Automated Classification of Glaucoma Detection used Deep Learninig

N.Prasad
Department of Electronics and
Communication Engineering,
Vel Tech Rangarajan Dr. Sagunthala
R&D Institute of Science and
Technology,
Chennai, India
vtu21271@veltech.edu.in

M.Anupriya
Department of Electronics and
Communication Engineering,
Vel Tech Rangarajan Dr. Sagunthala
R&D Institute of Science and
Technology,
Chennai, India
vtu20780@veltech.edu.in

P.Madhusudhan Rao
Department of Electronics and
Communication Engineering,
Vel Tech Rangarajan Dr. Sagunthala
R&D Institute of Science and
Technonology,
Chennai, India.
vtu20822@veltech.edu.in

Dr.Annalakshmi
Department of Electronics and
Communication Engineering,
Vel Tech Rangarajan Dr. Sagunthala
R&D Institute of Science and
Technology,
Chennai, India
annalakshmig@veltech.edu.in

Abstarct: Glaucoma is the term used to describe either the accumulated loss of retinal cells inside the optic nerve or the gradual visual loss brought on by optic neuropathy. Glaucoma is a disease that relates to the vision of the human eye and this disease is considered an irreversible disease that results in vision deterioration. People don't have any early warning indications of this glaucoma and might not notice a change in your vision because the effect is so subtle. It presents an architecture for proper glaucoma detection based on deep learning by making use of the convolutional neural network (CNN). The differentiation between the patterns formed for glaucoma and non-glaucoma can find out with the use of CNN. The proposed model is developed using the ResNet-50 robust image classification architecture.

Keywords: FeatureExtraction, Deeplearning, CNN, Image data Generator, Glaucomatous.

I. INTRODUCTION

The major components of the human eye involved in vision are the cornea, pupil, iris, lens, retina, optic nerve, and tears . The iris is located between the cornea and the lens and controls the light. The retina receives the light and transfers it to the brain for recognition by converting it into electrical signals. At the backside of the eye is a nerve known as the optic nerve, which comprises 1 million nerve fibers of the retinal ganglion cells . The primary function of this nerve is to transfer visual signals from the retina to the occipital cortex.

The human eye contains a fluid known as aqueous humor, which is continuously recycled. An obstruction in the drainage of aqueous humor leads to increased intraocular pressure (IOP). Consequently, the retina and optic nerve are damaged, which may lead to vision loss . This is partly due to the degeneration of ganglion cells in the retina .

The loss of optic nerve fibers changes the shape of the optic disc (OD) towards an increase in the cup-to-disc ratio (CDR), which is an early sign of glaucoma [5]. The anatomy of the eye is depicted in Figure 1 [6]. The visual loss in glaucoma is due to damage to the retinal ganglionic cells.The alterations in the visual field scope are essential for diagnosin glaucoma.

Glaucoma is the second leading cause of blindness worldwide. About 80 million people were affected by glaucoma worldwide in 2020, and the number may increase to 111.8 million by 2040 There are several types of glaucoma, but the most common is open-angle glaucoma, which affects nearly 57.5 million people worldwide . Regular checkups by ophthalmologists after age 50 can reduce the risk of developing glaucoma. Figure 3 shows the retinal fundus images of a healthy control and patients with early, moderate, and advanced-stage glaucoma from the RIM-ONE dataset.

If treated early, glaucoma progression can be slowed or stopped with medication, laser treatment, or surgery. The primary goal of these treatments is to reduce eye pressure. Various classes of glaucoma medications are available, and laser treatments can be effective for both open-angle and closed-angle glaucoma. For individuals who do not respond adequately to these treatments, several types of glaucoma surgeries may be considered. Closed-angle glaucoma, however, requires immediate medical attention as it is a medical emergency.

Globally, around 70 million people have glaucoma, with approximately two million cases in the United States. It is the leading cause of blindness among African Americans and is more common among older individuals. Additionally, closed-angle glaucoma occurs more frequently in women. Often referred to as the "silent thief of sight," glaucoma causes gradual vision loss over time. It is the second-leading cause of blindness worldwide after cataracts. In 2010, cataracts accounted for 51% of blindness cases, while glaucoma contributed to 8%. The term "glaucoma" originates from the Ancient Greek word "glaucous," meaning "shimmering." In English, the word has been in use since 1587 but became widely recognized after 1850, following the development of the ophthalmoscope, which enabled doctors to observe optic nerve damage.

Glaucoma occurs at different levels of severity—primary, secondary, and tertiary—corresponding to normal, moderate, and severe stages of the disease. It is primarily characterized by increased intraocular pressure (IOP) or pressure inside the eye. Several types of glaucoma exist, including open-angle glaucoma, angle-closure glaucoma, normal tension glaucoma, congenital glaucoma, primary glaucoma, secondary glaucoma, neovascular glaucoma, exfoliative glaucoma, pigmentary glaucoma, chronic glaucoma, and traumatic glaucoma.

Open-angle glaucoma typically progresses without noticeable symptoms in its early stages, making regular eye examinations crucial for early detection. The disease is characterized by a gradual loss of peripheral vision and changes to the optic nerve, such as an increased cup-to-disc ratio observed during fundoscopic examinations.

In contrast, approximately 10% of individuals with angle-closure glaucoma experience acute episodes marked by sudden eye pain, halos around lights, eye redness, significantly elevated intraocular pressure (often exceeding 30 mmHg), nausea, vomiting, sudden vision loss, and a fixed, mid-dilated pupil. These acute attacks are medical emergencies requiring immediate attention to prevent permanent vision loss.

