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OptiGuard: Detecting Glaucoma and Monitoring Eye Health Using Advanced Image Analysis

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ABSTRACT: Glaucoma, or as it is commonly known as the ‘gentle thief of sight’, is one of the main causes of irreversible blindness globally. Hypertensive retinopathy has also to be diagnosed early so that adequate steps can be taken for save vision before it becomes severely impaired. OptiGuard is an application involving the use of artificial neural networks intended for early diagnosis of glaucoma by assessing possible damage to the optic nerve from retinal images. With the help of the complicated algorithms, based on the image analysis, OptiGuard provides an efficient diagnostic of the patterns, which are characteristic for glaucoma and is non-invasive, easily accessible and effective. Furthermore, the application is enhanced to diagnose other eye ailments that are eye infections, and eye flu which can comprehensively diagnose the user’s eye health. This paper specifically seeks to describe OptiGuard and the ways in which it was developed, how its performance was measured and tested in terms of more accurate models and the extent to which it might very easily be slotted into clinical use. The findings allude to optimistic possibilities for OptiGuard in helping care providers in early detection, saving cost on diagnostics and enhancing comprehensiveness of treatment through eye care.

KEYWORDS: Glaucoma, Hypertensive retinopathy, Artificial neural networks, Eye infections, Eye flu.

I. INTRODUCTION

Glaucoma is a leading cause of irreversible blindness, accounting for about 15% of global cases. By 2040, nearly 100 million people are expected to be affected. This optic nerve disease is marked by increased cupping of the optic disc, thinning of the neuro-retinal rim, and visual field (VF) defects.

Visual field testing, commonly using the 24–2 Humphrey VF test, evaluates the central 24° of vision. A VF report typically includes five key maps: numerical displays (ND), total deviation plots, probability plots, pattern deviation plots, and visual field indices. ND maps show retinal sensitivity in decibels, while total deviation plots compare these values to age-matched controls. Probability plots highlight deviations from the norm, and global parameters like mean deviation (MD) and pattern standard deviation (PSD) provide an overview of damage. The visual field index (VFI), expressed as a percentage, measures overall visual function. Interpreting VF reports is challenging and requires expertise. Many early-stage glaucoma cases are missed by non-specialists due to the complexity of these reports. While parameters like MD and PSD give a broad picture, they often fail to reflect localized disease progression or the patient’s actual clinical condition.[2] Computer-Aided Diagnosis (CAD) of ocular diseases is receiving a lot of attention from research community due to its far-reaching benefits of providing swift and accurate large-scale screening as well as reducing physicians’ workload in routine clinical setup [7]. Machine Learning (ML) and Deep Learning (DL) based techniques are commonly used to automatically detect various ocular diseases like glaucoma.[9]

II. RELATED WORK

Many studies have applied CNN-based methods to glaucoma detection and screening. In 2016, the PEEK Retina system, a low-cost smartphone attachment with PEEK Grader software, allowed non-ophthalmologists to capture optic nerve photos and grade retinal diseases like glaucoma, achieving results comparable to table-top cameras. By 2018, the

Yanbao App introduced real-time glaucoma detection using U-Net and SVM algorithms, achieving 0.99 and 1.0 accuracy scores on datasets such as ORIGA and DRISHTI-GS1.

In 2019, researchers advanced to automated glaucoma screening, incorporating techniques like Cup-to-Disc Ratio (CDR) measurement, optic disc (OD) and optic cup (OC) segmentation, and ROI extraction. Another study introduced the GFI-ASPP-depth framework, combining U-Net and MobileNet architectures, achieving 0.91 accuracy on combined public datasets.

By 2020, the iGlaucoma app utilized ResNet-50 CNN for visual field analysis, achieving a 0.99 accuracy for pattern recognition. In 2021, smartphone apps further enhanced glaucoma screening with methods like OD localization, segmentation, and SVM classification.

