A Novel Approach Towards Glaucoma Detection Using Machine Learning Techniques

Submitted by

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Declaration

We certify that the work contained in this report is original and has been done by us under the guidance of my supervisor(s). The work has not been submitted to any other institute for any degree. We have followed the guidelines provided by the institute in preparing the report. We have conformed to the norms and guidelines given in the Ethical Code of Conduct of the institute. Whenever we have used materials (data, theoretical analysis, figures, and text) from other sources, we have given due credit to them by citing them in the text of the report and giving their details in the references. Further, we have taken permission from the copyright owners of the sources, whenever necessary

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Abstract

Glaucoma, a progressive optic neuropathy, is a leading cause of irreversible blindness worldwide. Early and accurate detection is critical for effective intervention and vision preservation. This study explores the application of deep learning techniques, specifically convolutional neural networks (CNNs), for glaucoma detection from retinal fundus images. Leveraging ResNet34 and ResNet50 architectures, the research aims to achieve high sensitivity and specificity in classification. The dataset comprises 8000 retinal fundus images, equally distributed between healthy and glaucomatous cases. Image augmentation techniques, including rotation, flipping, and Normalization, were employed to enhance model robustness and generalization.Performance was evaluated using metrics such as accuracy, sensitivity, specificity, and precision. Experimental results indicate that ResNet50 slightly better than ResNet34, The findings highlight the potential of ResNet-based architectures for reliable glaucoma detection. Future work includes expanding the dataset and integrating advanced architectures to further improve detection capabilities across diverse populations.

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Chapter 1: Introduction

Glaucoma is a group of progressive eye diseases that damage the optic nerve, often due to increased pressure in the eye (intraocular pressure).Age-related chronic illness described as a disorder of the eye around a group of progressive optic neuropathies. Optic neuropathy associated with increased glaucomatous damage is defined as the progression of glaucoma as loss of RGC during the early and undiagnosed stages of the disease, followed by narrowing of the retinal nerve fiber layer (RNFL) thinning, and ultimately damage to the visual acuity (VF). According to a previous study, the chances of developing from ocular hypertension to one-dimensional vision loss (i.e., formal blindness) are 1.5–10.5a result, early detection is essential to prevent further progression of the disease and loss of vision Early detection is critical to prevent blindness. Computer-assisted diagnostic tools and CNNs are increasingly used for accurate and reliable detection. (CNN) have been implemented as a result of recent developments in processing power capabilities, allowing for autonomous glaucoma classification based on complicated features extracted from thousands of available fundus pictures. fastai uses minor components of academics that be combined and matched to create novel techniques. It also uses major components that can provide avant-garde results in the convolutional neural networks by which the libraries that are used by practitioners can get access to deep learning libraries. It strives to achieve both goals without sacrificing usability, flexibility, or performance. The architecture has been designed such that it expresses most the common basic deep learning and data processing techniques ready and easy for use.

Chapter 2: Related Work

Christopher et al. proposed method that compares and contrasts deep learning algorithms to detect glaucoma in fundus images and to explore strategies for intro ducing new data into models. Two datasets consisting of fundus datasets have been taken from the Diagnostic Innovations in Glaucoma Study/African Descent and Glau coma Evaluation Study and Matsue Red Cross Hospital. Both the datasets have been independently used for detecting glaucoma at the University of California, San Diego, and University of Tokyo. They have concluded that deep learning glaucoma detec tion can achieve a high level of accuracy with appropriate strategies. A high range of sensitivity and specificity of the deep learning algorithms suggest that role of AI in detection of glaucoma in primary detection that range from moderate-to-severe for a wider population . Chen et al proposed a deep learning method that uses the automatic feature learning called ALLADIN in which the method adopts micro neural networks (multi layer perceptron). Unlike the traditional CNNs that uses linear filters firstly and then nonlinear activation function that scans the input. To extract the information from the receptive field that has got high complex structures, the network uses the concept of micro neural networks. Furthermore, in order to differentiate between glaucoma and the healthy images the network uses the outputs of other pre-trained CNNs as themes to improve the performance of the model and is also used to represent the images as a hierarchical way. Howard et al proposed a new deep learning tool-fastai, that grades the tensors in a semantic way as well as includes a novel Python dispatch system. For imple menting the code in few lines, the optimizer of the GPU-optimized computer library refactors the common functionality into two pieces. This is not only a new way of two-way callback system that can access any data points but also can change the optimizer or model at any point of time. We were able to use this package to success fully develop a whole deep learning course in less time than we could with previous approaches.