Additionally, opaque specks known as glaukomflecken may develop on the lens in cases of glaucoma. Glaucoma is a group of eye diseases that result in damage to the optic nerve (or retina) and causes vision loss. Open-angle glaucoma develops slowly over time and there is no pain. Peripheral vision may begin to decrease, followed by central vision, resulting in blindness if not treated. Closed-angle glaucoma can present gradually or suddenly. The most common type is open-angle (wide angle, chronic simple) glaucoma, in which the drainage angle for fluid within the eye remains open, with less common types including closed-angle (narrow-angle, acute congestive) glaucoma and normal-tension glaucoma. The sudden sight may involve severe eye pain, blurred vision, mid-dilated pupils, redness of the eye, and nausea. Vision loss from glaucoma, once it has occurred, is permanent. Eyes affected by glaucoma are referred to as being glaucomatous.

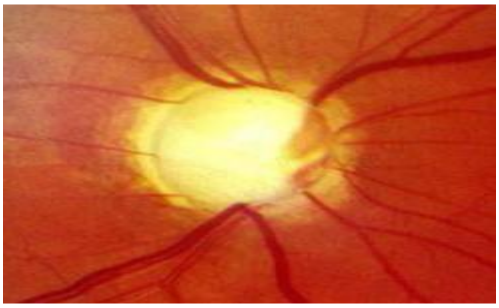

Figure 1.1: Optic nerve in advanced glaucoma disease

The research work that we are going to take up further is going to deal with the primary glaucoma detection along with the hardware implementation of the same so that both at the simulation level & at implementation level, it would have been validated. As open-angle glaucoma is usually painless with no symptoms early in the disease process, screening through regular eye exams is important. The only signs are gradually progressive visual field loss and optic nerve changes (increased cup-to-disc ratio on fundoscopic examination). About 10% of people with closed angles present with acute angle closure characterized by sudden ocular pain, seeing halos around lights, red eye, very high intraocular pressure (>30 mmHg (4.0 kPa)), nausea and vomiting, sudden decreased vision, and a fixed, mid-dilated pupil. It is also associated with an oval pupil in some cases. Acute angle closure is an emergency. Opaque specks may occur in the lens in glaucoma, known as glaukomflecken.

Figure 1.2: Photo showing conjunctival vessels dilated at the cornea edge and hazy cornea characteristics of acute closure glaucoma.

Classification predictive modeling involves assigning a class label to input examples. Classification is the process of finding or discovering a model or function which helps in separating the data into multiple categorical classes i.e. discrete values. In classification, data is categorized under different labels according to some parameters given in input and then the labels are predicted for the data. The derived mapping function could be demonstrated in the form of “IF-THEN” rules. The classification process deal with the problems where the data can be divided into binary or multiple discrete labels. Convolutional neural networks receive images as input and use them to train a classifier. The network employs a special mathematical operation called a “convolution” instead of matrix multiplication. The architecture of a convolutional network typically consists of four types of layers: convolution, pooling, activation, and fully connected.

Scalability and consistency issues plague traditional diagnostic techniques, which rely on professional assessment of fundus photos. A promising solution is provided by recent developments in deep learning, particularly with regard to Convolutional Neural Networks (CNNs).

glaucoma progression can be slowed or stopped with medication, laser treatment, or surgery. The primary goal of these treatments is to reduce eye pressure. Various classes of glaucoma medications are available, and laser treatments can be effective for both open-angle and closed-angle glaucoma. For individuals who do not respond adequately to these treatments, several types of glaucoma surgeries may be considered.

II. LITERATURE SURVEY

Ayesha Shouka[1]Glaucoma is a serious eye condition that can lead to irreversible vision loss if not treated promptly. To improve early diagnosis, a deep learning model utilizing the ResNet-50 architecture was developed and trained on four different datasets, including the G1020 dataset. This model focuses on the gray channels of fundus images and employs data augmentation techniques to enhance training diversity. On the G1020 dataset, the model achieved impressive results: 98.48% accuracy, 99.30% sensitivity, 96.52% specificity, an area under the curve (AUC) of 97%, and an F1-score of 98%. These outcomes suggest that such automated systems can assist clinicians in the timely diagnosis and treatment of glaucoma. Future research aims to develop models that integrate both fundus and optical coherence tomography (OCT) images, adopting a multimodal imaging approach to further enhance early-stage glaucoma detection.

Mohammad [2] Many researchers have studied how deep learning (DL) can help diagnose glaucoma using color fundus images. Several public datasets, like RIM-ONE, ORIGA, and REFUGE, provide eye images with expert labels, helping train DL models. Preprocessing techniques, such as image enhancement and filtering, improve image quality for better disease detection. Different deep learning models, including CNNs and transfer learning methods, have been tested for classifying and segmenting eye structures like the optic disc and cup, which are important for diagnosing glaucoma. Studies show that DL models can sometimes perform as well as or even better than eye specialists. However, using these models in real-world hospitals and clinics is still challenging due to limited data, difficulties in understanding how the models make decisions, and the need for clinical validation. To overcome these issues, researchers are working on improving data quality, making DL models more interpretable, ensuring fair and unbiased results, and creating guidelines for safe clinical use. Some new approaches, like explainable AI and federated learning, are also being explored to make these models more trustworthy and useful in healthcare.

Marriam Nawaz[3]The proposed method, EfficientDet-D0 with EfficientNet-B0 as the base network, is introduced for automated glaucoma detection and classification from retinal fundus images. Since manual detection requires experts and is complex, automation is necessary. The model is tested on the ORIGA database and further validated on the HRF and RIM ONE DL datasets to ensure its generalization ability. It achieves 97.2% accuracy on ORIGA, 98.21% on HRF, and 97.96% on RIM ONE DL. The approach proves to be robust in detecting glaucoma lesions despite variations in size, shape, position, and image distortions, outperforming other recent techniques. Future work aims to enhance feature selection in deep learning models and extend the method to detect other eye diseases.