Recent advancements include mobile apps for congenital glaucoma using Haar-based classifiers for home use and hybrid CNN-based Android apps combining image segmentation and classification, achieving accuracy scores up to 0.96 with SVM.[4]

III. GLAUCOMA: DEFINITION AND DIAGNOSIS

Definition: Glaucoma relates to the damage of Retinal Ganglion Cells (RGCs), which leads to a pathological process and alterations to the structure of the retina. These changes present with the development of the loss of Retinal Nerve Fiber Layer (RNFL), Ganglion Cell Inner Plexiform Layer (GCIPL), and Ganglion Cell Complex (GCC) architectural loss, the reduction of the Neuroretinal Rim (NRR) and an increase in the cupping of the Optic Nerve Head (ONH) or the Cup-Disc Ratio (CDR). In addition to these structural changes, visual field sensitivity loss is observed in patients as a result of structural changes brought about the disease. Glaucoma can be considered as a disease with both structural and functional loss components. Glaucoma is primarily understood as a structural disease. Based on that the definition of glaucoma is usually associated with changes of the optic nerve head and retinal nerve fiber.

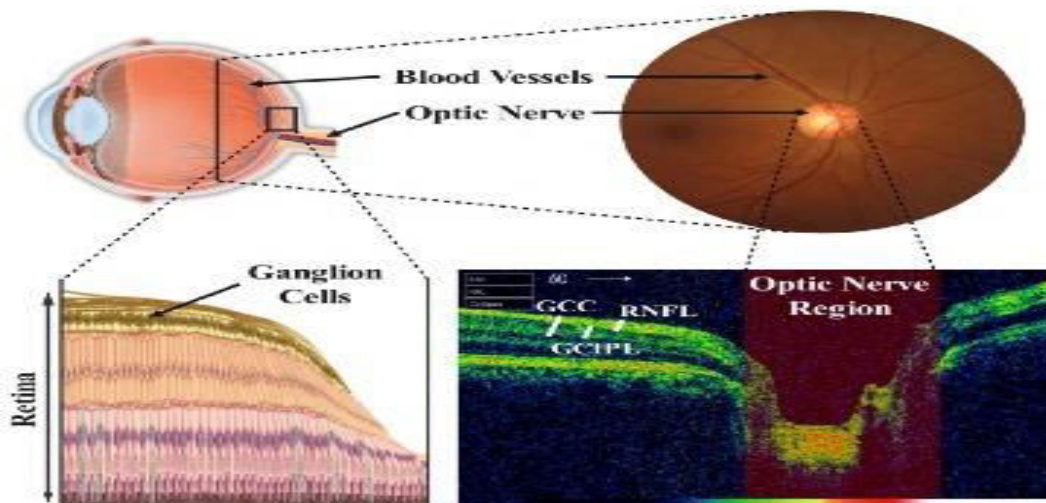


Figure 1: Anatomical structures of the human eye and optic nerve relevant to glaucoma detection. Schematic views, Fundus and OCT views. This figure was created using images licensed under Creative Commons.

IV. OPTIGUARD DIAGNOSIS PROCEDURE

OptiGuard takes its procedures with the utmost seriousness. The subsequent steps allow the user to see exactly what the demo for the program is designed for.

Step 1: Image Capture: In this step, we try to capture a maximum quantity of retinal clear details by taking pictures from within the patient's eye.

Step 2: Image Processing: The retinal photos are enhanced for shadows and their blurriness is reduced, with the primary features being enlarged. Parts of the photo may be rotated and cropped in order to enhance the learning of the model.

Step 3: Feature Extraction: Investigation of peculiar indicators including color, texture and structure like disc optic, as these signs may suggest ailment.

Step 4: Disease Detection Model: The AI model is able to evaluate processed inputs so as to detect anything out of the norm. The model utilizes a labeled data base which enables it to differentiate between healthy eyes and those with diseases such as glaucoma or infections.

Step 5: Diagnosis Report: The report provided by the model indicates if the eye is diseased or appears normal and along with each finding gives a probabilistic measure.

Step 6: Verification: In comparison with the experts, our results are accurate due to the models developed which avoid between overfitting and high confidence levels.

Step 7: Continuous Updates: As the knowledge of the development adds keen importance, this satisfies a clear gap in the market as with every stage the model constantly learns and becomes better.