Chapter 3: Materials and Methods

3.1 Dataset Description

The data set used in this study is the Glaucoma dataset, which originally contains a total of 2 different classes i.e RG (Referable Glaucoma) NRG (Non Referable Glaucoma). along with background images. The total number of images across these 2 classes is 8000.

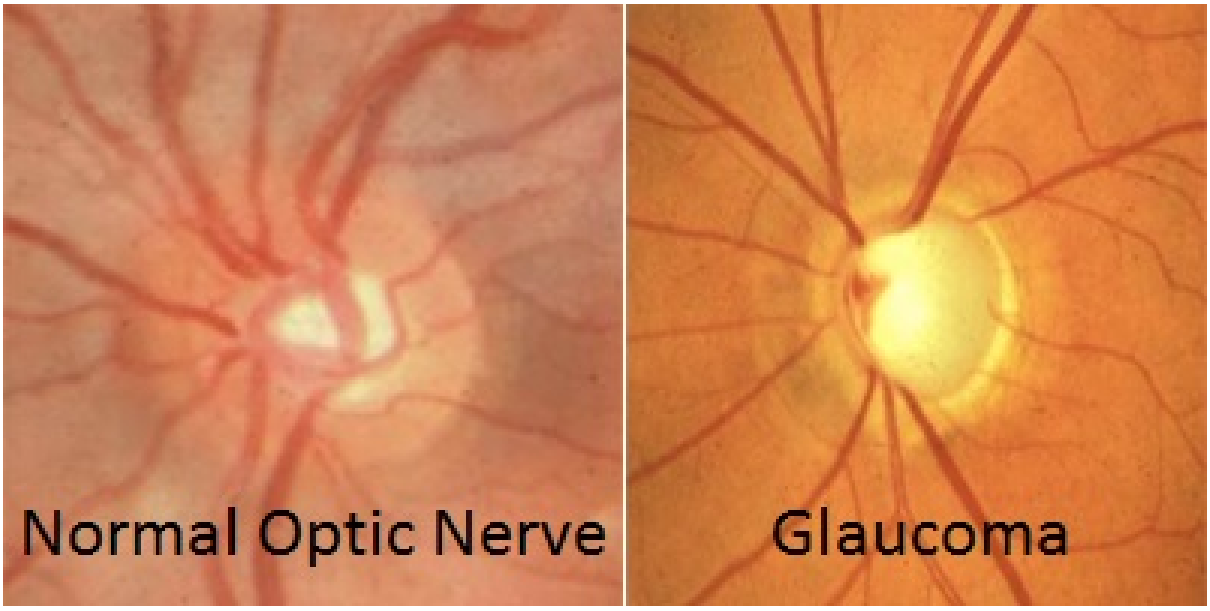

Figure 1: Normal vs Glaucoma

3.2 Methodology

In our project on Glaucoma detection, we started by using the RG and NRG dataset, which includes images of 2 different classes RG and NRG. We then split the dataset into three parts for training,testing and validation. The splitting process was done using code. Next, we employed different architectures, including ResNet34, and ResNet50. During training, we applied image transformations such as resizing,flipping,rotating. For each model, we extracted important features and saved the trained models and their extracted features. The models were saved as pickle files, and the features were saved as NumPy files. We then stored only the best-trained model from each architecture, which had the best loss score during the training process. We trained ResNet34 and ResNet50 for 20 epochs used the trained models to extract features from the testing data.