Cinare Oguz [4] Glaucoma is a serious eye disease that damages the optic nerve and can lead to permanent blindness if not detected early. Early diagnosis through regular eye exams and treatment can help prevent vision loss. Many recent studies have focused on Deep Learning (DL) methods for automated glaucoma detection using fundus images. In this study, a combination of Deep Learning and Machine Learning (ML) is used to assist experts in diagnosing glaucoma. A new Convolutional Neural Network (CNN) model extracts deep features from raw fundus images, which are then classified using different ML techniques, including Adaboost, kNN, Random Forest, MLP, SVM, and Naive Bayes. The performance of these hybrid models is tested on the ACRIMA dataset, which consists of 705 images, with 80% used for training and 20% for testing. Among the models, the CNN-Adaboost combination achieves the best results with 92.96% accuracy, a 93.75% F1 score,and an AUC value of 0.928. These findings suggest that the proposed approach can effectively aid in early glaucoma detection.

Nahida Akter [5] Our deep learning model, trained on segmented OCT images, demonstrated high accuracy in detecting glaucoma while maintaining a simpler architecture and significantly reducing training time compared to VGG16 and ResNet18. The use of Grad-CAM heatmaps validated the model's ability to effectively localize affected regions, reinforcing its interpretability. Furthermore, incorporating six cross-sectional B-scans enhanced diagnostic precision by capturing more comprehensive structural variations. Notably, ONH cup segmentation analysis revealed statistically significant differences, highlighting its potential as a novel imaging biomarker for glaucoma detection. However, the study had certain limitations, such as the absence of advanced diagnostic features like gonioscopy and OCT angiography, which could further refine disease characterization and improve diagnostic accuracy. Future research should explore integrating these modalities to enhance the robustness of automated glaucoma assessment

.

Marie Valerie [6] This feasibility study seems to indicate that the device was able to discriminate between phantoms modelling glaucoma with abnormal intraocular pressure and healthy phantoms in a significant way using electrical measurements. It will be necessary to validate the system on human subjects. To increase the sensitivity and specificity of the system for the global pathology (normal and abnormal IOP), the capacitive characteristics of the tissues, as well as the vascular characteristics of the ophthalmic artery, will be required to enrich human models. Knowing in addition that diabetic retinopathy is accompanied by alterations of the retinal capillary walls, allowing visible water leakage under the aspect of oedema, we hypothesise that the device could even become a predictive test on that other pathology. Other ailments are also accompanied by capillary alterations and extracellular fluid accumulations, for example: intraocular inflammation or uveitis, various forms of age-related macular degeneration (AMD) and certain intraocular tumours. We plan to explore them using the complete system.

Ruben Hemelings et al [7] propose a methodology that advances explainable deep learning in the field of glaucoma detection and vertical cup-disc ratio (VCDR), an important risk factor. Colour fundus images were subject to a series of pre-processing steps prior to model input. First, the images were cropped to a square shape, Subsequently, a widely-used local contrast enhancement through background subtraction was used to correct uneven illumination. The authors present a sound methodology that conclusively supports that deep learning can reliably identify glaucoma-induced damage outside the ONH. The researchers did not explicitly assess the influence of myopic changes, did not analyze the role of the disease stage

.

Mamta Juneja et al [8] presents an Artificially Intelligent glaucoma expert system based on segmentation of optic disc and optic cup. A Deep Learning architecture is developed with CNN working at its core for automating the detection of glaucoma. The proposed system uses two neural networks working in conjunction to segment optic cup and disc. The CAD system comprises three basic steps such as Pre-processing, Segmentation, and Classification. Preprocessing the input images for removal of outliers. Feeding the filtered images to a neural network is used to segment the optic disc to remove the unnecessary part of the image as the optic cup resides inside the optic disc and cropped image is used for cup segmentation. A modified version of U-net is used for segmentation of optic disc and cup. In order to determine which color channels provide the highest accuracy, the G-Net model was trained and validated several times on the RGB images, red channel images, blue channel images, and green channel images.

M Tabassum et al. [9] The researchers presented a deep convolution neural network based technique for the early identification of Glaucoma. Preprocessing and post-processing steps are avoided to reduce the computational cost of the system. There are no more images in the considered dataset, so augmenting the data with rotations ranging from 0 to 360 degrees is done, and brightness is increased and decreased to counter the contrast issue. The stochastic gradient descent with momentum with l2 regularization of weight decay = 0.005 for the training model, and a learning rate = 0.0001 was used for the segmentation network. This model resulted in a higher dice value for optical cup segmentation, which is difficult because of the blood vessels' presence. However, it can be trained with fewer epochs and few parameters and is 99.6 accurate on both datasets. The limitation of this model is that the dice value on the DRISHTI dataset is comparatively less than others.

Partha Sarathi Mangipudi et al [10] presented an effective system for optic disc and cup segmentation using deep learning architecture. Modified Ground Truth is utilized to train the proposed model. It works as fused segmentation marking by multiple experts that helps in improving the performance of the system. Extensive computer simulations are conducted to test the efficiency of the proposed system. The authors used a modified segmentation measure for accuracy and in representing the subsequent loss function. The intersection/union of two binary maps is now transformed into multiplication of two probability masks, which make more sense. The logarithm of the modified IOU function was chosen to be minimized for the purpose of optimization. The proposed algorithm utilizes the power of the encoder-decoder network which is trained on three different datasets. But there were some images where the optic cup was small or on images in which the contrast between optic disc and its background was low, the proposed algorithm produced poor results. This is where salient point detection algorithms could be put to good use along with CNNs to improve upon the model accuracy.

