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A Project Report on

Deep Learning Approach to Enhance Accuracy for Early Detection of Glaucoma

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CERTIFICATE

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ABSTRACT

Diabetes is a medical disorder when the blood sugar (glucose) level cannot be controlled by the body. This can occur if the body can't properly use the insulin it produces or if the body doesn't produce enough insulin. Diabetes can lead to major health issues and increase your chance of developing a number of eye illnesses such as Glaucoma, Diabetic Retinopathy, Strabismus and etc if it is not properly managed. The advancement of machine learning algorithms has made early detection of various eye illnesses using an automated method significantly more advantageous than manual detection. The ocular illness that lead to visual loss is Glaucoma which do not have any symptoms. Early detection can help to reduce disease-related vision loss. This project proposes a segmentation using UNet model (which is a U-shaped encoder-decoder network architecture, which consist of four encoder blocks and four decoder blocks that are connected via a bridge with Relu activation function) on fundus images followed with data augmentation. The CNN (Convolution Neural Network) model is then trained using pre-processed fundus image. The proposed model was trained using IEEE dataset REFUGE and Kaggle repository. In an evaluation after 100 epochs, the accuracy is 92%. The proposed model outperforms existing deep learning model for early detection of glaucoma.

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CHAPTER 1

INTRODUCTION

1.1 BRIEF INTRODUCTION

Glaucoma is a complex eye condition that can lead to blindness if left untreated. It is caused by an increase in intraocular pressure (IOP), which can result in damage to the optic nerve. In this article, we will take a closer look at the anatomy of the eye and how glaucoma develops [1]. The anatomy of the eye can be divided into three main layers: the outer layer, which includes the cornea and sclera; the middle layer, which includes the iris, ciliary body, and choroid; and the inner layer, which includes the retina and optic nerve as shown in Fig 1.1. The anterior chamber is a space located between the cornea and the iris, while the posterior chamber is a space located between the iris and the lens.

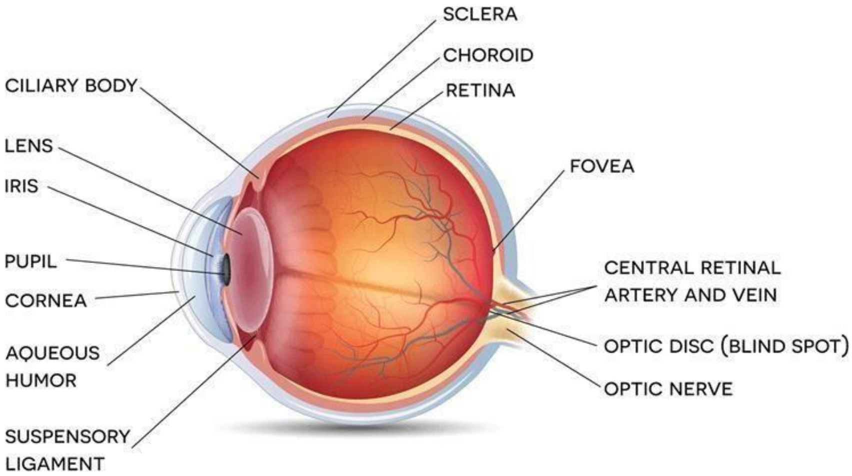

Fig 1.1: Anatomy of eye

In a healthy eye, the ciliary body secretes a clear fluid called the aqueous humor into the posterior chamber. This fluid flows through the pupil into the anterior chamber, where it provides nourishment to the cornea and lens. The aqueous humor then drains out of the eye through a meshwork of tiny channels called the trabecular meshwork. The trabecular meshwork is a critical structure in the eye because it regulates the flow of aqueous humor out of the eye. In glaucoma, the trabecular meshwork becomes partially or completely blocked, which can cause the aqueous humor to build up in the eye. This buildup of fluid can increase the pressure inside the eye, which can cause damage to the optic nerve.

There are several types of glaucoma, but the most common form is primary open-angle glaucoma (POAG). In POAG, the trabecular meshwork becomes clogged over time, which can cause a gradual increase in IOP. This increase in pressure can cause damage to the optic nerve and lead to vision loss [2]. Another form of glaucoma is angle-closure glaucoma, which occurs when the iris is pushed or pulled forward, blocking the drainage canals in the eye. This can cause a sudden increase in IOP, which can cause severe damage to the optic nerve and lead to vision loss.

In recent years, advances in technology and research have led to the development of various methods for detecting glaucoma. These methods range from traditional clinical exams to sophisticated imaging techniques and machine learning algorithms. The goal of glaucoma detection is to identify patients who are at risk of developing the disease or who already have early signs of the disease before significant damage occurs. The most commonly used method for glaucoma detection is through intraocular pressure (IOP) measurement [3]. Elevated IOP is a major risk factor for developing glaucoma, and reducing IOP through medication, laser treatment, or surgery can help to slow down the progression of the disease. Other methods used to detect glaucoma include visual field testing, optic nerve imaging, and anterior segment imaging. Medications such as eye drops can help to lower IOP by reducing the production of aqueous humor or increasing the outflow of fluid from the eye.

In recent years, machine learning algorithms, specifically convolutional neural networks (CNN), have shown promise in detecting and diagnosing glaucoma. CNNs are a type of deep learning algorithm that is able to recognize patterns and features in images, making it well-suited for analyzing medical images. By training CNN models on large datasets of images of healthy and glaucomatous eyes, researchers have been able to develop accurate and reliable models for detecting glaucoma.

A Convolutional Neural Network (CNN) is a deep learning model specifically designed for processing and analyzing visual data, such as images. It utilizes convolutional layers to extract features from the input data by applying a set of learnable filters. These filters convolve over the input, capturing patterns and spatial relationships. Pooling layers are used to reduce spatial dimensions and extract higher-level features. The output is then passed through fully connected layers for classification or regression as shown in Fig 1.2. CNNs are highly effective in image-related tasks, as they can automatically learn and recognize complex patterns, leading to accurate predictions and superior performance in visual data analysis.

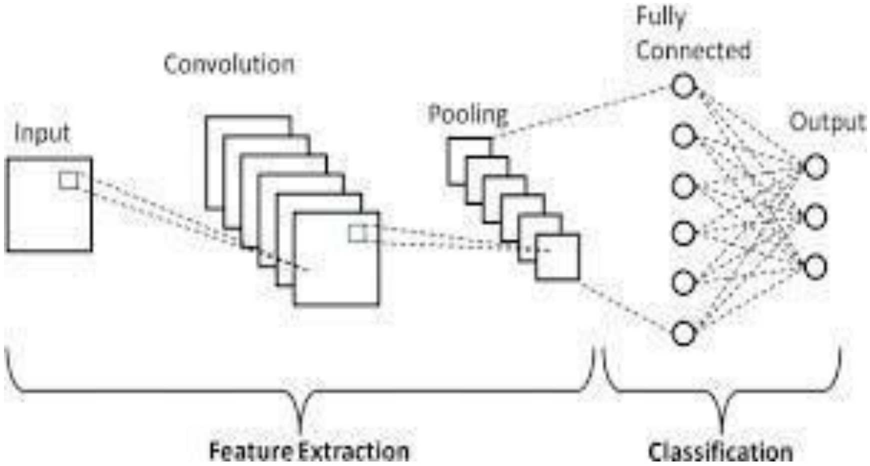

Fig 1.2: Basic structure of CNN model

Glaucoma detection is a critical aspect of managing this sight-threatening condition. Early detection and treatment are essential in preserving vision and preventing blindness. Various methods, including traditional clinical exams and advanced imaging techniques, as well as machine learning algorithms like CNNs, can aid in the early detection and diagnosis of glaucoma. As technology and research continue to advance, it is hoped that these methods will become even more effective in detecting glaucoma and improving patient outcomes [5].

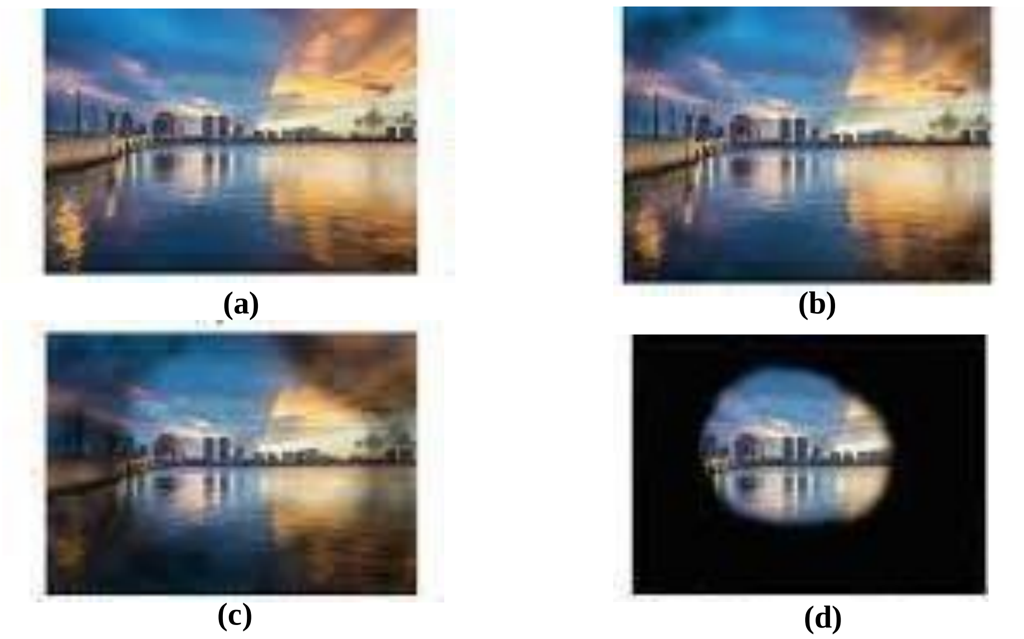

Fig 1.3: Stages of vision of eye **(a)** Vision of normal eye **(b)**Vision of eye at early stage of glaucoma **(c)**Vision of eye at advanced stage of glaucoma **(d)** Vision of glaucoma eye

1.2 OBJECTIVES AND SCOPE OF THE PROJECT

1.2.1 Objectives

The main objective of glaucoma detection using CNN models is to improve the accuracy and efficiency of diagnosing and monitoring glaucoma. The use of machine learning algorithms like CNNs can provide a more objective and quantitative assessment of glaucoma, compared to traditional subjective assessments.

1. To Develop CNN model with better accuracy.
2. To compare different algorithms based on multiple parameters.
3. To effectively classify glaucomatous and non-glaucomatous fundus.

1.2.2 Scope

The scope of glaucoma detection using CNN models is vast and holds significant potential in the field of ophthalmology. CNNs can aid in early detection, monitoring, and management of glaucoma by providing accurate and reliable diagnostic tools. Most significant advantage of CNN models for glaucoma detection is their ability to provide an objective and quantitative assessment of the disease. Traditional assessments of glaucoma, such as optic nerve head evaluation and visual field testing, are often subjective and require a trained ophthalmologist to interpret the results. By contrast, CNN models can provide a standardized and automated analysis of medical images, reducing the potential for human error and bias.

The scope of glaucoma detection using CNN models also extends to the development of personalized treatment plans for patients. By analyzing medical images over time, CNN models can monitor the progression of glaucoma and help ophthalmologists determine the most appropriate treatment course for each patient. This can lead to better outcomes for patients and a reduction in the risk of vision loss or blindness. Overall, the scope of glaucoma detection using CNN models is vast and holds significant promise in the field of ophthalmology. With continued research and development, CNN models may become an essential tool for detecting and managing glaucoma, ultimately improving patient outcomes and reducing the burden of this debilitating disease.

1.3 PROBLEM FORMULATION

1.3.1 Problem statement:

Glaucoma is a major cause of blindness worldwide, affecting millions of people. Early detection and treatment can prevent vision loss, but traditional screening methods can be time-consuming and expensive. A vision-based approach using convolutional neural networks (CNNs) can potentially provide a faster and more cost-effective solution for glaucoma detection. However, designing an effective CNN model for accurate glaucoma detection is a challenging problem.

1.3.2 Problem solution:

The proposed solution for the glaucoma detection problem using a CNN model involves several steps. Firstly, a dataset of retinal fundus images is collected, pre-processed, and annotated. Then, a CNN architecture is designed and trained using the annotated dataset. The CNN model is optimized by tuning the hyperparameters and regularization techniques. Finally, the trained model is evaluated using various performance metrics such as precision, selectivity, sensitivity and accuracy. The proposed approach can potentially provide a faster, cost-effective, and accurate solution for glaucoma detection, enabling early diagnosis and treatment to prevent vision loss.

