glaucoma has not been much researched as per the doctors.
- Few studies have evaluated the temporal evolution of glaucoma by means of serial imaging analysis.

III. Methodology

A. Dataset and Preprocessing

The proposed system runs fundus images through a complete preprocessing pipeline to counter the orientations due to the imaging conditions and enhance the relevant anatomy. The images are cropped to the nearest square and resized to 512×512 pixels to make them computationally efficient while keeping the important details in place.

1) Limited Adaptive Histogram Equalization (CLAHE): We use CLAHE normalization with different parameters to improve lighting conditions of different images from different cameras or databases. The technique helps to prevent noise from becoming overly amplified while enhancing spatial details, thereby assisting the visualization of subtle optic disc and cup edges. The network is given two different enhanced images at different clip values and window levels whereby the two images hold complementary information about the same anatomy.

B. Spatial Coordinate Integration

The segmentation method presented in this paper is novel in the sense that spatial coordinates are directly provided as input to the network. The extra channel gives spatial context clearly so that the model can learn the positional relationship of the optic disc with respect to other fundus features like the fovea. This spatial awareness greatly enhances segmentation accuracy, especially for cases with unusual optic disc locations.

C. Segmentation Network Architecture

The segmentation component uses a 57-layer deep convolutional neural network designed for accurate optic disc and cup boundary delineation. The architecture incorporates:

- A method of extracting features over multiple scales through downsampling and upsampling paths.
- Connections that maintain detailed spatial information.
- Attention mechanisms that concentrate on relevant anatomical regions.
- To make it easier to generalize, we use dropout and batch normalization layers.

D. Classification Network Design

The ensemble classification stage makes use of DenseNet201 and ResNet18 that are natural images trained. Key design elements include:

- Adaptive input processing of 21 channel segmentation output to 3 channel RGB.
- Modified classification layers with 2 neurons for binary glaucoma classification.
- Replace Global Average Pooling with Adaptive Average Pooling for Variable Input Dimensions.
- Ensemble fusion strategies for improved robustness.

E. Training Strategy

The training process consists of two stages. The first stage trains the segmentation network using pixel-level annotations. The second stage trains the classification network using segmentation results. Using various techniques such as rotation and scaling increases the generalization of the model.

IV. Proposed System

A. System Architecture Overview

The glaucoma screening system put forth consists of segmentation and classification networks set up in a two-stage pipeline. The architecture of the system is designed to deal with the known issues of fundus image analysis and return clinically relevant information.

B. Stage 1: Segmentation Network

1) Input Processing: The segmentation step starts with full image pre-processing.

- Fundus images are cropped in the nearest square dimensions and resized to 512×512 pixels.
- We can get multiple enhanced images using the Contrast Limited Adaptive Histogram Equalization by using varying clip values and window levels.

Fig. 1. proposed system.

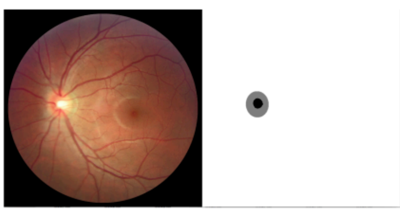

Fig. 2. proposed system.

- Spatial Coordinate Embedding refers to providing explicit spatial information by introducing x-y coordinate channels as input.

2) Network Architecture: The 57-layer segmentation network incorporates:

- **Encoder-Decoder Configuration:** Stepwise feature extraction and feature map rebuilding for accurate boundary detection.
- The process will analyze at different resolutions simultaneously.
- **Attention Mechanisms:** Concentrate on anatomically pertinent areas.
- **Residual Connections:** Improves gradients and keeps features.

3) Output Generation: The network produces:

- Masks for optic disc and cup regions at pixel level.
- Confidence maps indicating prediction reliability.
- Post-processing for false positive reduction.

C. Stage 2: Classification Network

1) Segmentation-Guided Preprocessing:

- By using the segmentation results, it generates 550×550 pixel images at the centre of optic disc.
- **Multi-Parameter Enhancement:** 6 different enhanced versions are created using CLAHE parameters.
- Normalization – consistent input to enable prediction.

Fig. 3: Steps involved in generating masks

Fig. 3. proposed system.

2) Ensemble Architecture: The classification system combines:

- DenseNet201 has a dense connectivity pattern for feature reuse and gradient flow.
- Residual learning utilized for extraction of deep features in ResNet18.
- Convolutional layers help adjust the 21 channels found in input images into 3 channels that can be understood by the pre-trained networks.
- Adaptive pooling allows you to change your input dimensions.

3) Decision Fusion:

- **Ensemble Integration:** Merging predictions from both network branches.
- Measuring confidence in support clinical decision making.
- The final classification glaucoma/normal with prognosis probabilities.