Hamid A [11] proposed a Glaucoma detection algorithm using Statistical and Textural Wavelet Features. In this study, images are first preprocessed (by enhancing the contrast of the red channel), followed by wavelet decomposition and feature extraction on the green and blue channels. The grey-level co-occurrence matrices were used to calculate all features in four angles (00, 450, 900, 1350). The suggested model demonstrated that wavelet statistical features perform better in the feature selection stage than wavelet texture features. In addition, statistical characteristics extracted from the green and blue channels produced better outcomes. The significant benefit is that this model only needs 3 seconds per image for a dataset of high resolution retinal images. The proposed method, which used the KNN classifier (k ranged from 1-15) and five-fold cross-validation, achieved an accuracy of 96.7%.

Javier Civit-Masot et al. [12] suggested an image segmentation and transfer learning based diagnostic tool for glaucoma identification. In this study, the proposed model consists of two subsystems: (1) Segmentation Subsystem using U-Net in which data from both datasets are split individually into training and testing datasets, and training datasets are combined, testing datasets are combined. Disc Segmentation and Cup Segmentation are applied to the combined training dataset and tested separately with the Disc testing dataset and Cup testing dataset, and features are extracted. (2) The Direct Classification Subsystem consists of a light-weighted network MobileNet v2 that has been pre-trained with ImageNet and an extra classifier network. The outcomes of both subsystems are combined to produce the diagnostic aid tool's ultimate result. Compared to the results generated by the heavier networks for individual datasets, the suggested light-weighted method performed well for mixed datasets.

Mijung Kim et al. [13] described web-applicable computer-aided diagnosis of glaucoma using deep learning. The revival of convolutional neural networks (CNNs) and the public availability of large-scale datasets like ImageNet have led to significant performance improvements in computer vision. CNN-based predictive models have shown to be highly successful in medical image analysis. The authors introduced a predictive model for computer aided diagnosis of glaucoma, leveraging CNNs and Grad-Class Activation Mapping. The authors advocate that in this paper, they introduced a predictive model for computer-aided diagnosis of glaucoma. The model has been developed by making use of a small-sized dataset of fundus eye images. The authors integrated the model into a publicly available prototype web application.

Ko Kim et al. [14] proposed a deep learning system for diagnosing glaucoma using Optical Coherence Tomography The group developed and validated a deep learning system for glaucoma diagnosis using OCT deviation and thickness maps of RNFL and GCIPL analyses. Deep learning systems using only the RNFL thickness map showed the best diagnostic performance. Despite no significant difference in diagnostic performance between VGG-19 (AUROC 0.987, 95% CI 0.971–0.995) and ResNet-34, the VGG-19 showed diagnostic patterns more compatible with those of glaucoma specialists. The glaucoma group had significantly higher mean age, lower retinal nerve fiber layer and ganglion cell–inner plexiform layer thicknesses, and lower mean deviation values compared to the control group. The strength of the study is that model employed on all the currently available RNFL and GCIPL deviation and thickness maps. 1822 eyes were involved in the research

.

Manal Abdel-Mottaleb et al.[15] presented an automatic glaucoma diagnosing framework based on convolutional neural network (CNN) models. The researchers compared proposed model performances with the performance of trained ophthalmologists. The lowest performance was achieved by the TCNN model because the transfer learning and the fine tuning of the pre-trained network layers utilized a small set of labeled samples. The transfer learning model is based on convolutional neural networks pre-trained with non-medical data and fine-tuned using domain specific labeled data. Unlike the previous works where the optic disc features were handcrafted, the presented models automatically extract the key features of the disease from raw images. The initial sizes of A and B were chosen to be 30 and 39 samples, respectively. With more iterations, the classifier performance improves, thus, these two sizes were increased during the learning process.

Huazhu Fu et al. [16] reported in ‘Glaucoma Detection Based on Deep Learning Network in Fundus Image that glaucoma is the leading cause of irreversible blindness worldwide. The balanced region helps avoid the overfitting during the model training and improves the segmentation performance. M-Net and Disc-aware Ensemble Network obtains the satisfied performances. Early detection is essential to preserve vision and life quality. The M-Net obtains better performance than the Disc-aware Ensemble Network (DENet). There were 168 glaucomatous eyes involved in the study. The researchers advocate that for this case, all the methods fail to produce accurate OC segmentation. This issue could potentially be addressed in future work through the use of more powerful networks or additional image enhancement pre-processing.

JinAhn et al.[17] proposed a deep learning model for the detection of both advanced and early glaucoma using photography. The researchers noted that both advanced and early glaucoma could be correctly detected via machine learning, using only fundus photographs. Transfer-learned GoogleNet Inception v3 model achieved accuracy and area under the receiver operating characteristic curve of 99.7%. Machine learning is a system of artificial computer intelligence that provides computers with the ability to automatically learn without being programmed. Transfer-learned GoogleNet Inception v3 model achieved accuracy and AUROC of 99.7% and 0.99 on training data. This study demonstrates that deep learning techniques can be combined with fundus photography as an effective approach to distinguish between normal controls and glaucoma patients.

Guangzhou An et al. [18] proposed a method on glaucoma diagnosis with machine learning based on optical coherence tomography and color fundus images. Machine learning technologies and deep learning, in particular, have seen dramatic progress and have enabled the development of new algorithms to automate eye disease diagnosis. The researchers describe a new machine learning algorithm for diagnosing glaucoma based on OCT-derived data, including disc fundus images as well as thickness and deviation maps of the macula and the optic disc. Glaucoma is a chronic, neurodegenerative ocular disease characterized by optic neuropathy and visual disturbance that corresponds to optic disc cupping and optic nerve fiber degeneration. Glaucomatous structural changes preceed functional changes.