CHAPTER 2

REVIEW OF LITERATURE

1. Hybrid CNN assisted Computer Aided Diagnosis System for Glaucoma Detection and Classification: GlaucoNet+ [6]

A hybrid deep learning model has been developed by researchers to improve the accuracy and efficiency of glaucoma detection using fundus images. The model utilizes two distinct CNN models, Alexnet and stacked auto-encoder (SAE), for feature extraction. The SAE is used to extract low dimension features while Alexnet is used for high dimension feature extraction. The model also incorporates feature selection and dimensional reduction techniques such as PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis) to retain only key characteristics of the fundus images. For classification, the model uses SVM, including 10-fold cross-validation assistance. The model was trained and evaluated on two datasets, DRISHTI-GS and DRISHTI-DB, with an overall efficiency of 98.8

2. Explainable AI based Glaucoma Detection using Transfer Learning and LIME [7]

In this study, transfer learning was utilized with three dense neurons each with varying numbers of layers for VGG-16, VGG-19, ResNet50, and DenseNet121. The convolutional layer included ReLU activation function, batch normalization, and dropout. The prediction was done with a dense neuron with two layers and softmax activation function. The dataset used in the study was obtained from LAG datasets and consisted of 4250 images for training, 302 for testing, and 302 for validation. Local Interpretable Model-agnostic Explanation (LIME) was utilized to identify the essential characteristics that affect image classification.

3. 2sRanking-CNN: A 2-stage ranking-CNN for diagnosis of glaucoma from fundus images using CAM-extracted ROI as an intermediate input [8]

The aim of this study was to develop a two-stage ranking CNN model for classifying fundus images into normal, suspect, or glaucoma categories. The dataset used in this study consisted of 1022 fundus images acquired with a non-mydriatic fundus camera at Korea University Ansan Hospital. The researchers used the first ranking CNN to determine the age of the patient from a human face image and then upgraded the second ranking CNN with the extracted CAM results. The second ranking CNN consisted of fully-connected, batch normalisation, and dropout layers to categorise the image as having glaucoma defects or not.

The average accuracy was improved by 10% over the existing 3-class CNN, while sensitivity was increased by up to 20%.

4. Combined Diagnosis of Diabetic Retinopathy and Glaucoma Using Non-Linear Features [9]

In this study, the authors proposed an automated approach to identify glaucoma by extracting non-linear features like higher order spectra, entropies, and fractal dimensions. Preprocessing was performed to resize images to 512x512 and remove uneven illuminations using CLAHE (Contrast Limited Adaptive Histogram Equalization). Radon transform was employed to extract higher order spectra, while 2D variational mode decompositions were used for entropies. Box counting was utilized to extract the fractal dimension parameter. SVM (Support Vector Machine) classifier was applied to these non-linear features to categorize the images using hyperplane techniques. The study achieved an accuracy, sensitivity, and specificity of 85% using SVM-RBF kernel combination.

5. A Glaucoma Detection using Convolutional Neural Network [10]

The study proposes a CNN model for glaucoma detection with the aim of reducing the time required for diagnosis. The datasets used for the study were obtained from SCES (Singapore Chinese Eye Study) and ORIGA (Optic Nerve Head Image Database Rotterdam), with the latter consisting of 168 glaucoma and 482 normal fundus images while the former has 46 glaucoma and 1676 fundus images. The traditional diagnostic tests for glaucoma such as tonometry, optical coherence tomography, ophthalmoscopy, perimetry, and gonioscopy are time-consuming, hence the need for a faster automated approach.. The model achieved an accuracy of .822 and .882 for the ORIGA and SCES datasets, respectively.

6. Evaluation of deep convolutional neural networks for glaucoma detection [11]

The study aimed to identify the parameters affecting the discriminative ability of three deep convolutional neural network (DCNN) models for glaucoma detection. The datasets included 3312 images of glaucoma and non-glaucoma patients, as well as low-quality images. The images were pre-processed by resizing them to 256x256 and 512x512 pixels. The three DCNN models used were VGG19, ResNet159, and DenseNet201. Results showed that image size had no significant impact on the models' ability to discriminate between glaucoma and other conditions. However, using heatmap analysis, the disc area was identified as the crucial region for glaucoma discrimination. Poor image quality was also found to have an impact on the models' performance.

7. Artificial intelligence based glaucoma and diabetic retinopathy detection using MATLAB — retrained AlexNet convolutional neural network [12]

The study aims to develop a glaucoma classification model using deep learning and transfer learning techniques. The researchers used several publicly available databases with varying image resolutions and sizes. The AlexNet algorithm was used, which only accepts RGB color images. The pre-processing step involved cropping the black areas and resizing theimages to 227x227 pixels. The researchers used transfer learning to retrain the AlexNet modeland created five new networks. The proposed model achieved high accuracy in classifying images from different databases. NetTransfer1 achieved an accuracy of 94.3% for the LAG database. The results demonstrate the effectiveness of the proposed model in classifying glaucoma images, which could aid in the early detection and management of glaucoma.

8. Automated Identification of Glaucoma from Fundus Images using Deep learning Techniques [13]

The study utilised three different datasets containing fundus images: HRF, Origa, and Drishti_GS1, with a total of 781 images. The proposed methodology involved a deep convolutional neural network (CNN) architecture consisting of eight trainable weight layers with various types of layers, including convolutional, fully connected, rectified linear unit (ReLU), normalisation, pooling, dropout, and softmax layers. The input layer accepted images with a resolution of 227 x 227 x 3 pixels. The ReLU layer and normalisation layer were used to improve the learning error rate and generalisation, respectively. The pooling layer was employed to reduce the spatial dimension of the representation, while the dropout and softmax layers addressed overfitting issues.

9. Glaucoma Detection and Classification Using Improved U-Net Deep Learning Model [14]

Feature extraction using DenseNet-201 model and categorization with DCNN model is crucial in achieving accurate segmentation outcomes. Transfer learning approach enables utilization of pre-trained models like ImageNet for smaller datasets, reducing training time and computer needs. Additional 1x1 convolution layers are included in each 3x3 convolution layer to expedite processing, while dropout is applied to first two FC layers to prevent overfitting.

Non-normalized input data prevents overfitting. The U-Net model produces positive or negative findings based on the presence of glaucoma. The accuracy of a model is defined by its ability to predict a subset's behavior. The proposed method improved training accuracy by 1.09% to 3.96% compared to previous methods.

10. Visualizing Deep Learning Models for the Detection of Referable Diabetic Retinopathy and Glaucoma [15]

This study aimed to visualize the convolutional neural networks of two validated deep learning models for detecting referable diabetic retinopathy (DR) and glaucomatous optic neuropathy (GON). A random sample of 100 true-positive and all false-positive cases from each validation dataset was selected. The original fundus images were processed using an adaptive kernel visualization technique, and threshold scales were adjusted for each model to generate heat maps highlighting localized landmarks on the input image. In the GON dataset, 90% of true-positive cases and 68% of false-positive cases displayed heat map visualization within regions of the optic nerve head only.

11. Glaucoma Detection Using Fundus Images of The Eye [16]

Glaucoma is one of the leading causes of irreversible blindness in people over 40 years old. In Colombia there is a high prevalence of the disease, being worse the fact that there is not enough ophthalmologists for the country’s population. Fundus imaging is the most used screening technique for glaucoma detection for its trade-off between portability, size and costs. In this paper we present a computational tool for automatic glaucoma detection. We report improvements for disc segmentation in comparison with other works on the literature, a novel method to segment the cup by thresholding and a new measure between the size of the cup and the size of the disc. Results were obtained from a set of fundus images in collaboration with the Center of Prevention and Attention of Glaucoma in Bucaramanga, Colombia, where the percentage of success of glaucoma detection was of 88.5%.

12. Comparison of CNN Algorithms for Feature Extraction on Fundus Images to Detect Glaucoma [17]

Glaucoma is a disease where the optic nerve of the eyes is smashed up due to the building up of pressure inside the vision point. +is has no symptoms at the initial stages, and hence, patients with this disease cannot identify them at the beginning stage. It is explained as if the pressure in the eye increases, then it will hurt the optic nerve which sends images to the brain. +is will lead to permanent vision loss or total blindness. +e existing method used for the detection of glaucoma includes k-nearest neighbour and support vector machine algorithms. +e drawback in using these algorithms is that we can get accuracy level only up to 80%. +e proposed methods in this study focus on the convolution neural network for the recognition of glaucoma.

13. Glaucoma Detection Using Machine Learning Algorithms [18]

Glaucoma is a chronic and irreversible eye disease that can lead to vision loss. Early detection is crucial to control its progression. We propose developing a model to detect glaucoma in its early stages using various machine learning algorithms such as CNN, logistic regression, K-nearest neighbors' classifier, and support vector machines. We will use different datasets like ARIA and RIGA, with fundus images that will be converted into segmented images. Our aim is to provide a comprehensive overview of these algorithms and find the best one with the highest accuracy to detect glaucoma based on fundus images.

14. Enhanced Detection of Glaucoma on Ensemble Convolutional Neural Network for Clinical Informatics [19]

Glaucoma detection on fundus images is a challenging task due to the interlace of blood vessels. This research proposes a Spatially Based Ellipse Fitting Curve Model (SBEFCM) for the reliable detection of glaucoma in the Optic Cup (OC) and Optic Disc (OD) boundary. The SBEFCM is combined with an Ensemble Convolutional Neural Network (CNN) classification for classifying Glaucoma or Diabetes Retinopathy (DR). The proposed method outperformed the current methods in terms of contrast, with accurate sensitivity, specificity, precision, and Area Under the receiver operating characteristic Curve (AUC) values. Preprocessing of input fundus image besides segmentation of blood vessels is also done.

15. Deep learning-based diagnosis of glaucoma using image data from different devices and image resolutions [20]

A novel approach for glaucoma diagnosis using deep learning techniques. The proposed method utilizes image data from multiple devices and resolutions, which is a common challenge in glaucoma diagnosis due to the variability in image quality and acquisition protocols. The authors collected a large dataset of 2,944 images from three different devices and two different resolutions, which was used for training and validation of the proposed method. The method consists of two main stages: a feature extraction stage and a classification stage. They employed a Support Vector Machine (SVM) with a linear kernel as the classifier. The proposed method achieved an accuracy of 0.95 in classifying healthy eyes and those with glaucoma, which is a significant improvement compared to previous methods.

16. Automated detection of glaucoma using deep convolutional neural networks [21]

A deep convolutional neural network (CNN) approach for automated detection of glaucoma using fundus images. The proposed CNN architecture consists of five convolutional layers, two fully connected layers, and a final output layer. The convolutional layers extract features from the input fundus image, while the fully connected layers perform the classification. The authors evaluated their approach on a public dataset, the Optic Disc and Cup Segmentation Challenge (ODCSC) dataset, and achieved an accuracy of 0.96 in detecting glaucoma. They also compared their approach to other state-of-the-art methods for glaucoma detection and found that their approach outperformed them in terms of accuracy.

17. Glaucoma detection using convolutional neural networks and principal component analysis [22]

A novel approach for glaucoma detection using a combination of convolutional neural networks (CNNs) and principal component analysis (PCA). The proposed method takes advantage of the high-level features extracted by CNNs and the dimensionality reduction capabilities of PCA. The method involves preprocessing the fundus images, segmenting the optic disc and cup, and extracting features using a pre-trained CNN. The proposed method was evaluated on a dataset of 330 fundus images, and achieved a high accuracy of 0.97 in detecting glaucoma. Overall, this paper contributes to the growing body of research on using deep learning for early detection and diagnosis of glaucoma.

18. Glaucoma detection using deep learning neural network based on optic nerve head region segmentation [23]

A deep learning-based approach for glaucoma detection that uses optic nerve head region segmentation. The proposed method involves the use of a deep learning neural network, which is trained using a dataset of fundus images of patients with and without glaucoma. The network is designed to learn the features of the optic nerve head region and use them to make accurate predictions about the presence or absence of glaucoma. The method involves several steps, including preprocessing of the fundus images to extract the optic nerve head region, segmentation of the optic nerve head region, and then feeding the segmented region into the neural network for classification. The authors evaluated the proposed method using a dataset of 651 fundus images and achieved an accuracy of 0.94 in detecting glaucoma.

19. Glaucoma Detection Using Convolutional Neural Networks in Fundus Photographs with and without Image Enhancement [24]

This paper presents a method for glaucoma detection using convolutional neural networks (CNNs) applied to fundus photographs, with and without image enhancement. The authors compare the performance of two different CNN architectures and evaluate the impact of image enhancement techniques on the accuracy of the model. The proposed method achieved an accuracy of 0.91 in detecting glaucoma, which is comparable to the performance of human experts. The study demonstrates the potential of CNNs for automated glaucoma diagnosis and highlights the importance of image quality and enhancement techniques in achieving high accuracy.

20. A deep learning approach to automatic detection of glaucoma from fundus images [25]

A deep learning approach for automatic detection of glaucoma from fundus images. The proposed method employs a deep convolutional neural network to learn features from the fundus images and classify them into normal or glaucomatous. The method was tested on a dataset of 740 fundus images, achieving an accuracy of 95.1%, sensitivity of 95.6%, and specificity of 94.6%. The proposed method utilizes transfer learning, where the pre-trained convolutional neural network VGG-16 is fine-tuned on the fundus image dataset. The fundus images are preprocessed to enhance the contrast, improve the illumination, and remove the noise before feeding them into the deep network.