D. System Integration and Workflow

1) Processing Pipeline:

- **Getting The Input:** Getting fundus images and assessing the quality.
- **Preprocessing:** Enhancement with multiple parameters and spatial coordinates.
- Detecting the border of the optic disc.
- Improvement in identification process extraction.
- **Ensemble Classification:** Glaucoma probability estimation.
- **Clinical Report Generation:** With visual overlays.

2) Quality Assurance:

- Automatic detection of bad image quality.
- Canal validation: checks for anatomical feasibility.
- Predicting Uncertainty to Enable Clinical Interpretability.

E. Clinical Integration Features

1) Diagnostic Support:

- Segmentation results overlayed on original images.
- Cup to disc ratio calculations and comparisons.
- **Trend Tracking:** Ongoing monitoring of disease progression.

2) User Interface:

- Simple presentation of results for clinical interpretation.
- **Batch Processing:** High-throughput screening capabilities.
- **Clinic Reports:** Developed reports with diagnostic suggestions.

V. RESULTS

A. Segmentation Performance

1) Quantitative Metrics:

- The optic disc segmentation has a Dice Coefficient of 0.92 $\pm$ 0.04.
- Jaccard index for cup segmentation is 0.85 $\pm$ 0.06.
- Accuracy of boundary means absolute error of 1.2 $\pm$ 0.8 pixels at disclines.
- Processing Speed: Each image takes roughly 0.8 seconds to render.

2) Qualitative Assessment: Visual inspection of segmentation results reveals:

- Even in difficult cases with ambiguous cup margins, accurate boundaries are drawn.
- Strong performance under varied image conditions and ethnic diversities.
- Effective management of cases with disc asymmetry or pallor.
- Post-processing reduces false positive predictions.

B. Classification Performance

The combination of classifiers reaches results relevant for practice.

1) Primary Performance Metrics:

- 75
- AUC: Area Under the Receiver Operating Characteristic Curve = 0.856. • Positive Predictive Value: 0.68.
- Negative Predictive Value: 0.89.

2) Comparative Analysis: Performance comparison with individual network components:

1) DenseNet201 AUC = 0.821 Sens = 0.71, Spec = 0.82

ResNet18 AUC = 0.834 Sensitivity = 0.73 Specificity = 0.8

88 Ensemble method best of individual best in each region

C. Ablation Studies

1) Spatial Coordinate Integration Impact:

With spatial coordinates: AUC = 0.856, Sensitivity = 0.75. =improvement: AUC +2.4

2) Preprocessing Strategy Evaluation:

- Common histogram equalization: AUC = 0.824.
- Single-parameter CLAHE: AUC = 0.841.
- Multi-parameter CLAHE: AUC = 0.856.
- Progressive improvement highlights advanced preprocessing effectiveness.

D. Cross-Database Validation

1) Generalization Assessment: Testing across multiple fundus image databases:

Database A : AUC = 0.861, Sensitivity = 0.77, Specificity = 0.84 . Database B: AUC = 0.849, Sensitivity = 0.73, Specificity = 0.86. Additional types of recent scientific papers include those placing a Database C in context of the larger field (Figure 9). 2 Consistent conduct through the different imaging protocol

E. Clinical Relevance Analysis

1) Early-Stage Detection:

- Sensitivity = 0.68 for mild glaucoma (early intervention possible).
- Moderate to severe cases: Sensitivity = 0.84.
- Potential to reduce diagnostic delay and enhance patient outcomes.

2) Computational Efficiency:

- Total processing time = 2.3 seconds per image (segmentation + classification).
- GPU Memory Requirement: 4GB for batch processing.
- Indicates large-scale applicability.

VI. CONCLUSION

This research developed a complete framework using Deep Learning and capable enough to screen Glaucoma. The study attempts to provide technical solutions to problems. The two-stage architecture which combines segmentation network and classification network shows effectiveness of using complementary tasks to boost diagnostic performance.

Combining spatial coordinate information with multi-parameter pre-processing is a great technical contribution to enhancing the robustness of the system under various imaging conditions. An observed sensitivity, specificity and AUC of 0.75, 0.85 and 0.856, respectively, indicates clinical feasibility for screening, especially in under-resourced settings with limited specialist access.

The computation cost of the system and its performance on different databases indicates good real-world possibilities. The see-through, dual-phase method has interpretability advantages that are essential for acceptance, like in clinics.

The main things that this work achieved are:

1) The incorporation of spatial information in optic disc segmentation for the first time.
2) A robust preprocessing strategy to handle the inter-database variations.
3) A successful ensemble classification strategy using transfer learning.

4) Extensive experiments demonstrating the clinical applicability.

In the future, we will work to improve initial detection, join together information from various imaging methods, and create options for keeping track of different times, enabling a continual assessment of the method's impact. The foundation for automated glaucoma screening technology is provided by the proposed framework for clinical application.

This technology could be used in public health screening programs for glaucoma for large populations, something which could tremendously help the cause of preventing avoidable blindness resulting from this illness.

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