Felix Grassmann et al.[19] developed an automated classification strategy based on training deep learning models to predict the Age-related macular degeneration stage in color fundus images. The team reported linear weighted and unweighted k measures, overall accuracy, as well as top 2 accuracy, which indicates that the true class of a fundus image is among the 2 classes that are predicted by the convolution neural nets. The researchers included 120,656 manually graded color fundus images from 3654 Age-Related Eye Disease Study (AREDS) participants and presented an automated classification scheme based on the AREDS 9-step plus 3 severity scale and ungradable fundus image with high classification accuracy. The F1 score was similar for all 6 neural net architectures across all AREDS classes, but differed significantly for class 12. The researchers believe that this is the result of 3 factors: class 12 contained the fewest samples, so the networks were not able to learn from many different training examples.

Feng Li et al.[20] presented a deep learning-based automated detection of glaucomatous optic neuropathy on color fundus photographs. Glaucoma is the collective name of a group of eye conditions which can cause vision loss and eventually result in blindness. The model was tested on 2371 adult patients for the detection of glaucoma using fundus images,which showed high accuracy compared to human experts. In a multi-class comparison between glaucomatous optic neuropathy-confirmed, GON-suspected, and NORMAL eyes, the model obtained an accuracy of 0.941. ResNet101was used to automatically and reliably detect GON from fundus images. The proposed model showed a superior performance compared with the human experts in identifying normal eyes.

III. METHODOLOGY

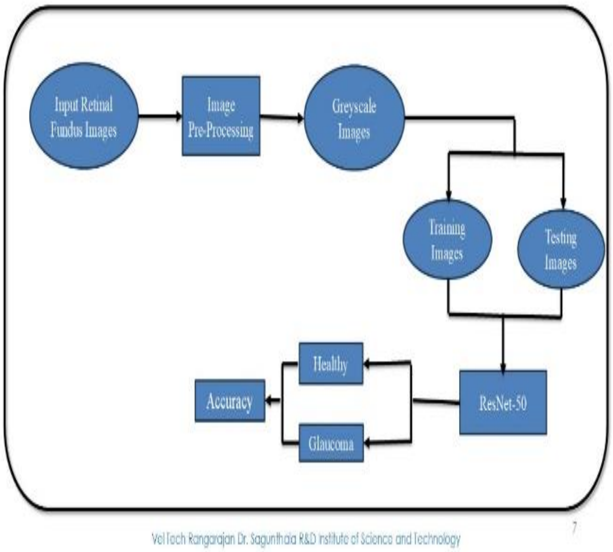

Figure 3.1 Block diagram

Many pretrained models like AlexNet, ResNet, VGGNet, etc. are used. The saliency maps are produced from these models on the considered data then these maps are used for further steps of the process. Most of the proposed models used ground truths and modified ground truths for the detection of glaucoma. Some researchers have used UNet for Image Segmentation, which slows down the middle layers of the model. Some of the existing methods used imbalanced data where, imbalance data caused disturbance in the results or detection. So balancing should be applied. Very few researchers used many parameters, it'll definitely effect the performance of the model. In this we propose a model consisting of a combined dataset of ACRIMA, DRISTI and RIMONE. The proposed methodology uses an image data generator for data augmentation. The original images have increased due to augmentation and a large dataset is prepared. The dataset is split intlo 80:10:10 for training data, testing and validation data. Later the augmented images have been sent for feature selection using CNN. The images are classified using binary classification as it has two outcomes. The model can predict the glacumatous eye accurately.

The proposed methodology for glaucoma detection using ResNet-50 begins with the acquisition of retinal fundus images from publicly available datasets or clinical sources. These images are subjected to pre-processing steps, including resizing to a standard resolution (such as 224x224 pixels), normalization, noise removal, and contrast enhancement. To reduce computational complexity and focus on structural features critical for glaucoma diagnosis, the images are converted to greyscale.
Following pre-processing, the dataset is divided into two subsets: training images and testing images. The training images are used to train the ResNet-50 model—a deep convolutional neural network with 50 layers that incorporates residual learning to improve feature extraction and classification performance. ResNet-50 processes the training data, learning hierarchical features that distinguish healthy eyes from those affected by glaucoma.
Once the model is trained, it is evaluated using the testing images. The ResNet-50 model classifies each image as either "Healthy" or "Glaucoma." The accuracy and effectiveness of the model are then assessed by comparing the predicted labels with the actual ground truth, using performance metrics such as accuracy, precision, recall, and F1-score. This approach ensures a reliable and automated method for early detection of glaucoma from retinal images.

Convolutional Neural Network(CNN): Convolutional Neural Networks (CNNs) are a type of deep learning model particularly effective for image analysis and recognition tasks. They are designed to automatically and adaptively learn spatial hierarchies of features through layers of convolutions, pooling, and non-linear activations. In the context of glaucoma detection, CNNs are widely used to analyze retinal fundus images or Optical Coherence Tomography (OCT) scans to identify patterns associated with glaucomatous damage. These networks can detect subtle structural changes in the optic nerve head and retinal nerve fiber layer that may be difficult to spot through traditional clinical examination. By training CNNs on large datasets of labeled eye images, they can achieve high accuracy in early diagnosis, aiding ophthalmologists in screening and monitoring glaucoma progression. This not only enhances diagnostic efficiency but also helps in preventing vision loss through timely intervention.

RestNet-50: ResNet-50 is a powerful deep convolutional neural network with 50 layers, introduced as part of the Residual Networks (ResNet) family. Its key innovation is the use of residual blocks, which allow the network to learn identity mappings and overcome the vanishing gradient problem commonly found in very deep networks. This architecture enables the model to train deeper networks without a significant loss in performance or an increase in training error. In glaucoma detection, ResNet-50 is frequently used to analyze retinal fundus or OCT images by extracting deep features that represent abnormalities in the optic nerve head, retinal nerve fiber layer, and other key regions. These features help the model distinguish between healthy and glaucomatous eyes with high accuracy.