CHAPTER 3

DATASETS USED

3.1 Dataset-1

Table 3.1: Distribution of Glaucoma and Non-Glaucoma Images in dataset-1

	Glaucoma images	**Non glaucoma images**	**Total images**
Train samples	140	140	280
Validation samples	40	40	80
Testing samples	20	20	40

The balanced distribution of glaucoma and non-glaucoma images in the dataset ensures that the models trained on this dataset are not biased towards one particular class. Additionally, the size of the dataset is relatively small, which makes it easier to train and test the models on personal computers without requiring large computational resources. However, it is worth noting that the small size of the dataset could also limit the performance of the models due to overfitting, and larger datasets could potentially yield better results (Table 3.1)

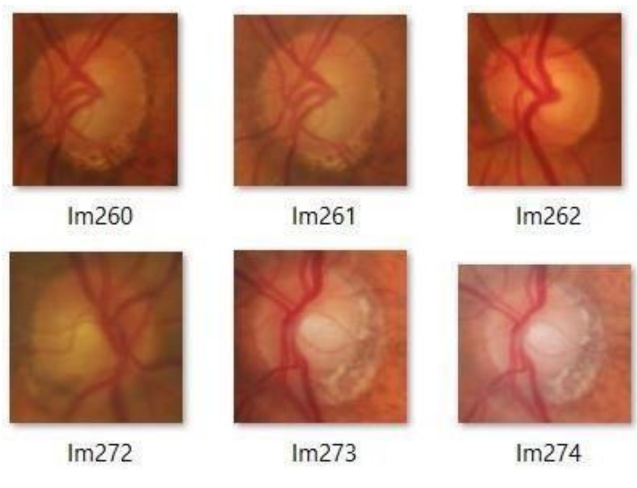

Fig 3.1: sample images from dataset-1

3.2 Dataset-2

Table 3.2: Distribution of Glaucoma and Non-Glaucoma Images in dataset-2

	Glaucoma images	Non glaucoma images	Total images
Train samples	260	260	520
Validation samples	65	65	130
Testing samples	14	14	28

The dataset is available for download from a link: https://www.kaggle.com/datasets/sshikamaru/glaucoma-detection

This dataset is larger than the previous one, which may help the models to generalize better to new, unseen data. However, the smaller size of the testing set may limit the ability to draw strong conclusions about the performance of the models on new data. It is important to carefully select appropriate training, validation, and testing sets to ensure reliable and accurate evaluation of the models. The dataset can be accessed via the provided link for further analysis and research purposes (Table 3.2)

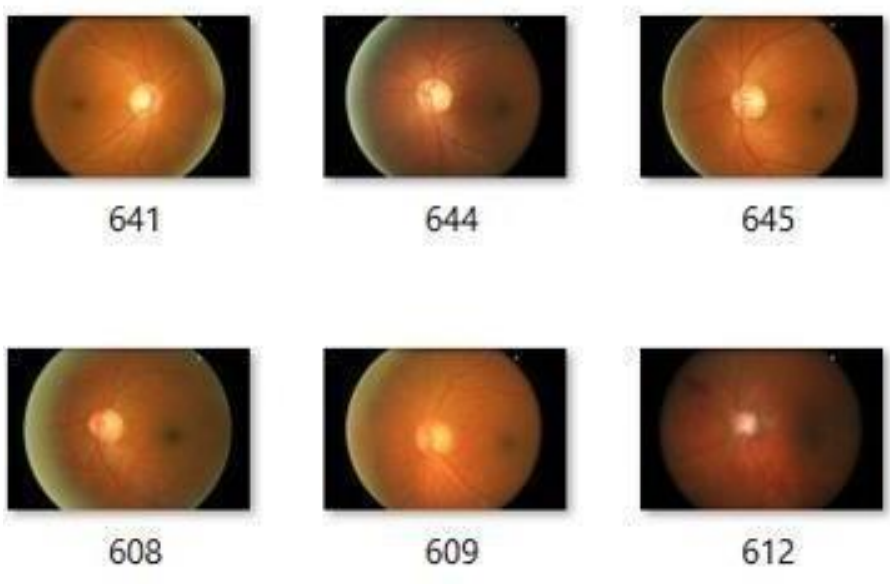

Fig 3.2: Sample images from dataset-2

3.3 Dataset -3

Table 3.3: Distribution of Glaucoma and Non-Glaucoma Images in dataset-3

	Glaucoma images	**Non glaucoma images**	**Total images**
Train samples	1800	1800	3600
Validation samples	600	600	1200
Testing samples	600	600	1200

The dataset is available for download from a link: https://www.kaggle.com/datasets/hindsaud/datasets-higancnn-glaucoma detection

The large number of samples in the dataset allows the models to learn a wide range of features and patterns that can help in accurately classifying glaucoma and non-glaucoma images. The distribution of glaucoma and non-glaucoma images in the dataset is balanced, which can help in training models that are not biased towards any particular class.

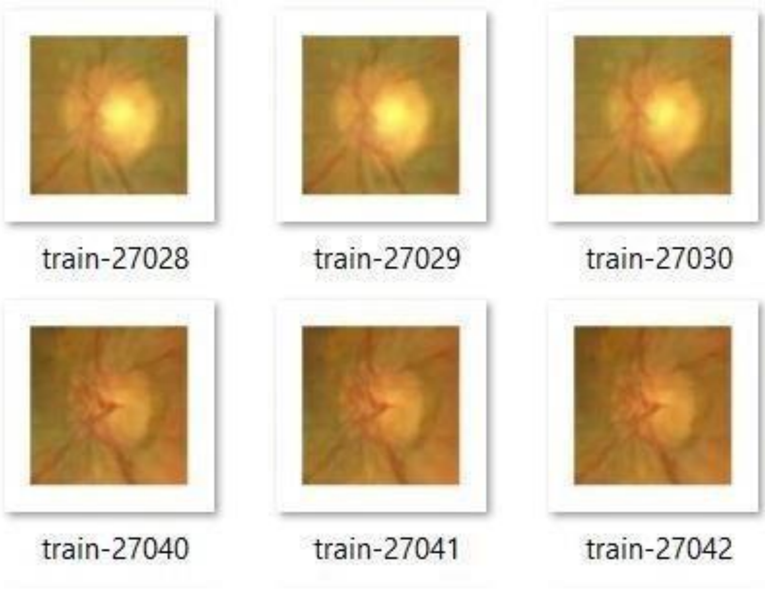

Fig 3.3: Sample images from dataset-3

CHAPTER 4

METHODOLOGY

4.1 Proposed methodology for model-1

4.1.1 Data Augmentation

Data augmentation is an important technique to help improve the generalization capability of deep learning models. By randomly applying various transformations to the training data such as flipping, rotating, zooming, etc., the model can learn to be more robust to variations in the input data.

The preprocessing operations are performed on the input images are given below:

1. Rescaling: The rescale argument is used to scale the pixel values of input images to the range [0,1].
2. Flipping: The horizontal_flip and vertical_flip arguments are used to randomly flip images horizontally or vertically during training. This helps to increase the diversity of the training data and makes the model more robust to changes in image orientation.
3. Setting size: The target_size argument is used to resize the input images to a fixed size before training. This is done to ensure that all input images have the same dimensions, which is necessary for feeding them into a neural network.

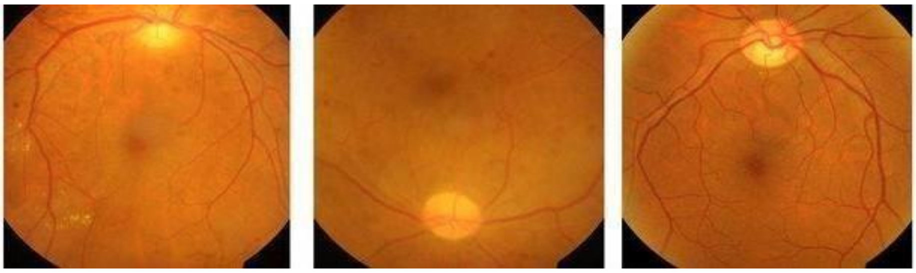

Fig 4.1: Horizontal and vertical flipped fundus images

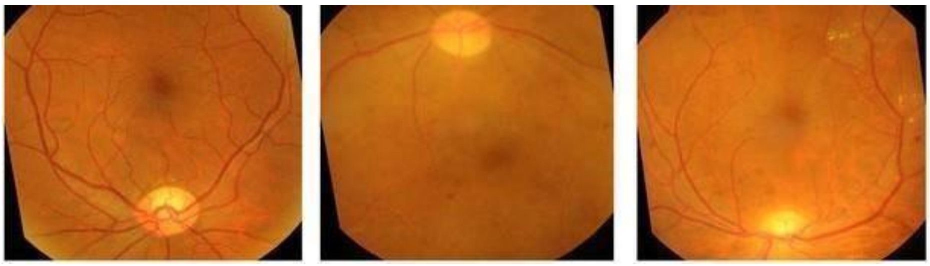

Fig 4.2: Flipped and randomly rotated fundus images

4.1.2 Feature extraction

The architecture of the model is designed to extract relevant features from the input images in a hierarchical manner. The first block of convolutional layers consists of 8 filters, which perform a series of convolutions on the input image to create a set of activation maps. These activation maps are then passed through a batch normalization layer, which helps to normalize the activations and prevent the model from overfitting to the training data. The max pooling layer in this block reduces the spatial dimensions of the activation maps by a factor of 2, which helps to decrease the number of parameters in the model and improve computational efficiency.

The second block of convolutional layers has 32 filters and performs a similar operation as the first block. The use of more filters in this block allows the model to capture more complex features of the input images. The batch normalization and max pooling layers in this block perform the same functions as in the first block.

The third block of convolutional layers has 64 filters and is designed to capture even more complex features of the input images. The use of more filters in this block allows the model to learn higher-level features of the input images that are important for distinguishing between positive and negative classes. The batch normalization and max pooling layers in this block help to stabilize the training process and reduce overfitting.

The fourth block of convolutional layers has 64 filters and is similar in structure to the third block. The purpose of this block is to further refine the feature representation of the input images before passing them through the fully connected layers. The use of multiple blocks of convolutional layers with increasing numbers of filters allows the model to learn a hierarchical representation of the input images, with each block capturing increasingly complex and abstract features.

After the convolutional layers and pooling layers, the resulting feature maps are flattened into a one-dimensional vector using the Flatten layer. This layer reshapes the multi-dimensional feature maps into a format that can be input to the fully connected layers. The Dense layer is the fully connected layer in this model, which takes the flattened feature vector as input and applies a linear transformation followed by a softmax activation function to produce the final output probabilities for each class. The output layer has two neurons, corresponding to the two classes (positive and negative) in the classification problem.

4.1.3 Classification

After training the CNN on a large dataset, the model is capable of classifying new images into one of the two categories with a high degree of accuracy. This process involves passing the new image through the same preprocessing steps as the training images, such as rescaling the pixel values to be between 0 and 1. Once the image is preprocessed, it is passed through the trained CNN, which extracts features and patterns from the image. These features are then used to predict the class label of the image using a softmax activation function. The softmax function normalizes the outputs of the final layer of the CNN and converts them into a probability distribution over the classes. The predicted class is the class with the highest probability, which represents the model's confidence in its prediction. This probability can be interpreted as the model's level of certainty about the predicted class. In some cases, the model may not be entirely certain about its prediction, in which case the probability values for the two classes may be similar. The ability to accurately classify new images is a critical aspect of any deep learning model. By using techniques such as data preprocessing, feature extraction, and probability-based classification, CNNs can be trained to classify images with high accuracy. This has important applications in fields such as medical diagnosis, object detection, and natural language processing.

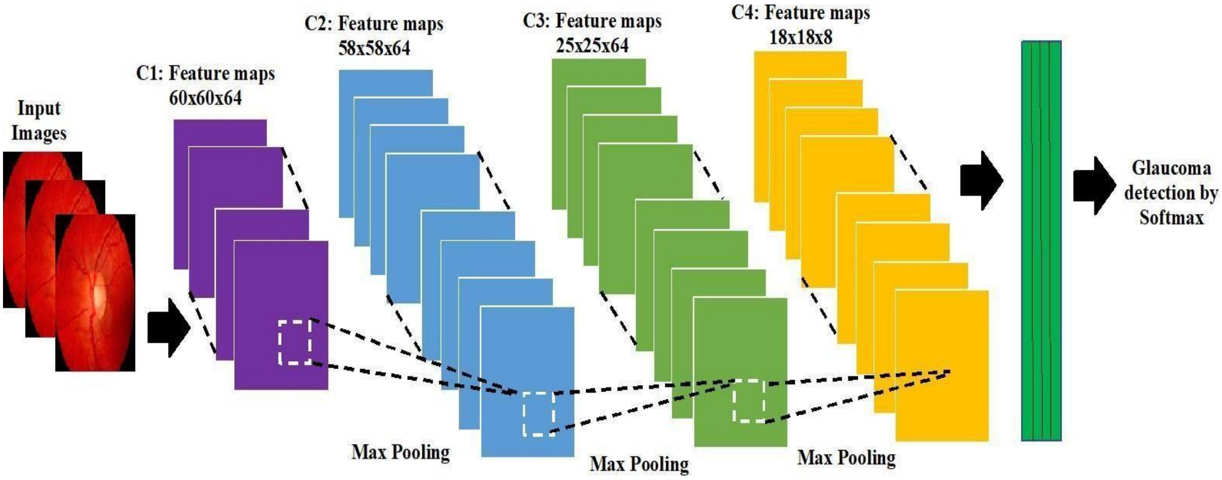

Fig 4.3: Process flow of model-1

4.2 Proposed methodology for model-2

4.2.1 Data Augmentation

Data augmentation is an important technique to help improve the generalization capability of deep learning models. By randomly applying various transformations to the training data such as flipping, rotating, zooming, etc., the model can learn to be more robust to variations in the input data.