Workflow

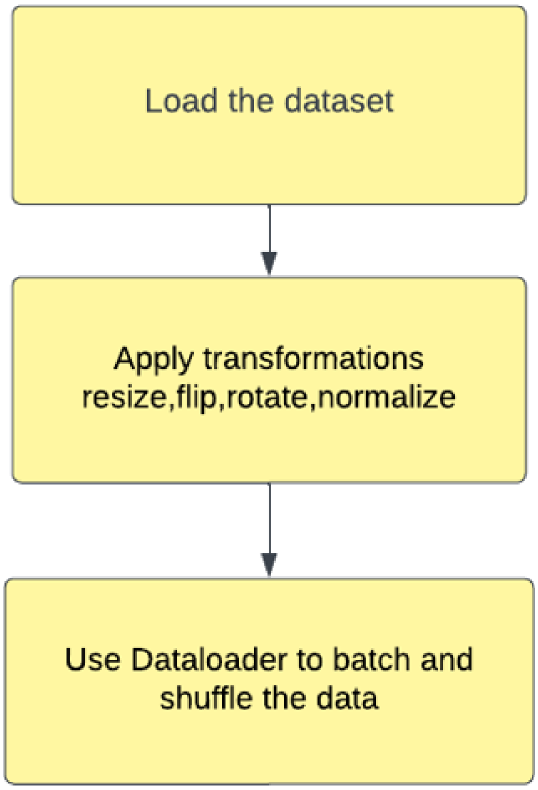

Figure 1: Data Preprocessing

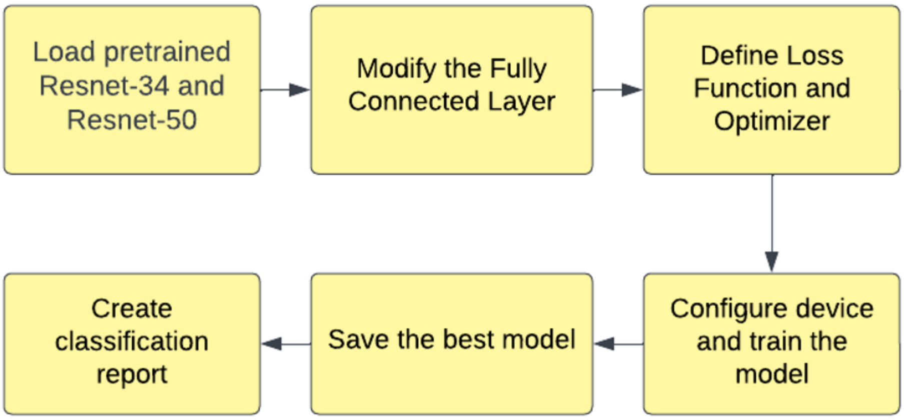

Figure 2: Model Training

Chapter 4: Results

The performance metrics (Accuracy, Precision, Recall, F1-Score) for ResNet-34.

Classification Report:

	precision	recall	f1-score	support
NRG	0.90	0.96	0.93	385
RG	0.96	0.89	0.92	385
accuracy			0.93	770
macro avg	0.93	0.93	0.93	770
weighted avg	0.93	0.93	0.93	770

Figure 1: ResNet-34 Model

The Performance metrics (Accuracy, Precision, Recall, F1-Score) for ResNet-50.

Classification Report:

	precision	recall	f1-score	support
Class 0	0.93	0.94	0.93	385
Class 1	0.93	0.93	0.93	385
accuracy			0.93	770
macro avg	0.93	0.93	0.93	770
weighted avg	0.93	0.93	0.93	770

Figure 2: ResNet-50 Model

Chapter 5: Conclusion

This study demonstrates the effectiveness of deep learning models in glaucoma detection using fundus images. By evaluating ResNet34 and ResNet50 architectures, it was observed that ResNet50 achieved slightly superior performance in terms of accuracy, sensitivity, specificity, and precision.

Future enhancements, such as incorporating larger datasets and more advanced models, can further improve accuracy and reliability, enabling early detection and reducing the burden of vision loss due to glaucoma.

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