V. VISUAL ASPECTS OF GLAUCOMA ON RETINAL IMAGES

Analysis of retinal images allows computerized glaucoma diagnosis. Understanding the recognizable glaucoma characteristics in these images is key to appreciating the challenges of computed glaucoma diagnosis. There are different types of retinal images obtained such as fundus (eye disease) imaging, stereo fundus imaging, hyperspectral imaging (HSI), fluorescein angiography (FA), scanning laser ophthalmoscopy (SLO) and optical coherence tomography (OCT) and any of these various techniques can be used to obtain images from the inside of the eye that can be used for glaucoma diagnosis using computer vision. However, retinal fundus imaging is widely used because it is relatively inexpensive and the diagnosis is relatively straightforward with computerized ophthalmology. Ophthalmoscopy, also known as funduscopy, is the method for obtaining retinal fundus images.

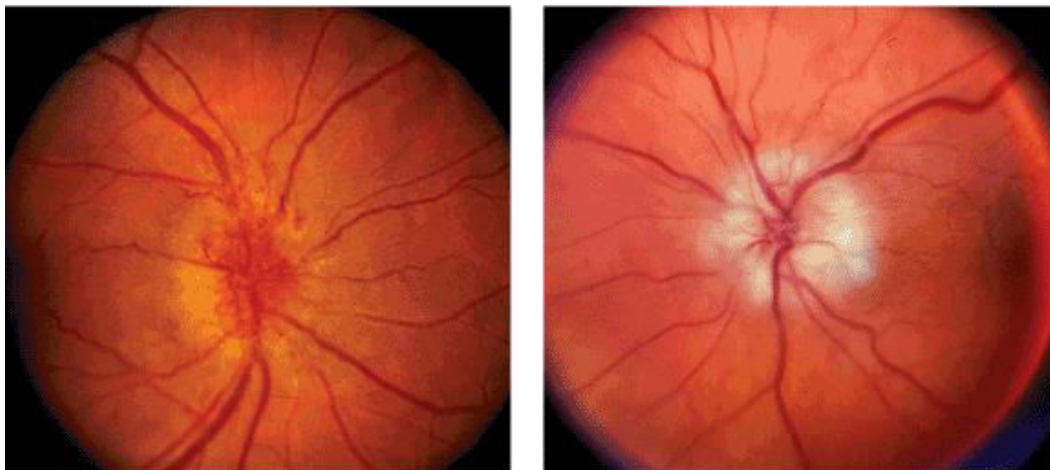


Fig 2: Retinal image

VI. FEATURE EXTRACTION FROM FUNDUS IMAGES

Feature extraction from fundus images has evolved with AI, enabling machine learning (ML) and deep learning (DL) models to improve glaucoma diagnosis. While ML models excel with small datasets and manual feature selection, they face challenges like convergence and overfitting. Deep learning models, particularly CNNs, have become popular for their automated feature extraction and superior predictive performance in medical image analysis.

Our approach enhances feature selection by focusing on regions of interest (ROIs) around the optic nerve head (ONH) and the retinal nerve fiber layer (RNFL). Unlike traditional methods, we incorporated CNN-based visualizations to understand extracted features.[8]

Contributions

1. Preprocessed fundus images with ROIs around ONH and RNFL for improved glaucoma classification.
2. Developed a CNN model to classify glaucoma stages (mild, moderate, severe) and validated predictions with CNN visualizations.
3. Compared the model with VGG16, ResNet50, and MobileNetV2, achieving a **93.75% accuracy**, outperforming these architectures.

VII. EVALUATION METRICS AND DATASETS

Evaluation metrics: Such that the ability of the OptiGuard model in terms of detecting the eye diseases can be evaluated, we used the following evaluation criteria:

Evaluation Metrics:

Accuracy: Measures the overall prediction performance in terms of the percentage correct. Calculated as

$$(TP + TN) / (TP + TN + FP + FN)$$

$$(TP + TN) / (TP + TN + FP + FN).$$

Precision: Contribution of Positives that are predicted positive. Calculated as

$$TP / (TP + FP)$$

$TP / (TP + FP)$ where TP is True Positives and FP is False Positives.