The preprocessing operations are performed on the input images are given below:

4. Rescaling: The rescale argument is used to scale the pixel values of input images to the range [0,1].
5. Flipping: The horizontal_flip and vertical_flip arguments are used to randomly flip images horizontally or vertically during training. This helps to increase the diversity of the training data and makes the model more robust to changes in image orientation.
6. Setting size: The target_size argument is used to resize the input images to a fixed size before training. This is done to ensure that all input images have the same dimensions, which is necessary for feeding them into a neural network.

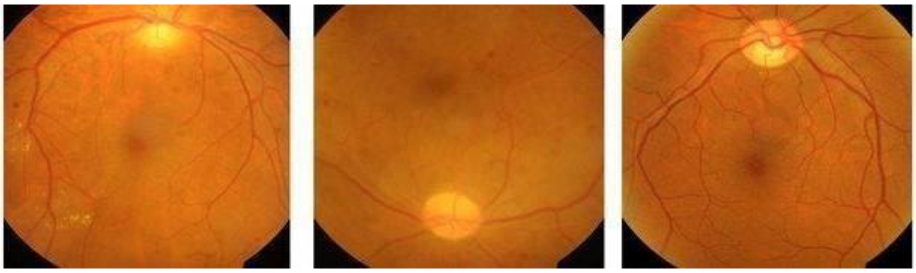

Fig 4.4: Horizontal and vertical flipped fundus images

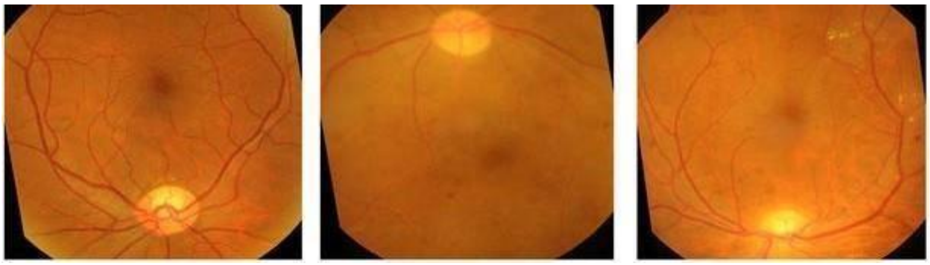

Fig 4.5: Flipped and randomly rotated fundus images

4.2.2 Feature extraction

The input to the model is a 3-channel image tensor of size 224x224, which is fed into a deep convolutional neural network consisting of four blocks of convolutional layers. The model architecture uses the concept of feature extraction and hierarchical representation learning, where lower-level features such as edges and corners are learned by the first block of filters, and higher-level features such as shapes and textures are learned by the subsequent blocks of filters.

The use of batch normalization layers in each block helps to normalize the activations and reduce internal covariate shift, which can cause the model to become unstable during training. The max pooling layers in each block perform a down sampling operation, which helps to reduce the spatial dimensions of the feature maps and increase their receptive field size, thereby allowing the model to capture more contextual information.

In addition to the convolutional layers, the model also employs ReLU activation functions after each convolutional layer to introduce non-linearity and improve the model's ability to capture complex patterns and relationships in the data. This helps to prevent the vanishing gradient problem, which can occur when gradients become very small during backpropagation and can cause the model to converge slowly or not at all.

The design of the model architecture, with its combination of convolutional layers, batch normalization layers, max pooling layers, and ReLU activation functions, helps to ensure that the model can effectively learn and represent the features of the input images, and make accurate predictions for the given task.

4.2.3 Classification

The batch normalization layers and max pooling layers have several benefits. Batch normalization is a technique that helps to normalize the activations of the previous layer in order to stabilize the training process and reduce overfitting. It also helps to improve the convergence speed of the optimization algorithm by reducing the dependence of the gradients on the scale of the weights. Max pooling is a down sampling operation that reduces the size of the feature maps while retaining the most important features. It also helps to introduce some degree of translation invariance into the model by selecting the maximum activation in each region. The Flatten layer is a necessary step in preparing the features extracted from the convolutional layers for input to the fully connected layers. It converts the multi-dimensional feature maps into a one-dimensional vector that can be processed by the Dense layer. The Dense layer is the part of the model that performs the actual classification. It applies a linear transformation to the input vector, followed by a softmax activation function to produce the output probabilities for each class. The number of neurons in the output layer corresponds to the number of classes in the problem. In this case, since there are only two classes (positive and negative), there are two neurons in the output layer.

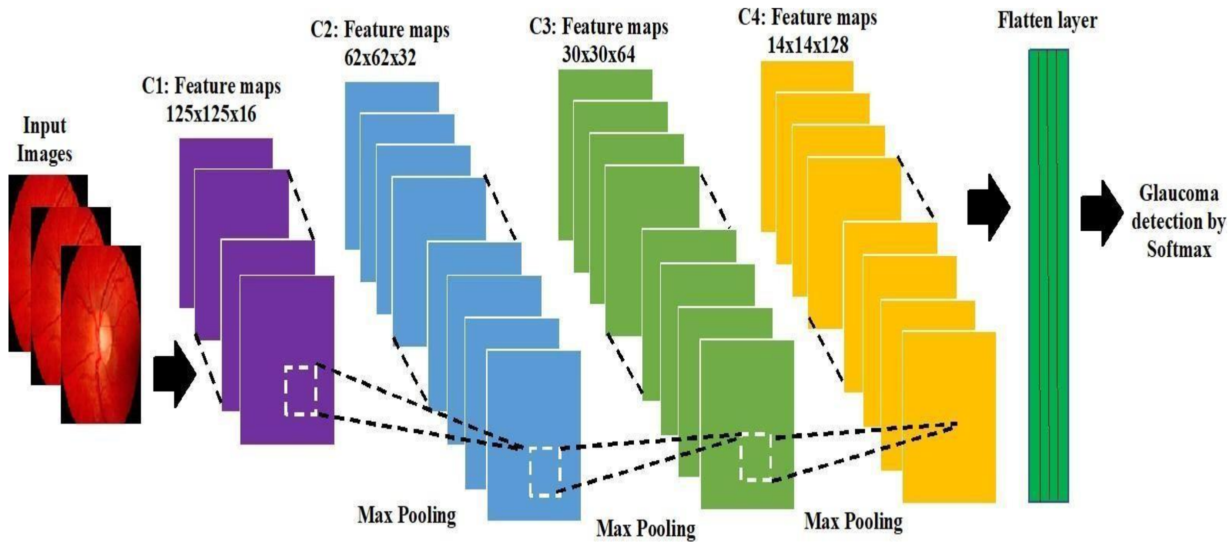

Fig 4.6: Process flow of Model-2

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 Evaluation Metrics

The confusion matrix Fig 5.1 visually represents the performance of a classification model. It is a grid-like structure that provides a clear overview of the predicted and actual class labels. The matrix displays the counts or percentages of true positives, true negatives, false positives, and false negatives in a tabular format.

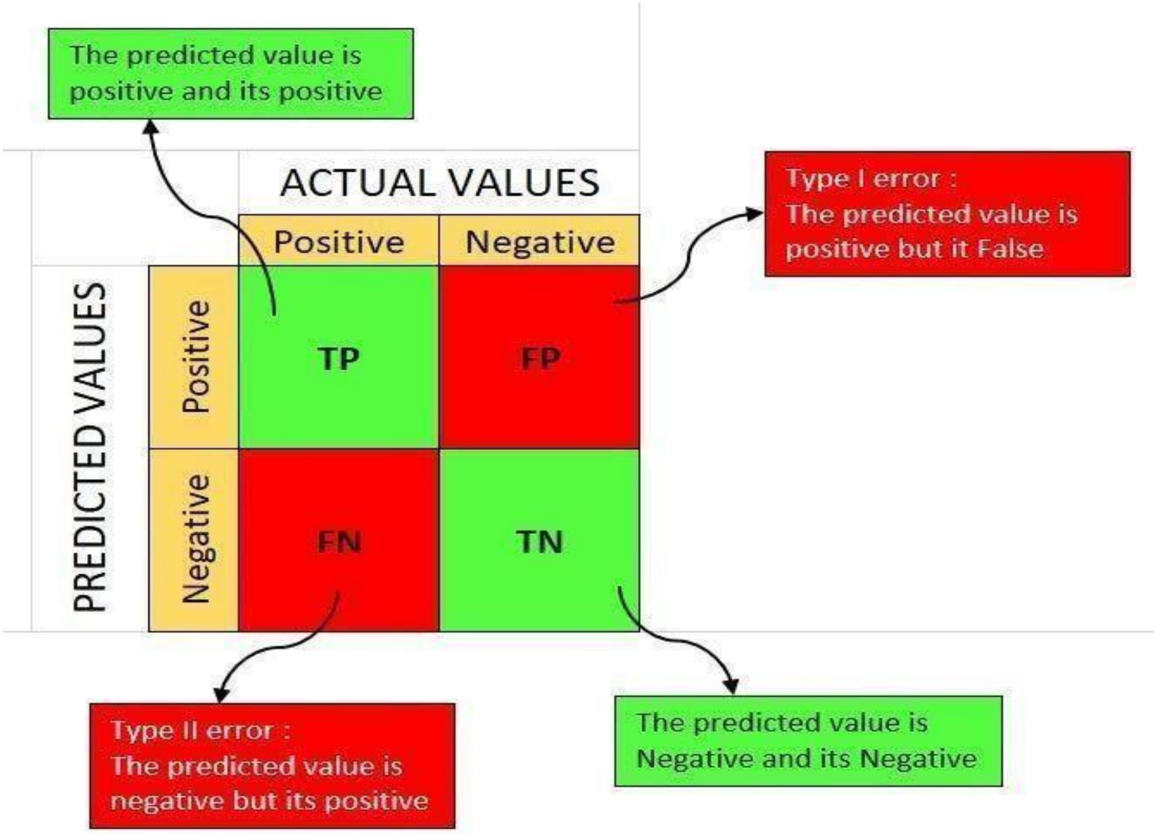

Fig 5.1: Confusion matrix

- True positives (TP) are the number of cases in which the machine learning model predicted the positive class correctly. In other words, it indicates the number of patients that have the disease and were correctly identified by the model. This metric is crucial in evaluating the performance of the model in the medical field, where correctly identifying positive cases is of utmost importance.

- True Negatives (TN) are instances where the model correctly predicts a negative outcome. This means that the model correctly identified instances where a condition was absent or not present, indicating the absence of a false positive. TN is an important metric in evaluating the specificity or selectivity of a model.
- False positives (FP) are the cases where the model incorrectly identifies a negative case as positive. In other words, it is a type I error where the model produces a positive result when the true result is actually negative. False positives can be harmful in many applications such as medical diagnosis where a false positive can lead to unnecessary treatments and surgeries.
- False Negatives (FN) are cases where the model incorrectly predicted a negative outcome, when in fact it should have predicted a positive outcome. This means that the model missed the presence of the condition or target variable, leading to an underestimation of its prevalence.

Based on the confusion matrix with true positive, true negative, false positive, false negative values the following evaluation matrices are calculated.

