

Automated Glaucoma Detection and Severity Classification from Retinal Fundus Images Using CNN and U-Net Deep Learning Architecture

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Abstract

Glaucoma, a leading cause of irreversible blindness affecting over 80 million individuals worldwide, is characterized by progressive optic nerve damage often associated with elevated intraocular pressure. Early detection is critical as the disease progresses asymptotically until significant vision loss has occurred. This paper presents an automated glaucoma detection and severity classification system using a dual deep learning architecture: Convolutional Neural Networks (CNN) for binary classification (glaucomatous vs. non-glaucomatous) and U-Net for semantic segmentation of the optic cup and disc regions in retinal fundus images. The system computes the Cup-to-Disc Ratio (CDR) from U-Net segmentation masks and classifies severity into three levels: Mild (CDR 0.3–0.5), Moderate (CDR 0.5–0.7), and Severe (CDR > 0.7). Trained on a Kaggle dataset of 3,600 fundus images, the CNN classifier achieves 96.2% accuracy, 95.8% precision, 96.5% recall, and an F1-score of 96.1%. The U-Net segmentation achieves a Dice coefficient of 0.912 for optic disc and 0.874 for optic cup. A web-based interface built with React.js frontend and Flask backend enables users to upload fundus images and receive instant diagnosis with severity classification and preventive precautions. The system addresses the global shortage of ophthalmologists by enabling accessible, automated glaucoma screening.

Keywords: Glaucoma Detection, Deep Learning, Convolutional Neural Networks, U-Net, Fundus Image, Cup-to-Disc Ratio, Optic Nerve, Semantic Segmentation

1. Introduction

Glaucoma is a group of eye diseases that damage the optic nerve, the vital connection between the eye and the brain. It is the second leading cause of blindness globally, affecting approximately 80 million people worldwide, with projections reaching 111.8 million by 2040 [1]. The disease is particularly insidious because it typically develops gradually without noticeable symptoms until significant irreversible vision loss has occurred, earning it the designation ‘silent thief of sight.’ The primary risk factor is elevated intraocular pressure (IOP), though glaucoma can also develop with normal IOP levels.

In India, the situation is particularly acute. With approximately 12 million glaucoma patients and only 1 ophthalmologist per 100,000 population in rural areas [2], early screening is severely limited. Manual examination of retinal fundus images by trained ophthalmologists remains the gold standard for glaucoma diagnosis, involving assessment of the optic nerve head morphology, specifically the Cup-to-Disc Ratio (CDR). A CDR exceeding 0.5 is considered suspicious for glaucoma, while values above 0.7 indicate advanced disease [3]. However, manual assessment is subjective, time-consuming, and requires specialized expertise unavailable in most primary healthcare settings.

Recent advances in deep learning have demonstrated the potential to automate medical image analysis with accuracy comparable to or exceeding human experts. Convolutional Neural Networks (CNNs) have achieved state-of-the-art results in image classification tasks, while U-Net architectures have proven highly effective for semantic segmentation of biomedical images [4]. These capabilities can be leveraged to automate both glaucoma classification and optic cup/disc segmentation from fundus photographs.

This paper presents an automated system with the following contributions:

- A dual deep learning architecture combining CNN for binary glaucoma classification (96.2% accuracy) and U-Net for optic cup/disc segmentation (Dice coefficient: disc 0.912, cup 0.874).
- Automated Cup-to-Disc Ratio computation from U-Net segmentation masks with three-level severity classification: Mild (0.3–0.5), Moderate (0.5–0.7), and Severe (> 0.7).
- A web-based screening interface (React.js + Flask) enabling non-specialist users to upload fundus images and receive instant diagnosis with precautionary recommendations.
- Validation on 3,600 Kaggle fundus images with comprehensive performance evaluation using accuracy, precision, recall, F1-score, and Dice coefficient metrics.

2. Related Work

Table 1 presents a comparative analysis of existing approaches to automated glaucoma detection from fundus images.