Recall (sensitivity): Calculates the proportion of positive cases that are actual positive findings. Calculated as

$$TP / (TP + FN)$$

$TP / (TP + FN)$, where FN is False Negatives.

F1-Score: Indicative of the balance in precision and recall but highly useful for imbalanced datasets. Calculated as

$$2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

AUC-ROC (Area Under the Receiver Operating Characteristic Curve): This determines how well the model separates diseased from healthy cases at different levels or thresholds.

Hypothesis matrix:

A confusion matrix was used to determine actual scores against model predictions for each disease stage (healthy, febrile, infectious, etc.).

The statistics provide insight into true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for each disease stage, allowing us to see where pattern is effective and where improvements may be needed.

Cross-validation of:

We used k-fold cross-validation (e.g., 5 or 10-fold) to ensure model robustness and reduce overfitting, yielding average performance scores across multiple subsets of the data

Error analysis:

After analyzing the sample, we searched for misclassified data to identify any patterns, such as specific disease types or imaging scenarios that the sample struggled in. This analysis helps refine the model.

VIII. TRANSFER LEARNING WITH CONVOLUTIONAL NEURAL NETWORKS (CNN)

Convolutional Neural Networks (CNNs) are widely used supervised learning algorithms in deep learning, especially for tasks like image classification. They consist of multiple convolutional and subsampling layers that are adept at designing robust filters to extract significant image features for classification tasks. In this study, we utilized the VGG19 architecture, a CNN model with 19 layers, which is recognized for its efficiency and reliability in solving complex image classification problems.

To adapt VGG19 for the classification of healthy and glaucomatous eyes, the original output layer was replaced with a new softmax layer consisting of two units tailored to this binary classification task. This modification allowed the model to categorize input images as either healthy or glaucomatous with high accuracy.

A key strategy employed in this study was transfer learning. Transfer learning involves leveraging a pre-trained model—one developed on a large-scale task—and fine-tuning it for a specific, often smaller, task. Here, the VGG19 model pretrained on the ImageNet dataset, a benchmark in large-scale visual recognition, was used as the foundation. Fine-tuning involved adjusting the pretrained model to our specific dataset using stochastic gradient descent (SGD) optimization. This approach enabled the reuse of learned features from the ImageNet model, such as edge detection and object localization, significantly reducing the training time and improving the model's performance.

The fine-tuning process involved data augmentation techniques to improve the model's generalization ability. These techniques included horizontal flipping, random rotations, and random shifts of input images, which simulate variations that the model might encounter in real-world scenarios. Dropout was also employed during training to prevent overfitting and enhance model robustness.

Five distinct VGG19 models were trained, each tailored to different types of input images. The training was conducted using SGD optimization with a momentum parameter of 0.9 and a fixed learning rate of 10^{-5} . Training was performed over 100 epochs for each model. The computational setup consisted of an Ubuntu 16.04 operating system and a single GTX 1080 TI GPU. Each model took approximately 80 minutes to complete the training process, demonstrating the efficiency of the transfer learning approach in reducing computational cost while maintaining high accuracy.[6]