1. Accuracy

Accuracy is a performance metric that measures how well a model classifies both positive and negative outcomes. It is calculated by dividing the number of correct predictions (True Positives and True Negatives) by the total number of predictions (True Positives, True Negatives, False Positives, and False Negatives). A higher accuracy value means that the model is making more correct predictions, while a lower accuracy value means that the model is making more incorrect predictions.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

2. Precision

Precision is a measure of how accurate the model's positive predictions are. It is calculated as the number of true positive predictions divided by the total number of positive predictions made by the model. A high precision value indicates that the model is making few false positive predictions and is therefore precise in identifying positive cases.

$$\text{Precision} = TP / (TP + FP)$$

3. Sensitivity

Sensitivity, also known as recall, is a measure of how well the model correctly identifies positive cases. It is the ratio of true positive predictions to the total number of actual positive cases, both identified correctly and incorrectly. A high sensitivity means the model is good at identifying positive cases.

$$\text{Sensitivity} = TP / (TP + FN)$$

4. Selectivity

Selectivity, also known as specificity, measures the ability of the model to correctly identify negative cases. It is calculated as the ratio of true negative (TN) cases to the sum of TN and false positive (FP) cases. A high selectivity score indicates that the model has a low rate of false positives, which is important in applications where false positives can have significant consequences, such as medical diagnosis.

$$\text{Selectivity} = TN / (TN + FP)$$

5.2 Behaviour of the Models for Dataset-1

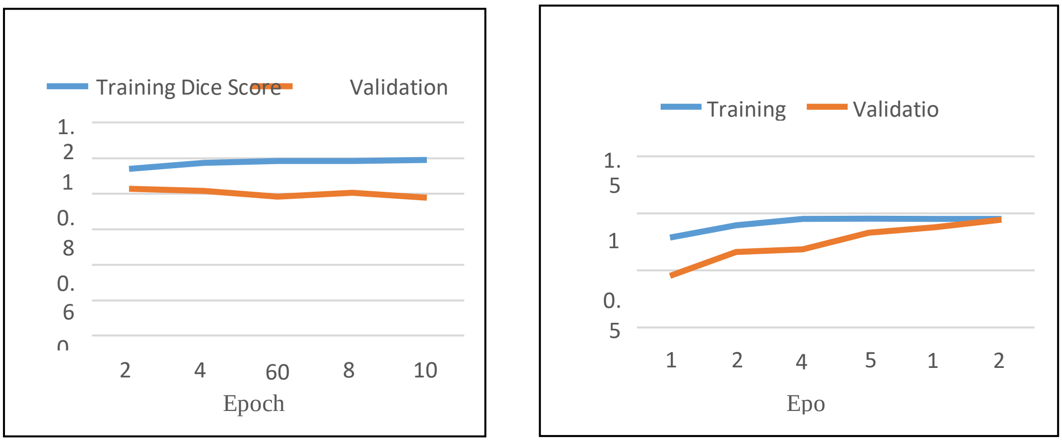

Fig 5.2: Behaviour of Model-1 for dataset-1

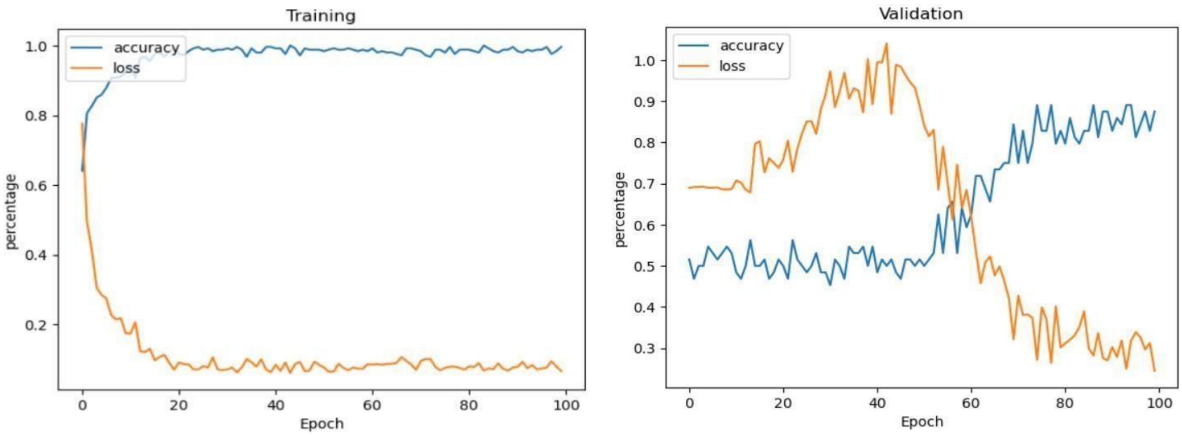

Fig 5.3: Behaviour of Model-2 for dataset-1

Table 5.1: Comparison of Models on evaluation matrices for dataset-1

	Precision	**Selectivity**	**Sensitivity**	**Accuracy**
Model-1	0.66	0.5	1	0.75
Model-2	0.56	0.3	0.92	0.61

The size of the dataset used for training and testing can have a significant impact on the performance metrics of a model. In this case, the model was trained and tested on a relatively small dataset, consisting of 400 images in total. The training set consisted of 280 images (140 glaucoma, 140 non-glaucoma), while the validation and test sets each consisted of 80 images (40 glaucoma, 40 non-glaucoma and 20 glaucoma, 20 non-glaucoma respectively).

With such a small dataset, it is possible that the model may have overfit to the training data, meaning that it may have learned to perform well on the specific images in the training set, but may not generalize well to new, unseen images. This can result in a model that has high accuracy on the training set, but lower accuracy on the validation and test sets.

In the provided evaluation metrics (Table 5.1), we see that Model-1 has higher precision and accuracy than Model-2, but lower selectivity and sensitivity. This suggests that Model-1 is better at correctly identifying positive cases (glaucoma), but may be more prone to false positives. On the other hand, Model-2 has higher sensitivity, meaning it is better at identifying positive cases, but lower precision and accuracy, suggesting that it may have more false negatives.

5.3 Behaviour of the models for dataset-2

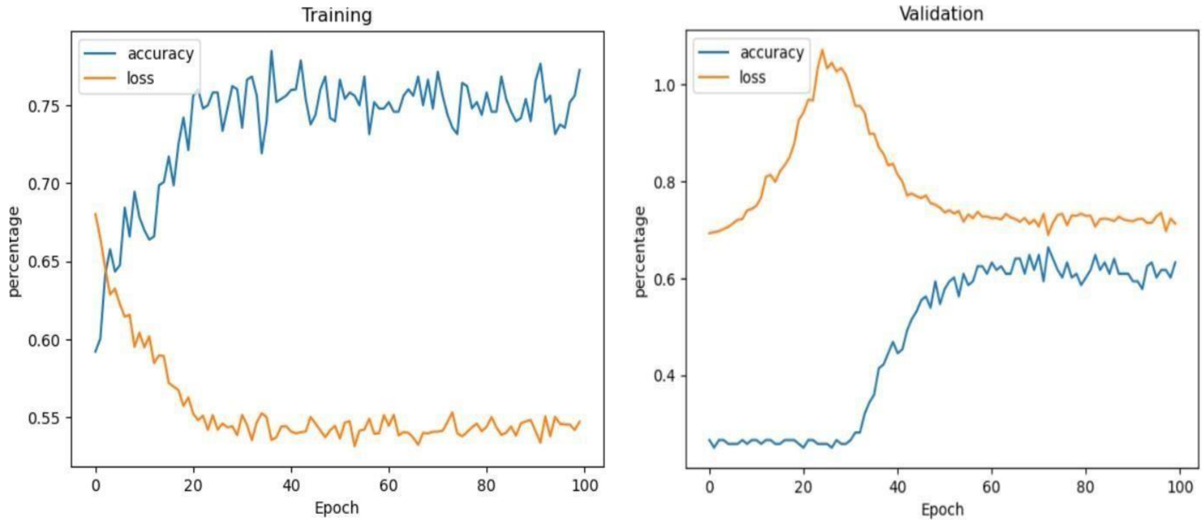

Fig 5.4: Behaviour of Model-1 for dataset-2

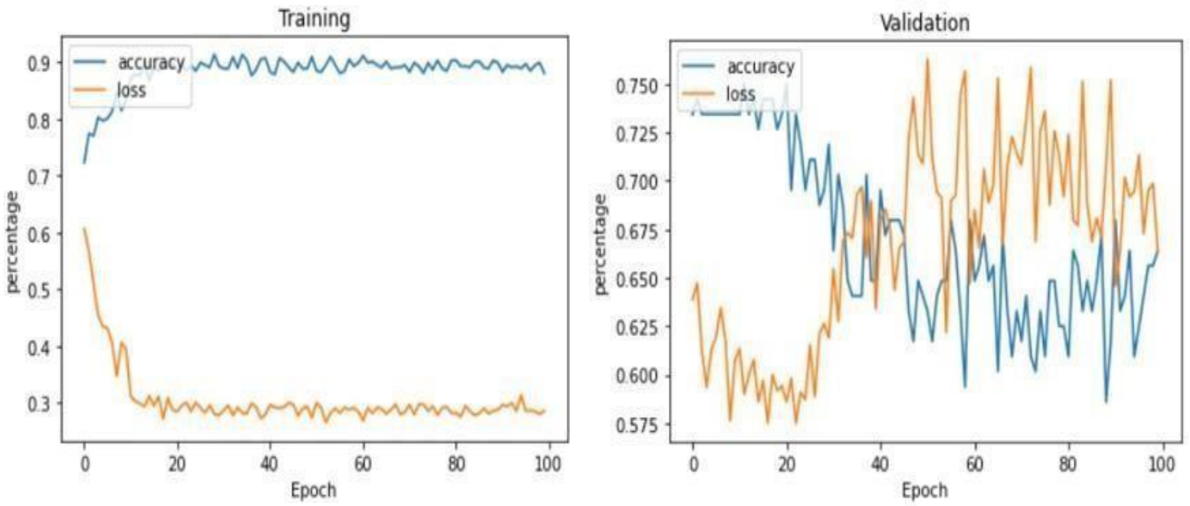

Fig 5.5: Behaviour of Model-2 for dataset-2

Table 5.2: Comparison of Models on evaluation matrices for dataset-2

	Precision	Selectivity	Sensitivity	Accuracy
Model-1	0.22	0.40	0.47	0.42
Model-2	0.34	0.34	0.77	0.64

It appears that increasing the size of the dataset has led to an improvement in the performance of both models. Model-2, in particular, shows a significant improvement in all evaluation metrics, indicating that the larger dataset has helped the model to better generalize to new, unseen data. In comparison, Model-1 shows poor performance with low precision as shown in Table 5.2, selectivity, sensitivity, and accuracy values. This suggests that the model is struggling to properly classify images of glaucoma and non-glaucoma eyes.

It is worth noting that the distribution of glaucoma and non-glaucoma samples in the dataset can also have an impact on the model's performance. In the first dataset, the number of glaucoma and non-glaucoma samples is equal, while in the second dataset, there are more samples of each class. This could be another factor contributing to the improved performance of both models with the larger dataset.

Overall, these results highlight the importance of having a sufficiently large and diverse dataset for training deep learning models. Additionally, evaluation metrics such as precision, selectivity, sensitivity, and accuracy can provide valuable insights into the performance of the models and help in selecting the best model for the given task.

5.4 Behaviour of the models for dataset-3

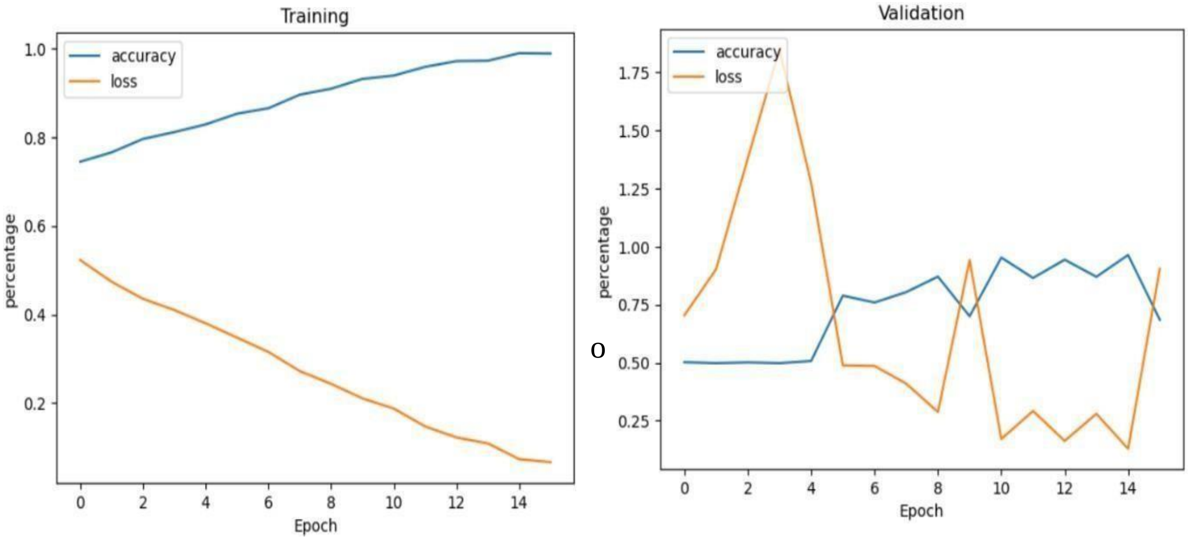

Fig 5.6: Behaviour of Model-1 for dataset-3

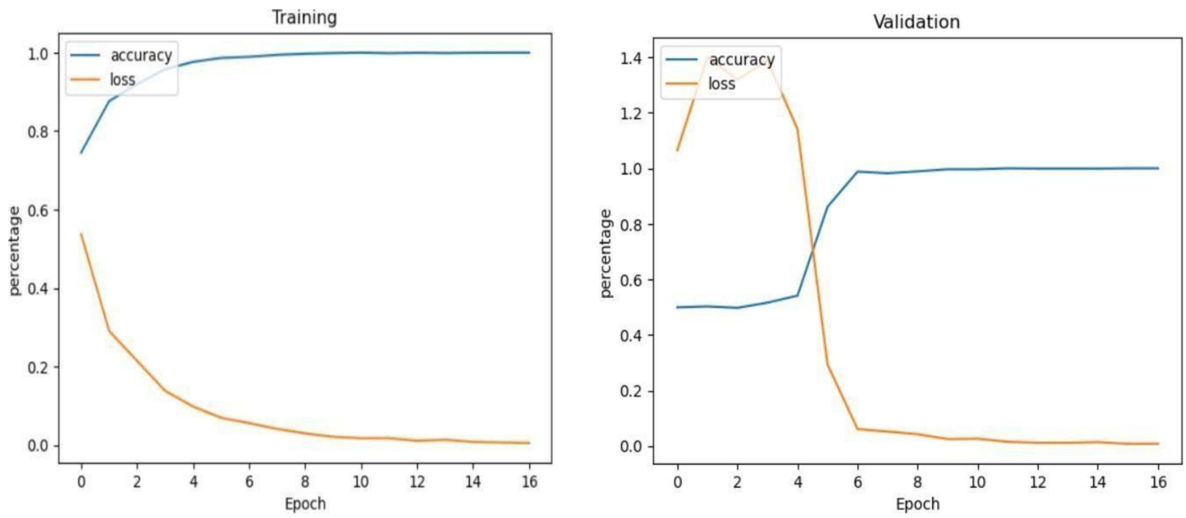

Fig 5.7: Behaviour of Model-2 for dataset-3

Table 5.3: Comparison of Models on evaluation matrices for dataset-3

	Precision	Selectivity	Sensitivity	Accuracy
Model-1	0.51	0.73	0.28	0.51
Model-2	0.74	0.71	0.83	0.77

In Table 5.3 shows that increasing the dataset size has had a positive impact on the performance of both Model-1 and Model-2. Model-2 performed significantly better than Model-1, achieving higher precision, selectivity, sensitivity, and accuracy values. This suggests that the larger dataset has helped the models to better generalize to new and unseen data. The improved performance of the models could also be attributed to the larger number ofsamples in each class in the second dataset.