ResNet-50 offers several important features: it includes skip connections that enhance gradient flow, supports transfer learning which allows using pre-trained weights on medical images, and achieves excellent generalization due to its depth and design. Compared to other deep learning models like VGGNet or AlexNet, ResNet-50 performs better in terms of accuracy, training efficiency, and robustness, especially when handling complex medical images. Its ability to learn rich, hierarchical representations makes it a preferred choice in glaucoma detection tasks, improving early diagnosis and patient outcomes.

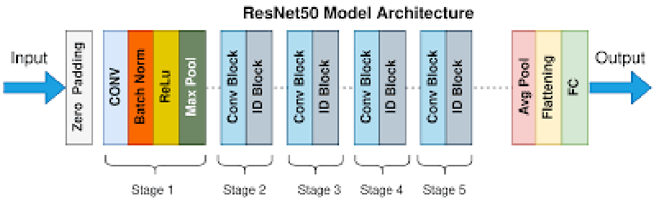

Figure 3.2 : ResNet-50 architecture diagram

IV. IMPLEMENTATION

Implementation is the stage where the theoretical design is turned into a working system. The most crucial stage in achieving a new successful system and in giving confidence is implementing the system. It involves careful planning, investigation of the current system and its constraints on implementation, design of methods to achieve the change over and an evaluation of change over methods a part from planning. Two major tasks of preparing the implementation are education and training of the users and testing of the system. The more complex the system being implemented, the more involved will be the system analysis and design effort required just for implementation. The implementation phase comprises of several activities. The required hardware and software acquisition is carried out. The system may require some software to be developed. For this Programs are written and tested.

Preprocessing : Preparing data for main processing or for further analysis through preliminary processing is known as data pre-processing. It is a technique for converting unclean data into clean data sets. The term refers to the modifications made to our data before we feed it to the algorithm. It may also be used to represent any first or preliminary processing stage where several steps are required to prepare data. The idea of transforming unclean data into data cleansing. Before the technique is applied, the collection is pre-processed to check for noisy data, missing values, and other anomalies. the procedure for structuring unstructured data such that it may be interpreted. It is also an important phase in data mining because to the difficulty to handle raw data. Data mining and machine learning should not be used without first assessing the quality of the data. Information from an open-source eye illness database was utilised to find and gather the datasets for the project.

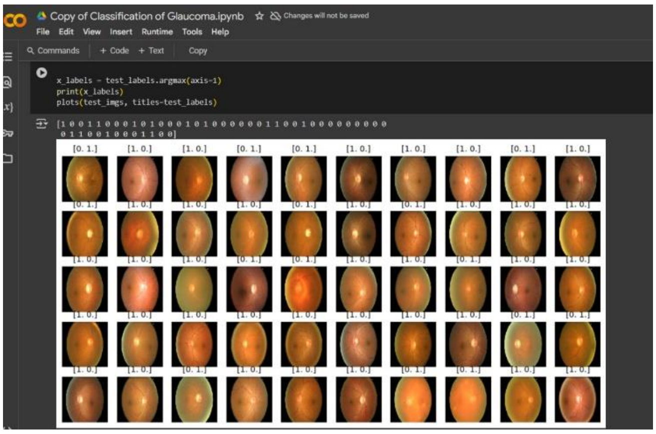

Figure 4.1 : Different Glaucoma Eyes

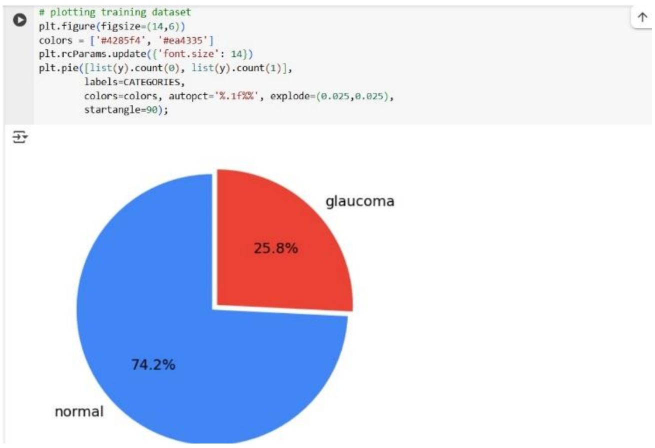

Figure 4.2: Glaucoma vs Normal eye

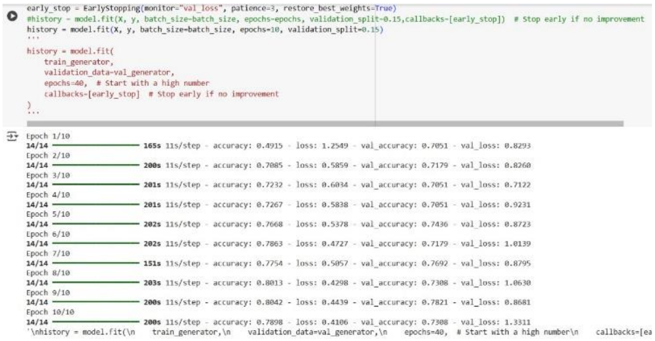

Figure 4 .3 : Validation

V. RESULTS

There are several different performance metrics that can be used to evaluate a model's performance. Performance is evaluated using the Specificity, Confusion Matrix, Accuracy, Recall, Precision, and F1 score. The confusion matrix provides a detailed explanation of values such as False Negatives, False Positives, True Positives, and True Negatives. With the use of all the training data, a neural network is trained for one cycle every epoch. In a given period, we only ever use a given piece of information. A pass is when two passes are combined, one forward and one backward. One or even more batches in each epoch are used to train the neural network using a portion of the dataset. We refer to the process of going through one batch of training samples as an "iteration." In order to train the model effectively, there are 10 epochs overall distributed.