Table 1: Comparative Analysis of Related Work

S.No	Title / Method	Year	Approach	Limitations	Ref
1	ResNet for Glaucoma Screening (Shibata et al.)	2018	Deep residual learning achieving AROC 96.5%	Excludes images with diagnostic interference	[5]
2	U-Net for Retinal Segmentation (Ronneberger et al.)	2015	Encoder-decoder with skip connections for biomedical segmentation	Requires precise ground truth masks for training	[4]
3	ISNT Rule for Glaucoma (Harizman et al.)	2006	Neural rim width rule: Inferior > Superior > Nasal > Temporal	Fails with long axial length eyes, not automated	[6]
4	CDR-based Detection (Cheng et al.)	2013	Superpixel classification for optic disc/cup segmentation	Depends on superpixel quality, limited accuracy	[7]
5	GlaucomaNet (Orlando et al.)	2020	Ensemble CNN for joint segmentation and classification	Computationally expensive, large model size	[8]
6	Transfer Learning VGG16 (Raghavendra et al.)	2018	Pre-trained VGG16 for glaucoma classification	No segmentation, no severity classification	[9]

7	U-Net Lite + XGBoost	2023	Lightweight U-Net for segmentation + XGBoost for CDR classification	Accuracy compromised by poor image quality	[10]
8	Proposed System (This Work)	2026	CNN classification + U-Net segmentation + CDR severity + web interface	Dataset limited to Kaggle, no real-time video	-

The literature reveals three gaps: (1) most systems perform either classification or segmentation but not both in an integrated pipeline; (2) existing approaches lack severity grading based on computed CDR values; (3) no system provides an accessible web interface for non-specialist screening with precautionary recommendations.

3. Methodology

3.1 Dataset

The system uses a publicly available Kaggle dataset containing approximately 3,600 retinal fundus images categorized into glaucomatous and non-glaucomatous classes. Images are captured using standard fundus cameras and include diverse patient demographics, lighting conditions, and image qualities. The dataset is split into 80% training (2,880 images) and 20% testing (720 images) with stratified sampling to maintain class balance.

3.2 Data Preprocessing

Preprocessing involves five steps: (1) resizing all images to 224×224 pixels for CNN input and 256×256 for U-Net input; (2) normalization of pixel values to [0, 1] range; (3) data augmentation including horizontal/vertical flipping, rotation (0–30°), brightness adjustment, and zoom (0.8–1.2×) to increase training diversity; (4) contrast enhancement using CLAHE (Contrast Limited Adaptive Histogram Equalization) to improve optic disc visibility; (5) RGB to grayscale conversion for segmentation preprocessing.

3.3 CNN Architecture for Classification

The CNN classifier consists of four convolutional blocks, each containing a convolutional layer (3×3 filters), batch normalization, ReLU activation, and max pooling (2×2). Filter counts progress as 32, 64, 128, and 256 across blocks. The feature maps are flattened and passed through two fully connected layers (512 and 256 neurons) with dropout (0.5) for regularization, culminating in a sigmoid output for binary classification. Algorithm 1 presents the classification pipeline.

Algorithm 1: CNN Classification Pipeline

Input: Fundus Image I (224x224x3)

Output: Class (Glaucoma/Normal), Confidence

1. $I_{norm} \leftarrow \text{normalize}(I) / 255.0$
2. $I_{aug} \leftarrow \text{augment}(I_{norm})$ if training
3. $features \leftarrow \text{ConvBlock1}(I_{norm}, 32)$
4. $features \leftarrow \text{ConvBlock2}(features, 64)$
5. $features \leftarrow \text{ConvBlock3}(features, 128)$
6. $features \leftarrow \text{ConvBlock4}(features, 256)$
7. $flat \leftarrow \text{Flatten}(features)$
8. $fc1 \leftarrow \text{Dense}(flat, 512, \text{ReLU}, \text{drop}=0.5)$
9. $fc2 \leftarrow \text{Dense}(fc1, 256, \text{ReLU}, \text{drop}=0.5)$

10. output ← Dense(fc2, 1, Sigmoid)
11. class ← 'Glaucoma' if output > 0.5
 else 'Normal'
12. RETURN (class, output)

3.4 U-Net Architecture for Segmentation

The U-Net encoder-decoder architecture with skip connections performs semantic segmentation of the optic disc and cup regions. The encoder path uses four down-sampling blocks (64, 128, 256, 512 filters) to capture spatial features. The decoder path uses four up-sampling blocks with transposed convolutions and skip connections from corresponding encoder layers to preserve fine-grained spatial information. The bottleneck layer contains 1024 filters. The output layer uses a 1×1 convolution with sigmoid activation producing a binary segmentation mask.

The CDR is computed from the segmentation masks as: $CDR = \text{Area}(\text{Cup Mask}) / \text{Area}(\text{Disc Mask})$. Severity is classified as: Mild (CDR 0.3–0.5), Moderate (CDR 0.5–0.7), and Severe (CDR > 0.7). CDR below 0.3 indicates a normal, healthy optic nerve.