These results emphasize the significance of having a sufficiently large and diverse dataset for training deep learning models. Evaluation metrics such as precision, selectivity, sensitivity, and accuracy provide valuable insights into the performance of the models and can help in selecting the best model for the given task. Thus, it is important to carefully evaluate the performance of the models on various evaluation metrics before selecting the best model for deployment.

It is also important to note that the performance of the models may vary depending on the specific task or application. In the case of glaucoma detection, sensitivity and selectivity are particularly important metrics as they measure the ability of the model to correctly identify positive and negative cases.

5.5 Comparison of model’s behaviour

Table 5.4: Performance Metrics of Model 1 on Different Datasets

Model 1	Precision	Selectivity	Accuracy	Sensitivity
Dataset-1	0.66	0.5	0.75	1
Dataset-2	0.22	0.40	0.42	0.47
Dataset-3	0.51	0.73	0.51	0.28

In Table 5.4 Dataset-1 consists of 400 images, evenly divided between glaucoma and normal cases. The model achieved relatively high precision and accuracy, indicating that it correctly classified a significant portion of both glaucoma and normal cases. However, the selectivity is relatively low, indicating that it classified some normal cases as glaucoma. The sensitivity is high, suggesting that it effectively identified glaucoma cases.

Dataset-2 consists of 678 images, but the precision, selectivity, and accuracy values are significantly lower compared to Dataset-1. This indicates that the model struggled to accurately classify both glaucoma and normal cases in this dataset. The sensitivity value suggests that it performed better in identifying glaucoma cases compared to normal cases.

Dataset-3 is the largest with 6000 images. However, the model's performance in this dataset is relatively poor. The precision and accuracy values are moderate, indicating that it correctly classified a reasonable number of cases. The selectivity is relatively high, suggesting that it correctly identified most of the normal cases. However, the sensitivity is low, indicating that it struggled to identify a significant number of glaucoma cases.

Table 5.5: Performance Metrics of Model 2 on Different Datasets

Model 2	Precision	Selectivity	Accuracy	Sensitivity
Dataset-1	0.56	0.3	0.61	0.92
Dataset-2	0.34	0.34	0.64	0.77
Dataset-3	0.74	0.71	0.88	0.83

In Table 5.5 Dataset-1, the model achieved moderate precision and accuracy. The selectivity is relatively low, indicating that it classified a significant number of normal cases as glaucoma. However, the sensitivity is high, suggesting that it effectively identified a large portion of glaucoma cases.

Dataset-2 shows relatively lower precision, selectivity, and accuracy compared to Dataset-1. The model struggled to accurately classify both glaucoma and normal cases in this dataset. However, the sensitivity value suggests that it performed better in identifying glaucoma cases compared to normal cases.

Dataset-3 demonstrates the best performance among the three datasets. The model achieved high precision, selectivity, accuracy, and sensitivity values. This indicates that it correctly classified a significant number of glaucoma and normal cases with high accuracy and sensitivity.

5.6 Glaucoma Detection Website

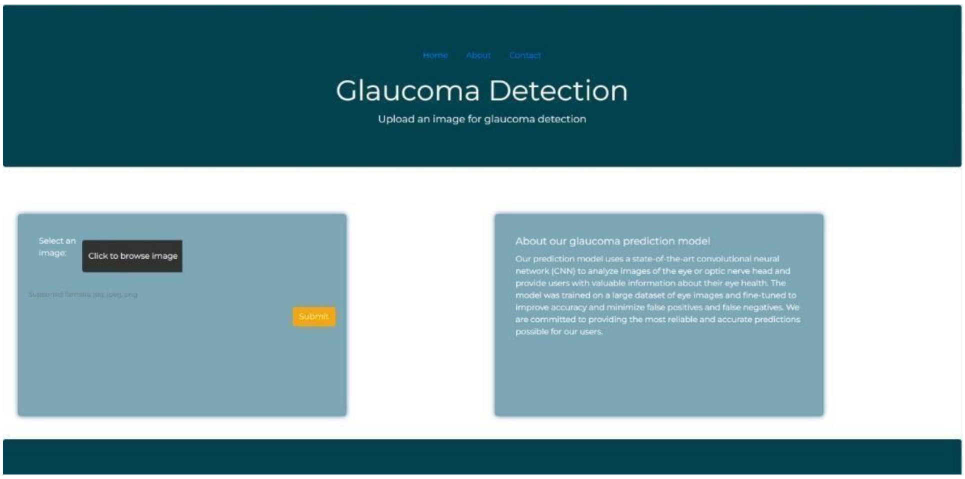

Fig 5.8: Glaucoma detection website

Fig 5.9: Prediction result of non-glaucoma image

Fig 5.10: Prediction result of glaucoma image

Our website is a comprehensive platform designed for the detection of glaucoma using advanced computer vision techniques. Leveraging the power of convolutional neural networks (CNNs), the website provides an efficient and accurate way to analyze retinal images and identify signs of glaucoma.

The website offers a user-friendly interface where users can upload their retinal images for analysis. The uploaded images are then processed using state-of-the-art CNN models trained on large datasets of normal and glaucoma-affected retinas Fig 5. .The models utilize deep learning algorithms to extract meaningful features and classify the images based on the presence or absence of glaucoma.

Upon analysis, the website provides detailed reports on the likelihood of glaucoma, including accuracy. These metrics provide valuable insights into the performance of the model and its ability to correctly identify glaucoma cases.

With its automated and efficient approach, the website simplifies the glaucoma detection process, allowing for early and accurate diagnosis. It serves as a valuable tool for both healthcare professionals and individuals concerned about their eye health, enabling timely intervention and improved patient outcomes.

CHAPTER 6

6.1 ADVANTAGES

1. Reduces the time required for testing
2. The testing process is not expensive
3. Accurate and Faster Diagnosis
4. Does not require skilled supervision

6.2 APPLICATIONS

1. Automated Screening: CNNs can be used for automated screening of large populations for glaucoma.
2. Clinical Diagnosis: CNNs can assist ophthalmologists in the diagnosis of glaucoma by analyzing medical images and providing objective assessments of optic nerve head and retinal nerve fiber layer changes.
3. Telemedicine: CNNs can be integrated into telemedicine systems to enable remote diagnosis and monitoring of glaucoma. This can improve access to diagnosis and reduce the need for patients to travel long distances for appointments.
4. Personalized Treatment: CNNs can be used to analyze medical images and provide personalized treatment recommendations based on the severity of glaucoma and the individual patient's characteristics.

6.3 FUTURE ENHANCEMENTS

Can be used to detect more eye diseases and improve the accuracy.

CONCLUSION

Glaucoma is a serious eye disease that can lead to vision loss and even blindness if not detected and treated early. Convolutional Neural Networks (CNNs) have shown promising results in detecting glaucoma from fundus images. In this study, a CNN model was trained and evaluated using three different datasets of fundus images to detect glaucoma. The model consisted of four convolutional blocks with increasing filters followed by max pooling and batch normalization layers, and a fully connected output layer with softmax activation. Data augmentation techniques such as flipping and rescaling were also used to increase the dataset size and improve model performance. The trained model achieved moderate accuracy on each datasets,indicating its effectiveness in detecting glaucoma from fundus images. Furthermore, the modelwas able to detect glaucoma at an early stage, allowing for timely treatment and prevention ofvision loss. The results of this study suggest that CNNs can be a valuable tool in the early detection of glaucoma and improve patient outcomes. However, further research is needed to validate the model on a larger and more diverse dataset and optimize the hyperparameters to improve its performance. Overall, this study highlights the potential of deep learning techniques in the field of ophthalmology for the early detection of eye diseases and improvingpatient care.

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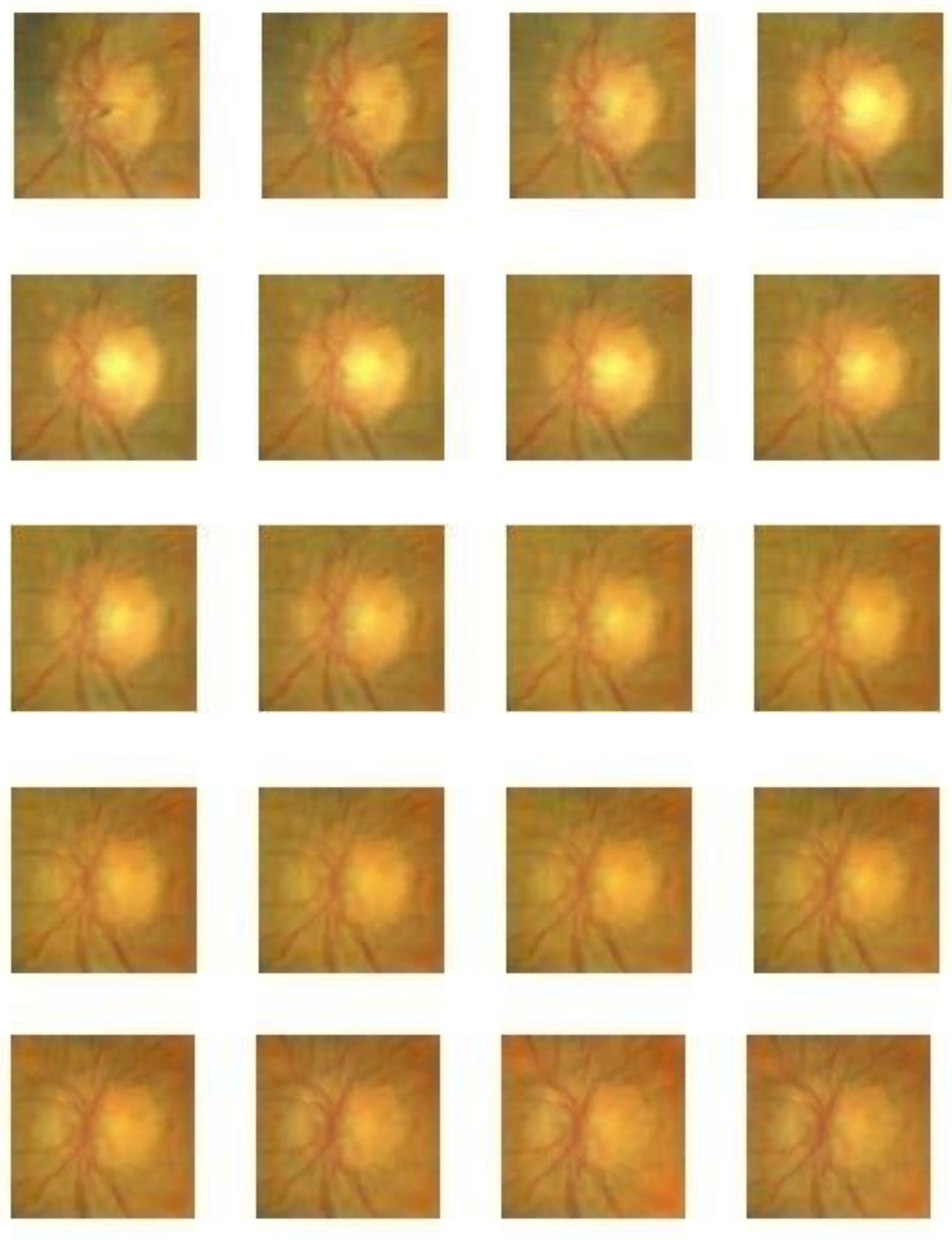
APPENDIX

