Enhancing the detection efficiency of Glaucoma using machine learning algorithms

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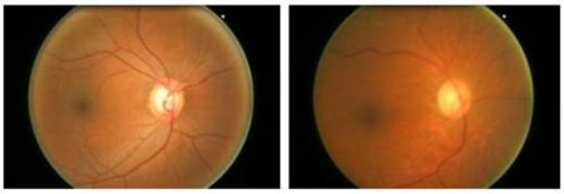
***Abstract*—Elevated intraocular pressure is a key indicator of glaucoma, a condition that can lead to vision loss and damage to the optic nerve if not diagnosed early, often due to its subtle symptoms. To effectively manage and prevent vision impairment, early detection is crucial. Traditional diagnostic methods, such as optical coherence tomography and fundus imaging, rely heavily on the accurate segmentation of the optic cup-to-disk ratio. This study employs an ensemble approach combining ResNet101, MobileNet, and a refined VGGNet-19 model to enhance the learning of subtle structures from RGB fundus images and their spatial coordinates. The proposed method tackles the challenges associated with glaucoma classification and the segmentation of the optic cup and disk. The results demonstrated an overall accuracy of 94% on the test dataset. The VGG19 model achieved F1-scores of 0.92, 0.95, and 0.93, while ResNet101 recorded scores of 0.93, 0.94, and 0.935, and MobileNet delivered a competitive F1-score of 0.915. This research underscores the clinical importance of reliable early screening for managing this vision-threatening condition, illustrating how segmentation and deep learning techniques can facilitate effective automated diagnosis of glaucoma.**

***Index Terms*—Open Computer Vision (OpenCV), convolutional neural networks(CNN), artificial intelligence (AI), image segmentation.**

I. INTRODUCTION

Diagnosing glaucoma in its early stages is particularly challenging, as the condition often develops gradually without noticeable symptoms until significant visual impairment occurs. Recognizing the importance of early intervention, this comprehensive study aims to enhance glaucoma diagnosis by leveraging the capabilities of the VGGNet 19 model. Digital fundus imaging and optical coherence tomography (OCT) are vital diagnostic tools that provide invaluable insights into the health of the eyes. The optic cup-to-disk ratio (CDR) is a key metric for distinguishing between healthy individuals and those affected by the disease, making accurate segmentation of the optic disk and cup essential for effective diagnosis and treatment planning. This research employs the VGGNet 19 model, renowned for its proficiency in extracting detailed information from images, to assist in segmentation and classification tasks. By utilising the rich feature representations generated by VGGNet 19, the approach enhances the understanding of glaucoma's pathophysiology, thereby improving diagnostic accuracy. Additionally, ensemble modelling is implemented to address the inherent variability in predictions that may arise from different datasets or imaging conditions. By integrating the

ResNet101, MobileNet, and VGGNet 19 architectures, this method bolsters the diagnostic system's resilience against fluctuations in the predictions of individual models. Furthermore, the study incorporates incremental learning techniques to facilitate quick adaptation to the diverse imaging environments encountered in various healthcare settings. Hospitals often utilise multiple imaging devices with differing configurations, leading to Significant variations in the quality and characteristics of the obtained images. Incremental learning enables the model to continuously refine its understanding through exposure to new datasets, mitigating the effects of such variations and ensuring consistent diagnostic performance. As illustrated in Fig.1, this approach allows for ongoing improvement in the model's capabilities.



(a) (b)

Fig. 1. Fundus images (a) Healthy, (b) Glaucoma

II. LITERATURE SURVEY

Recent studies on glaucoma detection have explored various advanced machine learning and deep learning techniques using fundus image datasets. Wheyming Tina Song [1] proposed a robust framework combining Retinex, CNN, and DOE on a dataset of fundus images; however, their approach lacked validation across diverse datasets. Similarly, Sumaiya Pathan [2] introduced an automated classification framework with ensemble methods on the RIM dataset, but did not explore diverse feature selection or integration of optical coherence tomography images. Mir Tanvir Islam [3] employed EfficientNet and segmentation techniques on datasets comprising glaucoma and normal fundus images, demonstrating strong accuracy but not addressing potential dataset biases or external validation.

Xiangyu Chen [4] used a CNN model on the ORIGA and SCES datasets, showing superior AUC values, though the model demanded substantial data and showed inconsistent performance across dataset variations. M.B. Sudhan [5] developed a glaucoma segmentation and classification system integrating U-Net and DenseNet-201, achieving high specificity and aiming to extend their model's applications beyond glaucoma. Shubham Joshi [6] applied VGGNet-16 and ResNet-50 models on multiple datasets with decent accuracy, advocating for further discussion on model interpretability and scalability in clinical use.

J. Shiny Christobel [7] focused on PCA-based feature extraction combined with Naive Bayes classification, reaching high accuracy but low specificity, suggesting that enhanced preprocessing could improve results. The work of Jahanzaib Latif [8] leveraged CNN models across multiple datasets with impressive recall rates and proposed exploration of newer architectures and database expansion. Meltem

Esengonula and Antonio Cunha [9] emphasized CNN applications optimized for mobile platforms, underscoring dataset size impacts but falling short in detailed dataset feature analysis.