Evaluation Metrics: For Evaluation of the model, we are using metrics like accuracy, F1score, recall, precision. A machine will always produce an outcome and we have no idea it is the correct one or not unless someone hints that out in our model. For calculating these metrics, we can use the confusion matrix which consist of four characteristics.

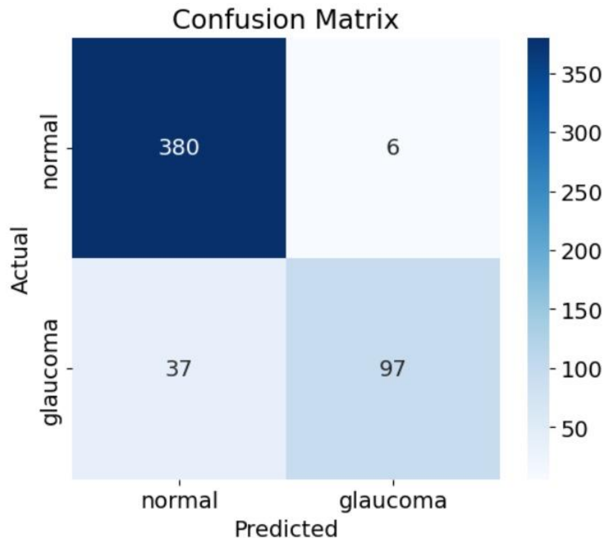

Figure 5.1 Confusion Matrix

Accuracy: The model's accuracy is a measure of its performance across all classes. When each course is equally important, it helps. In order to calculate it, divide the total of forecasts by the total of guesses. Be aware that the accuracy could be misleading. When the data are unbalanced is one instance. Accuracy is simply the percentage of correctly classified items when it comes to multiclass classification.

```
train_acc = history.history['accuracy'][-1]
val_acc = history.history['val_accuracy'][-1]

print(f"Final Training Accuracy: {train_acc:.4f}")
print(f"Final Validation Accuracy: {val_acc:.4f}")

Final Training Accuracy: 0.9231
Final Validation Accuracy: 0.7949
```

Figure 5.2 : Accuracy

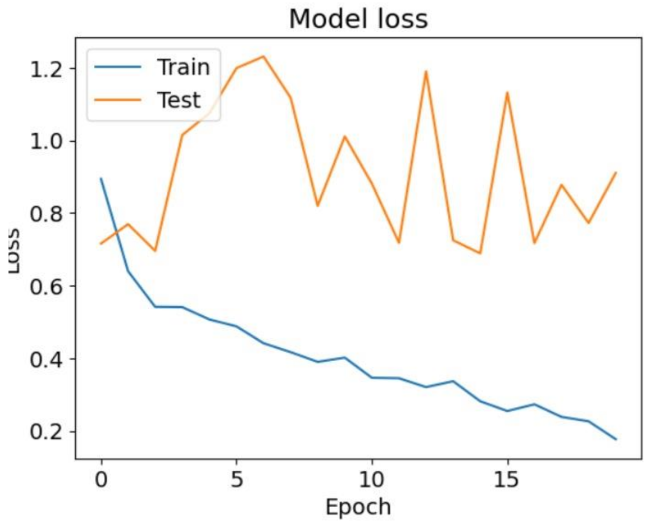

Figure 5.3 : The Model's loss at each epoch

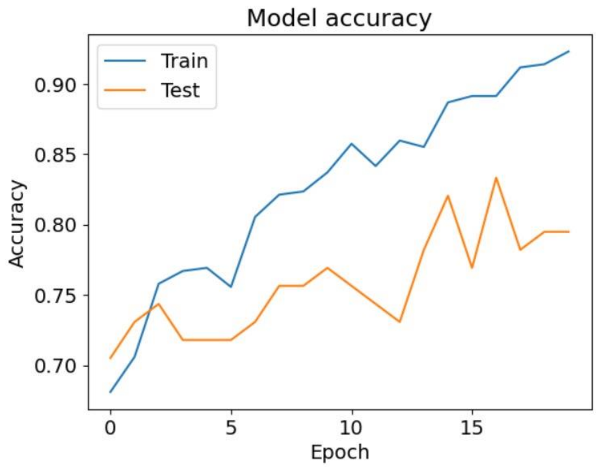

Figure 5.3 : The proposed model's Accuracy

VI. CONCLUSION

Permanent blindness caused by glaucoma is primarily due to optic nerve damage.The proposed glaucoma detection system adopts a deep learning-based methodology using the ResNet-50 architecture. Beginning with retinal fundus image input, the data is preprocessed and converted to grayscale to highlight key features. These processed images are then split into training and testing datasets. ResNet-50 is utilized for feature extraction and classification into healthy or glaucomatous categories. This approach enables accurate binary classification and supports clinical decisions. The system achieved a final training accuracy of 92.31% and a validation accuracy of 79.49%, indicating strong performance in learning and generalizing glaucoma detection from fundus images.Overall, the system demonstrates a reliable and effective method for early glaucoma detection, supporting clinical decision-making and potentially reducing the risk of permanent vision loss.