4. Implementation

Table 2: Technology Stack

Layer	Technology	Purpose
Language	Python 3.10+	Core programming language
Deep Learning	TensorFlow 2.x + Keras API	CNN and U-Net model building/training
Image Processing	OpenCV + Pillow	Preprocessing, CLAHE, augmentation
Data Handling	NumPy + Pandas	Array operations, data management
ML Utilities	Scikit-Learn	Metrics, train/test split, evaluation
Backend	Flask	REST API for model inference
Frontend	React.js + Bootstrap + CSS	Interactive web interface
IDE	VS Code + Google Colab	Development and GPU training
Dataset	Kaggle (3,600 fundus images)	Glaucomatous + non-glaucomatous images

The system workflow follows six modules: (1) Data Collection from Kaggle with 3,600 fundus images; (2) Data Preprocessing with resizing, normalization, augmentation, and CLAHE enhancement; (3) Data Splitting into 80% training and 20% testing with stratified sampling; (4) Model Training of CNN classifier and U-Net segmentation model using TensorFlow/Keras with Adam optimizer, binary cross-entropy loss, and early stopping; (5) Model Testing and evaluation on the held-out test set; (6) Prediction and Output through the Flask API serving the React.js web interface, providing classification result, severity level, CDR value, and precautionary recommendations.

The web interface provides a simple upload workflow: the user opens the detection page, selects a fundus image file, clicks analyze, and receives results showing whether glaucoma is detected, the severity level (if positive), the computed CDR value, and recommended precautions. Additionally, the system provides global glaucoma statistics with interactive charts showing regional case distributions and projections from 2010 to 2040.

5. Results and Discussion

5.1 Classification Performance

Table 3: CNN Classification Performance

Metric	Target	Achieved	Status
Accuracy	> 95%	96.2%	✓ Met
Precision	> 94%	95.8%	✓ Met
Recall (Sensitivity)	> 95%	96.5%	✓ Met
F1-Score	> 95%	96.1%	✓ Met
Specificity	> 93%	95.4%	✓ Met
AUC-ROC	> 0.95	0.978	✓ Met

5.2 Segmentation Performance

Table 4: U-Net Segmentation Performance

Metric	Optic Disc	Optic Cup
Dice Coefficient	0.912	0.874
IoU (Jaccard Index)	0.838	0.776
Pixel Accuracy	97.3%	95.8%
Mean Boundary Error (px)	2.4	3.1

5.3 Severity Classification Results

Table 5: Severity Classification Based on CDR

Severity	CDR Range	Test Samples	Correctly Classified	Accuracy
Normal	< 0.3	380	372	97.9%
Mild	0.3 – 0.5	145	134	92.4%
Moderate	0.5 – 0.7	120	112	93.3%
Severe	> 0.7	75	71	94.7%
Overall	-	720	689	95.7%

5.4 Comparison with Existing Methods

Table 6: Comparison with Existing Glaucoma Detection Methods

Feature	Manual	ResNet	VGG16	U-Net+XGB	Ours
Classification	Manual	Yes	Yes	Yes	Yes
Segmentation	Manual	No	No	Yes	Yes
CDR Computation	Manual	No	No	Yes	Auto
Severity Grading	Expert	No	No	No	3-level

Web Interface	No	No	No	No	Yes
Precautions	Doctor	No	No	No	Auto
Accuracy	Varies	96.5%	93.1%	94.2%	96.2%
Specialist Needed	Yes	No	No	No	No

5.5 Testing

Four functional test cases validate the system: (1) uploading a non-glaucomatous fundus image correctly classified as Normal with $CDR < 0.3$; (2) uploading a glaucomatous image correctly classified as Glaucoma Positive; (3) severity check correctly identifying Moderate Glaucoma with appropriate precautions; (4) severity check correctly identifying Severe Glaucoma with urgent referral recommendation. All 4 test cases passed successfully.

6. Conclusion

This paper presents an automated glaucoma detection and severity classification system using a dual deep learning architecture. The CNN classifier achieves 96.2% accuracy on binary glaucoma classification from retinal fundus images, while the U-Net segmentation model achieves Dice coefficients of 0.912 for optic disc and 0.874 for optic cup. The automated CDR computation enables three-level severity classification (Mild, Moderate, Severe) with 95.7% overall accuracy.

The web-based interface built with React.js and Flask enables non-specialist healthcare workers to perform glaucoma screening by simply uploading a fundus image, receiving instant classification, severity grading, CDR value, and precautionary recommendations. This addresses the critical shortage of ophthalmologists, particularly in rural areas where 65% of India's population resides with minimal access to eye care specialists.

Future work includes expanding the dataset with multi-center clinical images, integrating OCT (Optical Coherence Tomography) imaging for enhanced diagnosis, implementing real-time video fundus analysis, developing a mobile application for field screening, and deploying the model with TensorFlow Lite for on-device inference without internet dependency.

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