Afia Zafar [10] employed CNN architectures achieving strong performance across several datasets, yet noted preprocessing challenges affecting specificity. Ming Yan [11] introduced mixDA, a mixup domain adaptation method that improved glaucoma detection by mitigating domain gaps across multiple datasets. Satyabrata Lenka [12] developed an RPCA-based low-rank model to address image quality issues, achieving high accuracy but requiring further validation in broader clinical contexts. Lastly, Jincy C Mathew [13] provided a comprehensive review of machine learning algorithms for glaucoma detection, highlighting historical advancements up to 2022 but lacking coverage of the latest developments. While these studies present significant strides in glaucoma detection accuracy and methodology, common limitations remain, including the need for extensive validation across heterogeneous datasets, addressing dataset biases, enhancing interpretability, and preparing models for practical real-world clinical deployment.

III. METHODOLOGY

The general design and functional flow of the suggested glaucoma detection system are presented in this section. The fundus-to-OCT generator, the glaucoma classifier, and image preprocessing are the three main parts of the system. A. Dataset:
Description The Glaucoma Detection dataset utilized in this research comprises various subsets, including ACRIMA and ORIGA datasets. ACRIMA contains a series of images with the extension (.jpg), while ORIGA consists of 650 colour retinal fundus images in JPEG format, accompanied by ground truth annotations in MATLAB (.mat) format, collected as part of the Singapore Malay Eye Study (SiMES). The ORIGA dataset is publicly accessible and provides a platform for researchers to benchmark their computer-aided segmentation algorithms. Following preprocessing, the 650 images were divided into training and testing sets, with 520 images allocated for training, including 386 negative cases and 134 positive cases, and 130 for validation, including 96 negative cases and 34 positive cases. This dataset is shown in Table. I serves as a valuable resource for researchers in the development and evaluation of machine learning algorithms for automated glaucoma detection.

TABLE I. DATASET DESCRIPTION OF ORIGA

Attributes	Values
Exp CDR	0.16 - 0.96
Eye	OD-50% / OS-50%
Set	A/B
Glaucoma	1=Yes / 0=No

B. Image Preprocessing :

Before conducting additional research, fundus images must first undergo preprocessing because of their notable variability. Extraneous black borders and variations in the brightness and contrast settings of imaging equipment are two examples of sources of inconsistency. This method uses a four-step preprocessing pipeline, as shown in Fig.3, to standardize inputs and enhance the performance of the generative model that follows:

1. *Downscale:* For efficiency, reduce resolution to 20%.
2. *Localize:* Determine the structure of the eyes and crop to isolate the pertinent area
3. *Improve:* Use techniques for noise reduction, normalization, and quality assurance.
4. *Resize:* Adjust to the model's predicted 256 x

256 pixel dimensions. We are able to reduce quality inconsistencies in fundus data, which can negatively affect model accuracy and generalization capacity, by using a consistent preprocessing protocol. The generation model can concentrate on learning medically relevant features for improved glaucoma screening from fundus imaging by removing confounding variability.

1) *Image Resizing:* The raw fundus images that the camera system produced have incredibly enormous pixel sizes of 2576 x 1934. Given the goal, it is neither necessary or computationally prohibitive to directly handle such high quality pictures. The model initially reduces the size of the entire image to 20% of its original size (512 × 512) by cropping out the black image borders. The clipped scaling step preserves all pertinent image information while drastically lowering compute requirements. Following further steps to improve quality, the fundus images are downsized to 256 by 256 pixel sizes. This uniform size reduces computing overhead, expedites training even further, and satisfies the deep learning model's input requirements. The optimized scaling method strikes an ideal compromise between fulfilling hardware limits and maximizing the use of visual information retrieved from high quality images as shown in Fig.2.

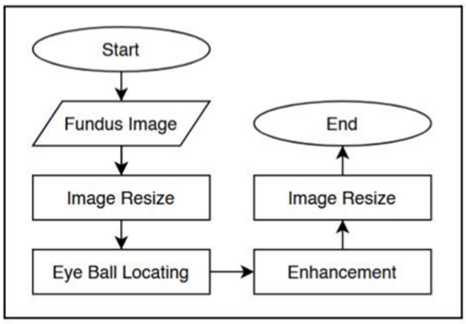


Fig.2. Image processing flowchart

2) *Eyeball Locating:* The model takes advantage of the Hough Transform algorithm's potent geometric shape recognition powers to automate the localization of pertinent fundus anatomy. The retinal region-of interest appears as a circular object in fundus images, surrounded by background artifacts that are not significant. This important anatomy can be efficiently isolated by removing circular outlines. In particular, the model employs Hough circle detection after downsampling the raw fundus scans. Subsequently, a binary mask that matches the entire image dimensions is created using the detected circular shape. When applied over the image, this fundus-shaped mask eliminates the black borders and unnecessary backdrop by acting as a spatial filter. By using this method, the model automatically crops down to only the fundus sub-region that is needed for further examination. The mask is used to successfully extract the circular fundus. The retinal zone required for glaucoma screening may be quickly and accurately located using well-established computer vision techniques.