IX. RESULT



Fig3: First Image

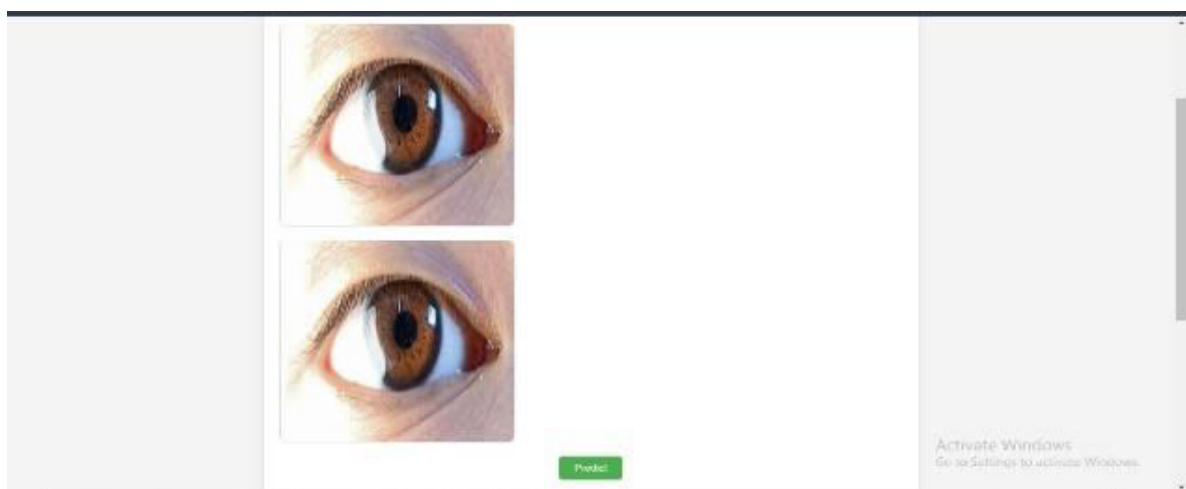


Fig 4: Second Image

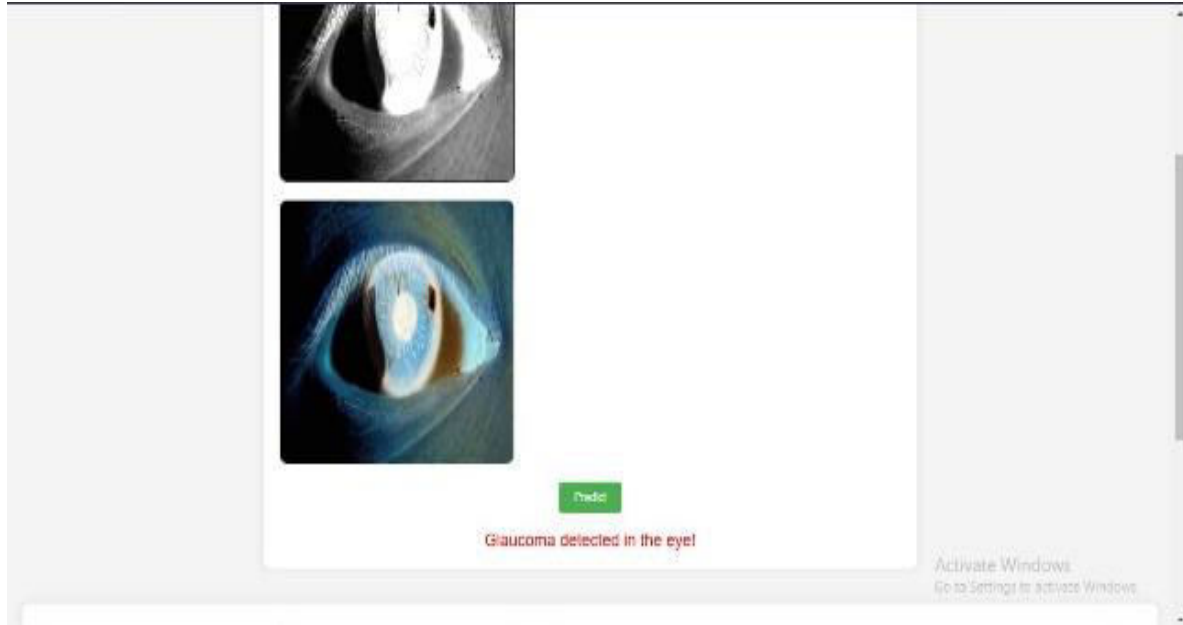


Fig 5: Third Page

X. CONCLUSION

Therefore, OptiGuard forms a breakthrough in the sphere of ophthalmology, with an emphasis upon the simplest methods of diagnosing glaucoma and other ocular diseases at their initial stage. With the help of machine learning as well as the highly developed image processing, OptiGuard can successfully solve significant problems of healthcare workers as well as patients.