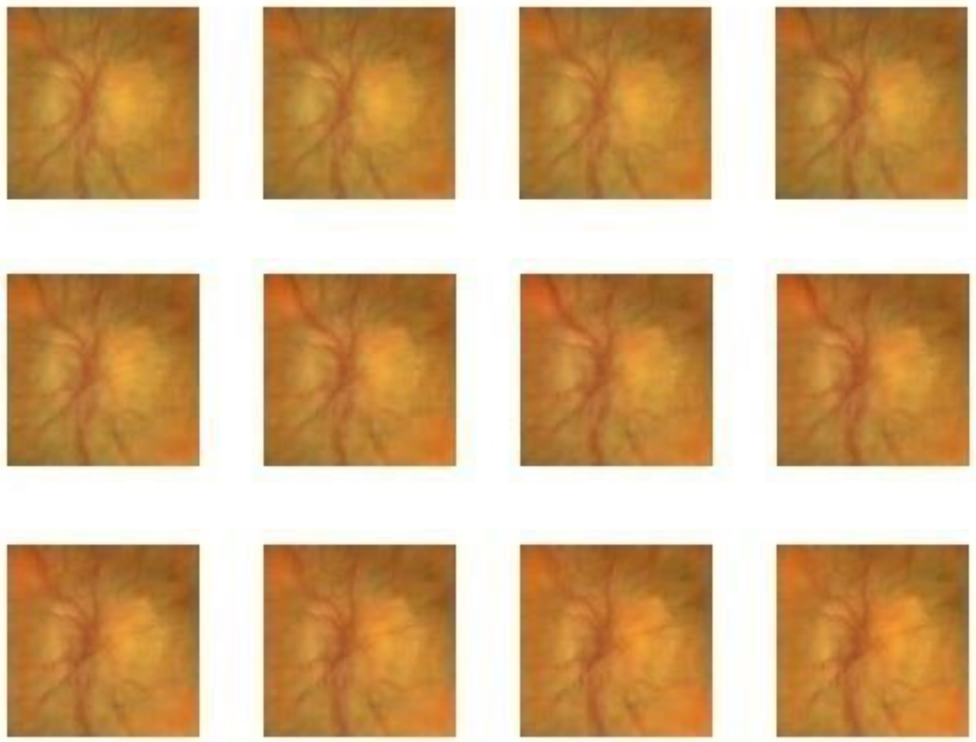
APPENDIX A

DATASET-1

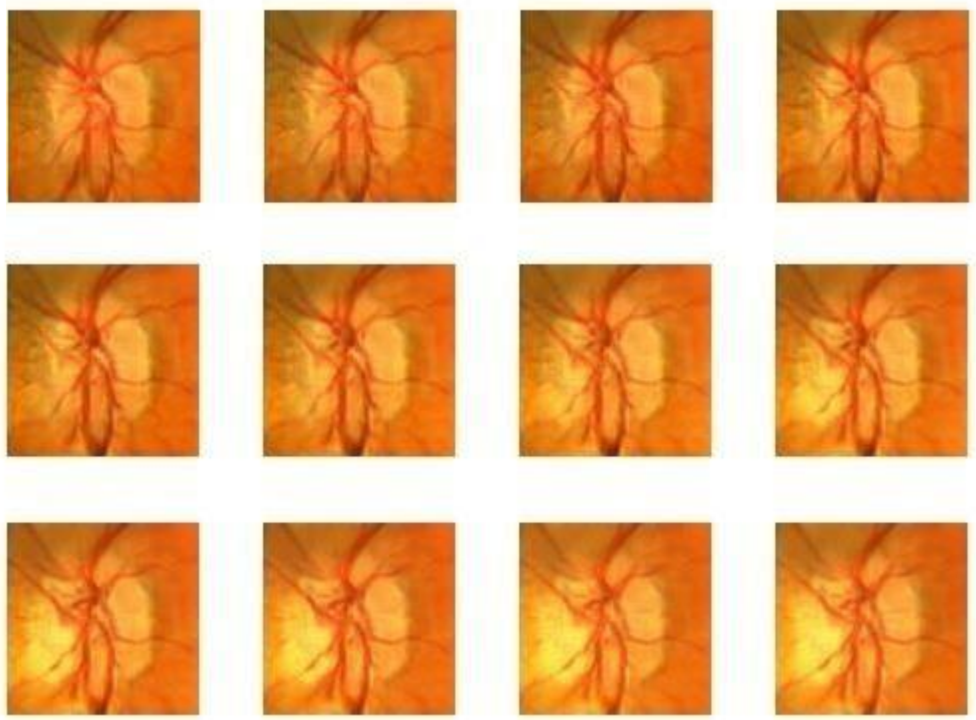
https://drive.google.com/file/d/1bjsH1wijxXmXH1quyEpOW1vLgPCZIFZ3/view?usp=share_link