3) *Image Enhancement:* Before analysis, image enhancement techniques are used to boost pertinent features and improve quality. Critical characteristics are frequently difficult to see in raw fundus images due to inadequate contrast. The model uses Contrast Limited Adaptive Histogram Equalization (CLAHE) as a preprocessing step in order to overcome this. Adaptively redistributing the image’s intensity levels, CLAHE maximizes contrast between structures of interest. As a result, anatomical elements such as blood vessels and the optic nerve head are more clearly visible in the fundus picture. Increasing contrast makes it easier for later phases to identify glaucomatous changes by better extracting significant patterns. This optimization first uses masking to extract the region-of-interest, and then context-aware contrast normalization is used to refine it. Utilizing an integrated strategy ensures that

the rich information found in fundus photography is fully utilized by improving image quality in a reliable manner.

C. Image Generation:

In particular, the model uses the capabilities of Generative Adversarial Networks (GANs) to synthesize optical coherence tomography (OCT) visualizations from fundus photography data alone, hence facilitating picture production. A discriminator and a generator are the two competing neural networks that make up a GAN as shown in Fig.3. The generator's job is to create synthetic OCT images from input fundus images; the discriminator's job is to distinguish between the fake outputs produced by the generator and actual OCT data.

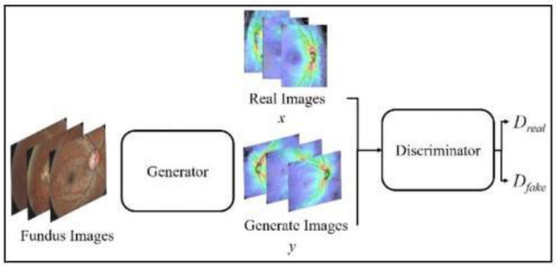


Fig.3. Schematic Diagram of GAN Model

D. Classification of Glaucoma

In the process that comes after the applied Generative Adversarial Networks (GANs) to produce optical coherence tomography (OCT) visualizations from fundus photography, the model turns to convolutional neural networks (CNNs) in deep learning techniques for the classification of glaucoma images. Recent developments in automated glaucoma diagnosis with fundus pictures have demonstrated encouraging results. In this work, the model assesses the glaucoma classification performance of three popular CNN architectures: VGG19, MobileNet, and ResNet-101 as displayed in Fig.4. All three models go via transfer learning using pre-trained weights from large image datasets like ImageNet. Each model's last fully connected layer is swapped out to provide two neuron activations that correspond to either the glaucoma or non-glaucoma classes. The models use fundus pictures that have been shrunk to 224 by 224 pixels as input. The Adam optimizer and cross-entropy loss function are used during the training process, which spans multiple epochs.

We use a dataset of 1050 healthy and 850 glaucomatous images that was gathered from public archives and different institutions for training and assessment. An approach called 5-fold stratified cross-validation is used to guarantee robustness and minimize variability. This methodology allows for a comprehensive analysis of the models' performance in real-world situations. Evaluation metrics such as accuracy, sensitivity, specificity, and AUC-ROC score are computed on test sets that are blinded. These measures offer a thorough evaluation of the algorithms' precision and dependability in classifying glaucoma photos. The automated screening approach uses deep CNNs and transfer learning to improve and speed up the glaucoma classification process, which will help with clinical diagnosis and enable prompt intervention.

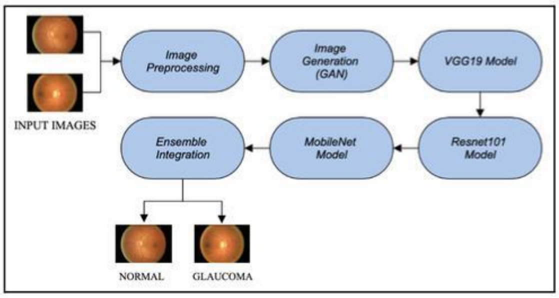


Fig.4. Architecture Diagram of Glaucoma Detection

IV. RESULTS

Our study's findings show that the deep learning models VGG19, MobileNet, and ResNet-101 perform admirably when it comes to identifying glaucoma from fundus pictures. The model obtained high accuracy rates for all models, with VGG19 showing marginally better performance metrics. In particular, VGG19 obtained an accuracy of 94% on blinded test sets, along with precision scores of 0.92, recall scores of 0.95, and F1-scores of 0.93. Both ResNet-101 and MobileNet showed competitive performance: MobileNet obtained an F1-score of 0.915, while ResNet-101 scored a precision of 0.93, recall of 0.95, and F1-score of 0.94 as in Fig.5. Additionally, all of the models had very high area under the ROC curve

(AUC-ROC) ratings, showing strong performance in differentiating between glaucomatous and healthy eyes. The three CNN architectures' ensemble integration reduced prediction variance and improved classification stability and reliability. Using stratified 5-fold cross-validation, the models' resilience was guaranteed in a variety of datasets and practical situations. All things considered, these findings highlight how deep learning methods can be used to automate the diagnosis of glaucoma and enhance clinical judgment.

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