The application offers several key benefits:

1. Early and Accurate Diagnosis: OptiGuard has effective detection mechanism due to its refined methods, helps to detect glaucoma on timely basis that helps to avoid blindness.
2. Comprehensive Ocular Health Monitoring: In addition to working specifically for glaucoma, OptiGuard's feature can expand the application by diagnosing other diseases of the eyes, therefore increasing its versatility as a diagnostic program.
3. Accessibility and Affordability: Intended for use in various clinical practice environments, OptiGuard increases access to eye care services by targeting the markets where it is needed most, and helping extend the benefits of enhanced community health.
4. User-Friendly Experience: This feature makes OptiGuard easy to adopt in clinical practices based on the retinal images to ease the work of healthcare providers while improving the patient experience.
5. Robust Security Measures: as the result of the focus on compliance, data protection, and privacy, OptiGuard can protect the patient's data while working with health-care regulations that can let users develop confidence in the application.

The evaluation of the performance also shows us that OptiGuard can possibly define or even out perform the current benchmarks in diagnosing glaucoma thus presenting it as an eye health diagnostics model of the future. However, development and testing revealed constraints that have to be admitted, including the lack of larger and more diverse datasets for training and validation.

The further work will concern the fine tuning of the algorithms, the increase of the set, and the elaboration of new possible functionalities to enrich the diagnostic possibilities of OptiGuard. Continued R&D is OptiGuard's next step toward becoming an indispensable part of ophthalmology that will promote improved vision and health among people around the globe.

REFERENCES

- [1] T. Saito and M. Rehmsmeier, "The Precision-Recall Plot Is More Informative than the ROC Plot When Evaluating Binary Classifiers on Imbalanced Datasets," *PLoS One*, vol. 10, no. 3, p. e0118432, Mar. 2015, doi: 10.1371/journal.pone.0118432
- [2] F. Li et al., "Development and clinical deployment of a smartphone-based visual field deep learning system for glaucoma detection," *npj Digital Medicine*, vol. 3, no. 1, pp. 1–8, Sep. 2020, doi: 10.1038/s41746-020-00329-9.
- [3] J. Martins, J. S. Cardoso, and F. Soares, "Offline computer-aided diagnosis for Glaucoma detection using fundus images targeted at mobile devices," *Comput. Methods Programs Biomed.*, vol. 192, Aug. 2020, doi: 10.1016/j.cmpb.2020.105341.
- [4] "A Fast and Accurate Method for Glaucoma Screening from Smartphone-Captured Fundus Images," *IRBM*, Jun. 2021, doi: 10.1016/j.irbm.2021.06.004
- [5] Raghavendra U, Fujita H, Bhandary SV, Gudigar A, Tan JH, Acharya UR. Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images.
- [6] G. An, K. Omodaka, K. Hashimoto, S. Tsuda, Y. Shiga, N. Takada, T. Kikawa, H. Yokota, M. Akiba, and T. Nakazawa, "Glaucoma diagnosis with machine learning based on optical coherence tomography and color fundus images," *Journal of healthcare engineering*, vol. 2019, 2019.
- [7] Y. Hagiwara, J. E. W. Koh, J. H. Tan, S. V. Bhandary, A. Laude, E. J. Ciaccio, L. Tong, and U. R. Acharya, "Computer-aided diagnosis of glaucoma using fundus images: A review," *Computer methods and programs in biomedicine*, vol. 165, pp. 1–12, 2018.
- [8] Early detection of glaucoma: feature visualization with a deep convolutional network Jisy N K Md. Hasnat Ali Sirisha Senthil & M.B. Srinivas Article: 2350508 | Received 16 May 2023, Accepted 27 Apr 2024, Published online: 20 May 2024
- [9] T. W. Rogers, N. Jaccard, F. Carbonaro, H. G. Lemij, K. A. Vermeer, N. J. Reus, and S. Trikha, "Evaluation of an ai system for the automated detection of glaucoma from stereoscopic optic disc photographs: the european optic disc assessment study," *Eye*, vol. 33, no. 11, pp. 1791–1797, 2019.



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