REFERENCES

1. Borwankar, S.; Sen, R.; Kakani, B. Improved Glaucoma Diagnosis Using Deep Learning. In Proceedings of the 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, 2–4 July 2020; pp. 2–5.
2. Huang, X.; Sun, J.; Gupta, K.; Montesano, G.; Crabb, D.P.; Garway-Heath, D.F.; Brusini, P.; Lanzetta, P.; Oddone, F.; Turpin, A.; et al. Detecting Glaucoma from Multi-Modal Data Using Probabilistic Deep Learning. *Front. Med.* **2022**, *9*, 923096.
3. Mahdi, H.; Abbadi, N. El Glaucoma Diagnosis Based on Retinal Fundus Image: A Review. *Iraqi J. Sci.* **2022**, *63*, 4022–4046.
4. Hemelings, R.; Elen, B.; Barbosa-Breda, J.; Blaschko, M.B.; De Boever, P.; Stalmans, I. Deep Learning on Fundus Images Detects Glaucoma beyond the Optic Disc. *Sci. Rep.* **2021**, *11*, 20313.
5. Saeed, A.Q.; Abdullah, S.N.H.S.; Che-Hamzah, J.; Ghani, A.T.A. Accuracy of Using Generative Adversarial Networks for Glaucoma Detection: Systematic Review and Bibliometric Analysis. *J. Med. Internet Res.* **2021**.

6. Mohamed, N.A.; Zulkifley, M.A.; Zaki, W.M.D.W.; Hussain, A. An Automated Glaucoma Screening System Using Cup-to-Disc Ratio via Simple Linear Iterative Clustering Superpixel Approach. *Biomed. Signal Process. Control.* **2019**.
7. Natarajan, D.; Sankaralingam, E.; Balraj, K.; Karuppusamy, S. A Deep Learning Framework for Glaucoma Detection Based on Robust Optic Disc Segmentation and Transfer Learning. *Int. J. Imaging Syst. Technol.* **2022**.
8. Norouzifard, M.; Nemati, A.; Gholamhosseini, H.; Klette, R.; Nouri-Mahdavi, K.; Yousefi, S. Automated Glaucoma Diagnosis Using Deep and Transfer Learning: Proposal of a System for Clinical Testing. In Proceedings of the 2018 International Conference on Image and Vision Computing New Zealand (IVCNZ), Auckland, New Zealand, 19–21 November 2018.
9. Elizar, E.; Zulkifley, M.A.; Muharar, R.; Hairi, M.; Zaman, M. A Review on Multiscale-Deep-Learning Applications. *Sensors* **2022.**
10. Abdani, S.R.; Zulkifley, M.A.; Shahrimin, M.I.; Zulkifley, N.H. Computer-Assisted Pterygium Screening System: A Review. *Diagnostics* **2022**.
11. Fan, R.; Alipour, K.; Bowd, C.; Christopher, M.; Brye, N.; Proudfoot, J.A.; Goldbaum, M.H.; Belghith, A.; Girkin, C.A.; Fazio, M.A.; et al. Detecting Glaucoma from Fundus Photographs Using Deep Learning without Convolutions: Transformer for Improved Generalization.*2023*
12. Zhou, Q.; Guo, J.; Chen, Z.; Chen, W.; Deng, C.; Yu, T.; Li, F.; Yan, X.; Hu, T.; Wang, L.; et al. Deep Learning-Based Classification of the Anterior Chamber Angle in Glaucoma Gonioscopy. *Biomed. Opt. Express* **2022**.
13. Afroze, T.; Akther, S.; Chowdhury, M.A.; Hossain, E.; Hossain, M.S.; Andersson, K. Glaucoma Detection Using Inception Convolutional Neural Network V3. *Commun. Comput. Inf. Sci.* **2021**.
14. Chai, Y.; Bian, Y.; Liu, H.; Li, J.; Xu, J. Glaucoma Diagnosis in the Chinese Context: An Uncertainty Information-Centric Bayesian Deep Learning Model. *Inf. Process. Manag.* **2021**.
15. Balasopoulou, A.; Kokkinos, P.; Pagoulatos, D.; Plotas, P.; Makri, O.E.; Georgakopoulos, C.D.; Vantarakis, A.; Li, Y.; Liu, J.J.; Qi, P.; et al. Symposium Recent Advances and Challenges in the Management of Retinoblastoma Globe—Saving Treatments. *BMC Ophthalmol.* **2017**
16. Ferro Desideri, L.; Rutigliani, C.; Corazza, P.; Nastasi, A.; Roda, M.; Nicolo, M.; Traverso, C.E.; Vagge, A. The Upcoming Role of Artificial Intelligence (AI) for Retinal and Glaucomatous Diseases. *J. Optom.* **2022**, *15*, S50–S57.
17. Xue, Y.; Zhu, J.; Huang, X.; Xu, X.; Li, X.; Zheng, Y.; Zhu, Z.; Jin, K.; Ye, J.; Gong, W.; et al. A Multi-Feature Deep Learning System to Enhance Glaucoma Severity Diagnosis with High Accuracy and Fast Speed. *J. Biomed. Inform.* **2022.**
18. Raghavendra, U.; Fujita, H.; Bhandary, S.V.; Gudigar, A.; Tan, J.H.; Acharya, U.R. Deep Convolution Neural Network for Accurate Diagnosis of Glaucoma Using Digital Fundus Images. *Inf. Sci.* **2018**.
19. Saba, T.; Bokhari, S.T.F.; Sharif, M.; Yasmin, M.; Raza, M. Fundus Image Classification Methods for the Detection of Glaucoma: A Review. *Microsc. Res. Tech.* **2018.**
20. An, G.; Omodaka, K.; Hashimoto, K.; Tsuda, S.; Shiga, Y.; Takada, N.; Kikawa, T.; Yokota, H.; Akiba, M.; Nakazawa, T. Glaucoma Diagnosis with Machine Learning Based on Optical Coherence Tomography and Color Fundus Images. *J. Healthc. Eng.* **2019**