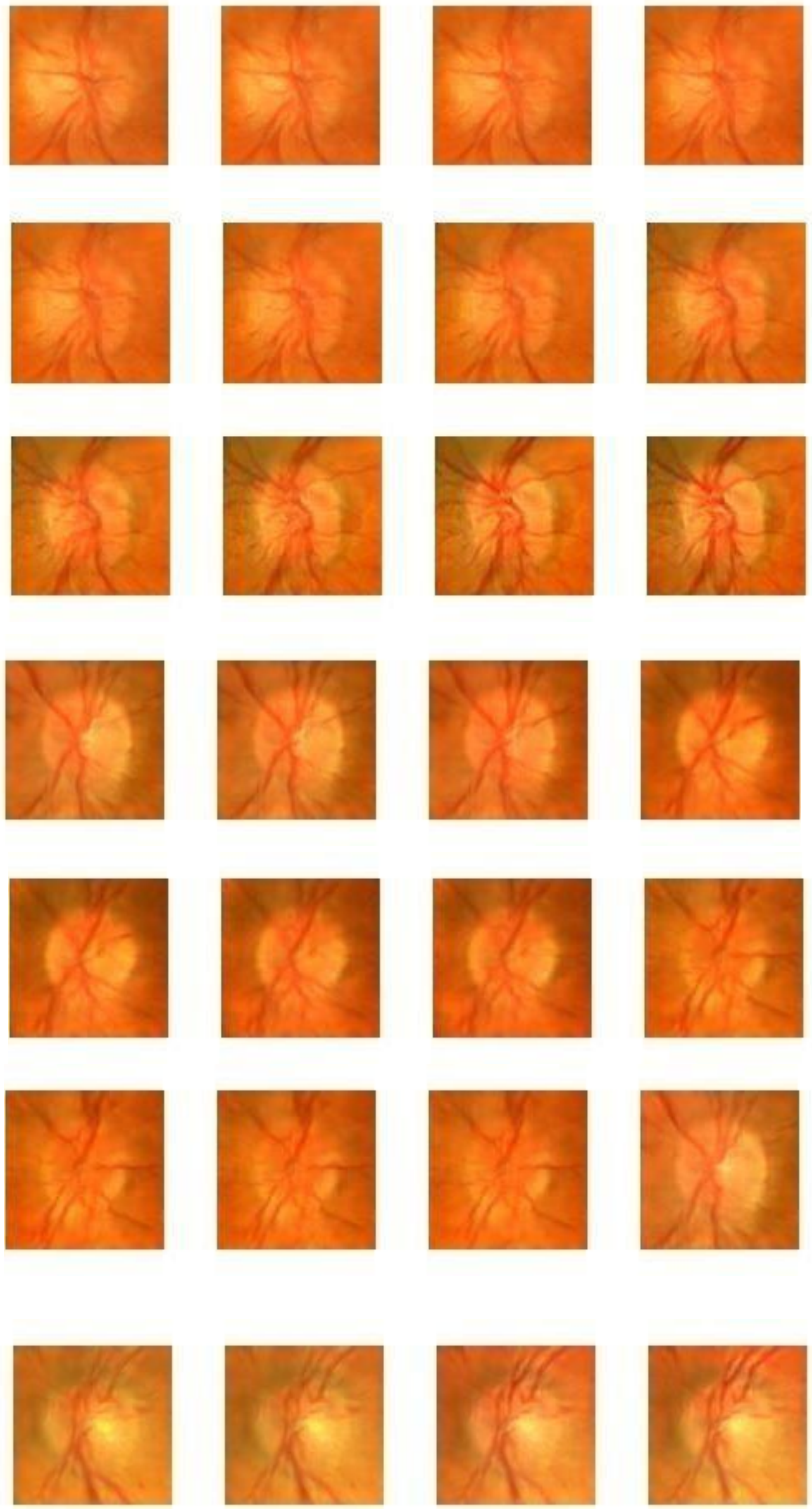
Sample images of Glaucoma





Sample images of non-Glaucoma

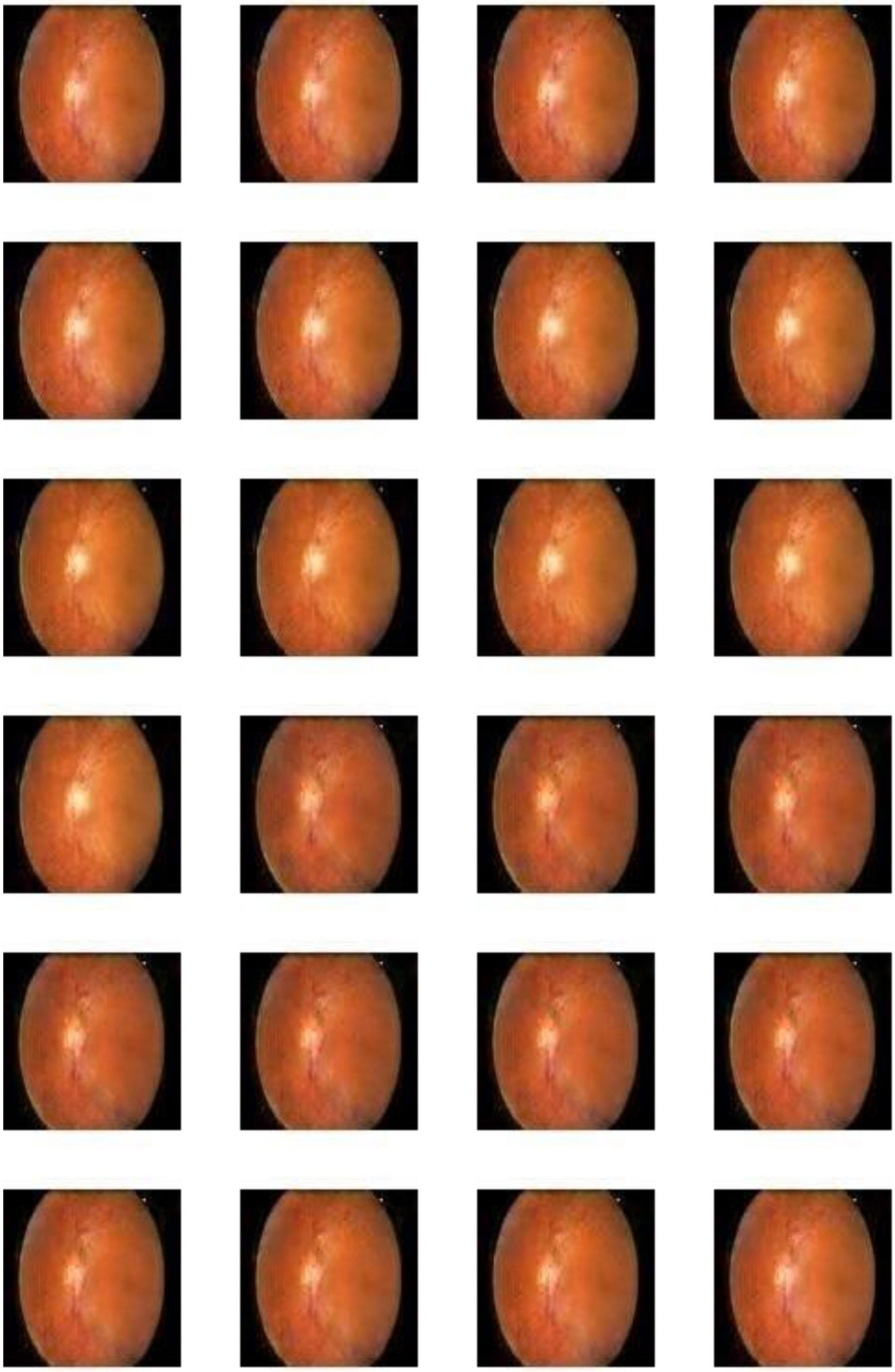




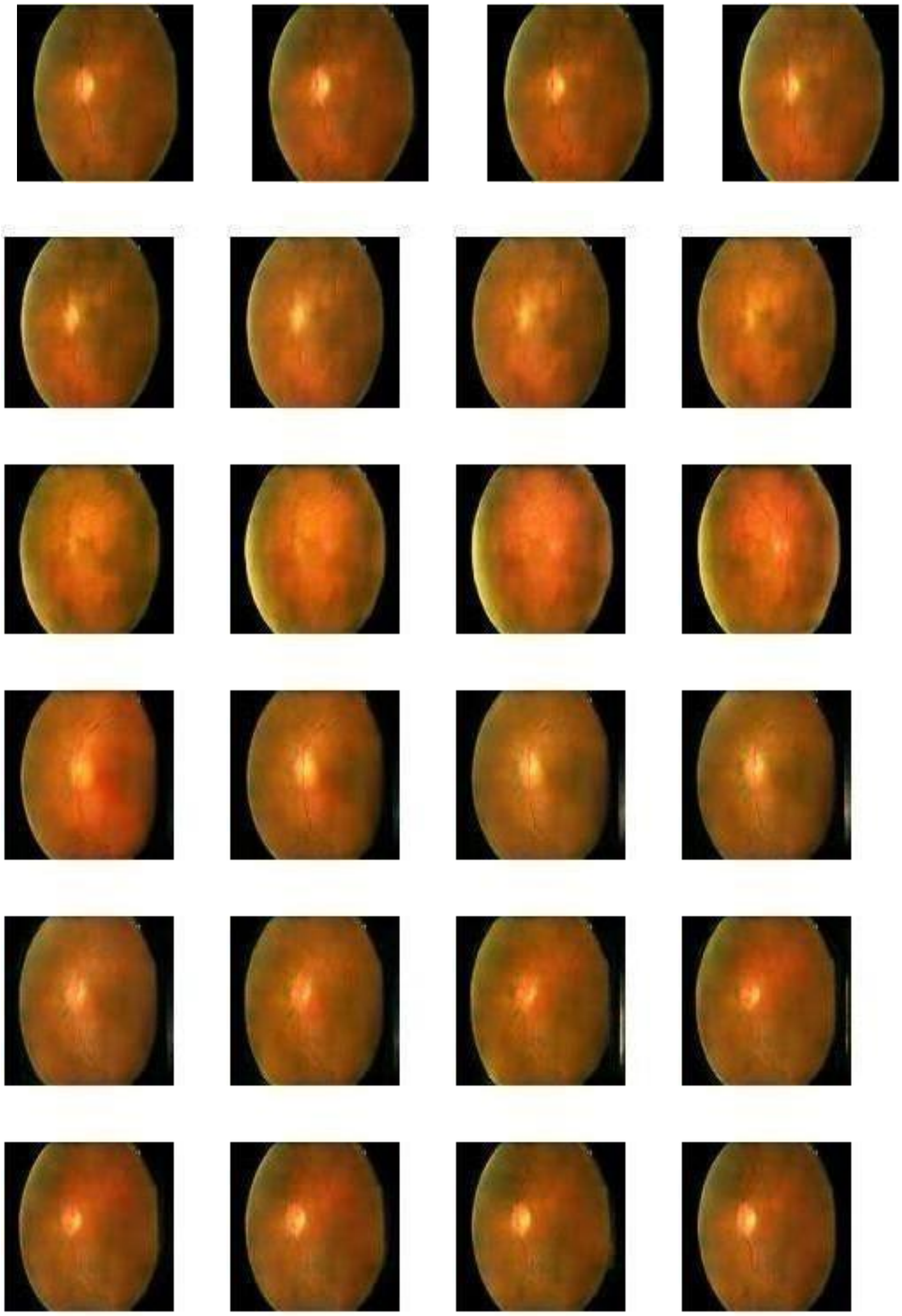
DATASET-2

https://www.kaggle.com/datasets/sshikamaru/glaucoma-detection

Sample images of Glaucoma



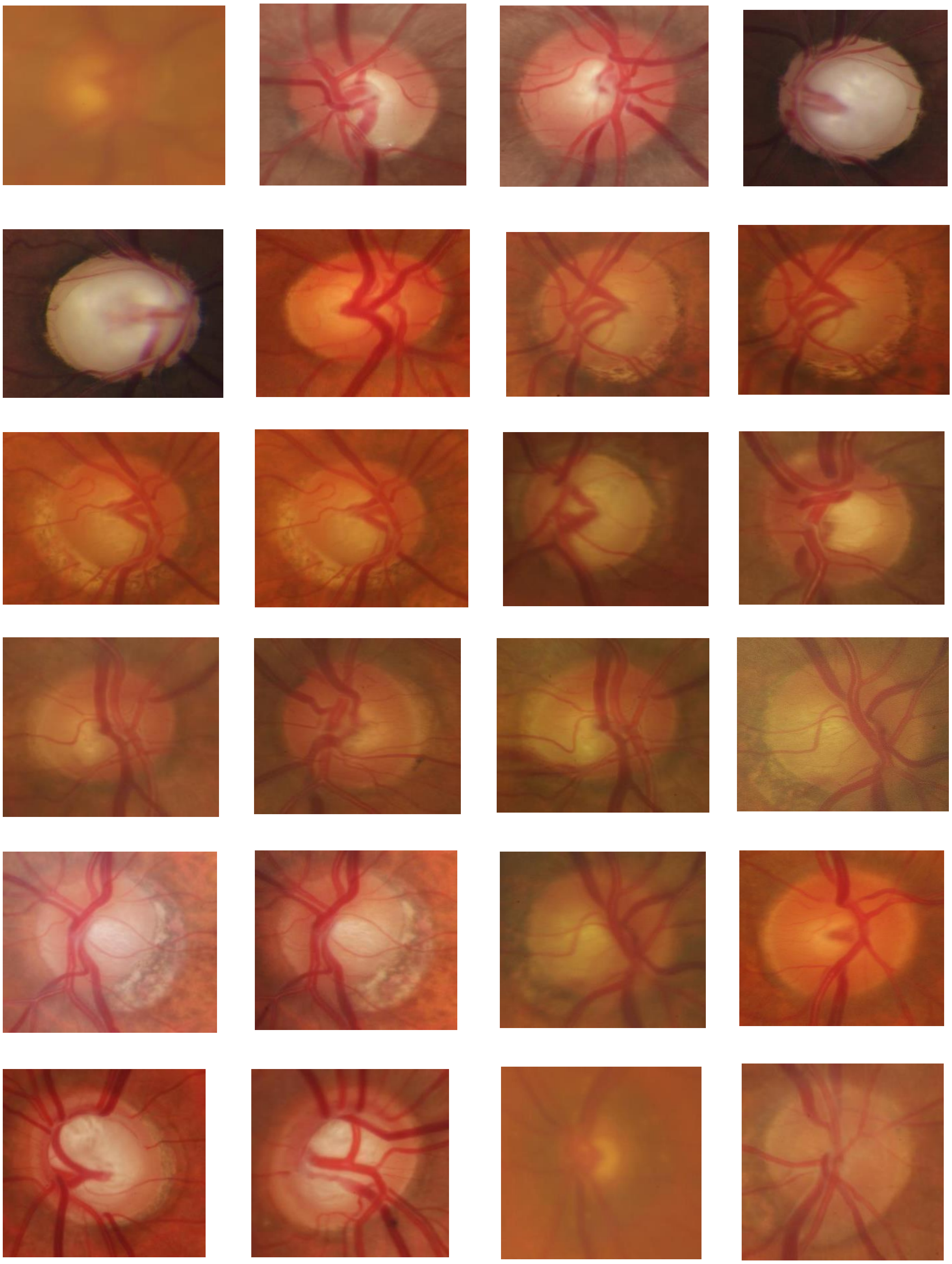
Sample images of non-Glaucoma



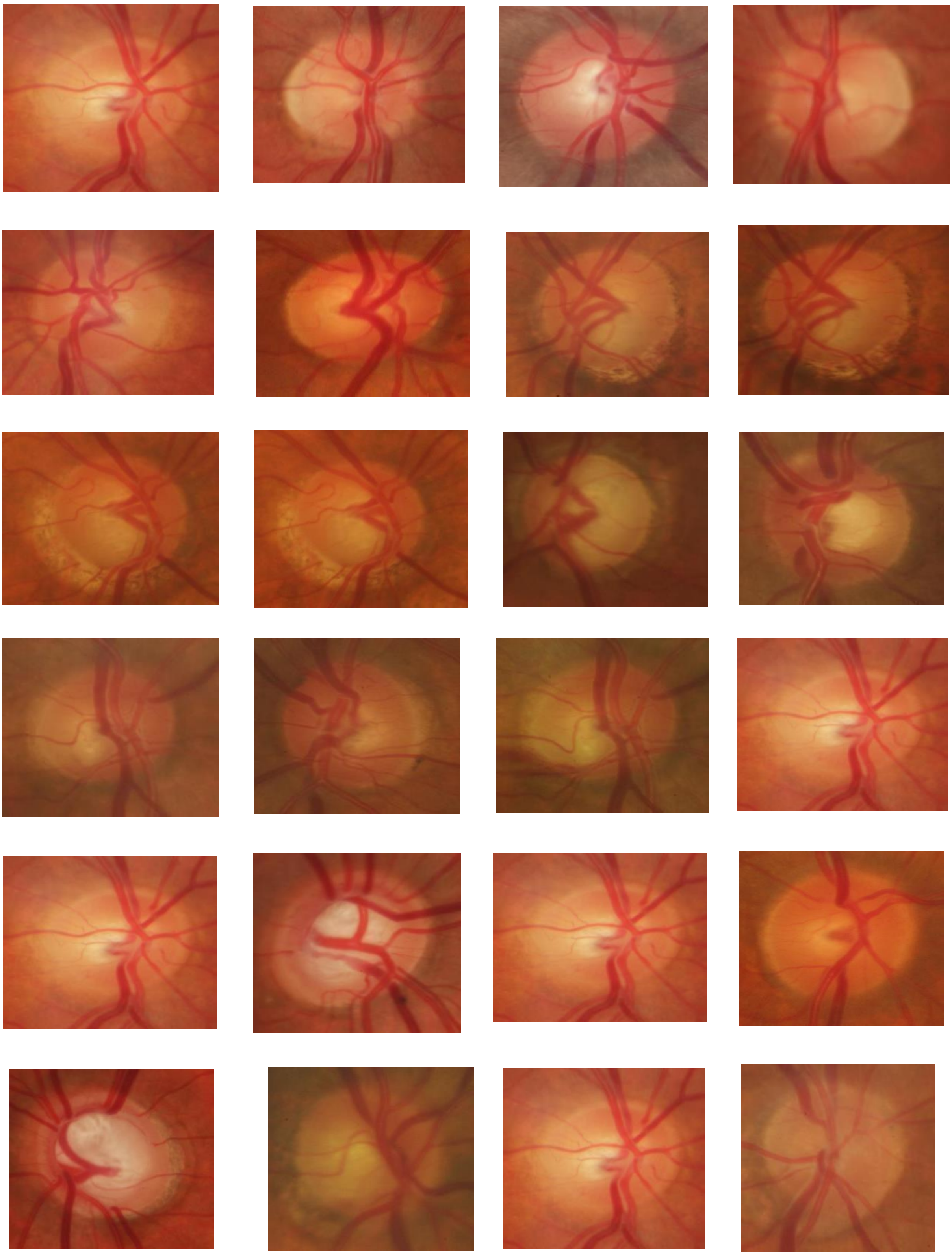
DATASET-3

https://www.kaggle.com/datasets/hindsaud/datasets-higancnn-glaucoma detection

Sample images of Glaucoma



Sample images of non-Glaucoma



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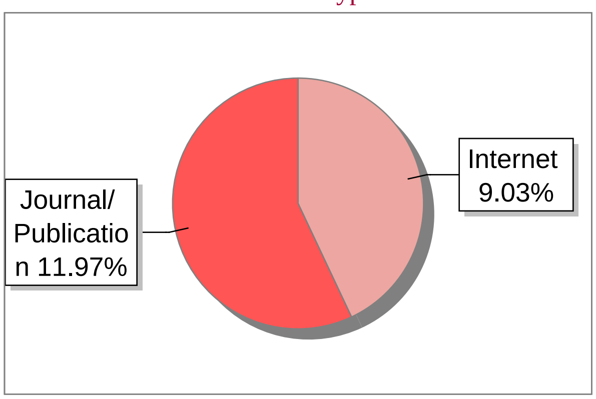

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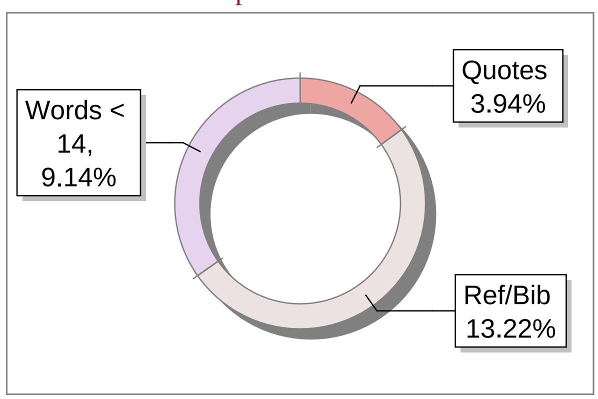

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