Multi-disease Classification of Retinal Images using Convolutional Neural Network

N. Devi, PhD
Associate Professor
Department of Information Technology,
Sri Venkateswara College of Engineering, Sriperumbudur,
Kancheeepuram, Tamil Nadu, India

P. Leela Rani, PhD
Associate Professor
Department of Information Technology,
Sri Venkateswara College of Engineering, Sriperumbudur,
Kancheeepuram, Tamil Nadu, India

A.R. Guru Gokul
Assistant Professor
Department of Information Technology,
Sri Venkateswara College of Engineering, Sriperumbudur,
Kancheeepuram, Tamil Nadu, India

ABSTRACT
In ophthalmology, early fundus screening is a cost-effective and efficient method to prevent blindness caused by eye diseases. Due to the lack of clinical evidence, manual detection is labor-intensive and can result in clinical delays. The advent of deep learning has shown promising results in diagnosing various eye diseases, though most studies focus on a single disease. Thus, a multi-disease classification approach using fundus images is highly effective. This paper introduces a method based on Convolutional Neural Networks (CNN) for classifying multiple diseases. The proposed method uses multi-scale ridge detection for segmentation and Dijkstra's algorithm to create a fully connected vascular tree. Typically, surgeons have angiographic data on hand and mentally register the images to pinpoint abnormalities. Superimposing angiographic edges onto the patient's retinal image accurately highlights the treatment area, making it easier to detect eye defects such as myopia, hyperopia, and diabetic retinopathy. The registered image is visually precise with high accuracy. The proposed model can classify five disease categories: age-related macular degeneration (ARMD), central retinal vein occlusion (CRVO), optic disc center (ODC), diabetic retinopathy (DR), and branch retinal vein occlusion (BRVO) with an overall accuracy of 92%.

General Terms
Ophthalmology, Dijkstra's algorithm, Angiographic Data

Keywords
Convolutional Neural Networks, Deep Learning, Age-related macular degeneration, central retinal vein occlusion, optic disc center, diabetic retinopathy, and branch retinal vein occlusion

1. INTRODUCTION
Eye disease identification techniques play a crucial role in the field of ophthalmology. As people age, it is normal for vision to deteriorate gradually. Additionally, certain medical conditions can further impair vision or even lead to blindness. One such condition is age-related macular degeneration (AMD), a chronic disorder typically affecting both eyes due to a metabolic issue. Another condition, diabetic retinopathy, arises when prolonged diabetes damages the small blood vessels and nerves in the retina. The retina functions like the film in a camera, capturing images and sending them to the brain for processing. In diabetic retinopathy, damaged blood vessels may leak, or new, weaker vessels may grow on the retina. Without treatment, this can result in long-term vision loss.

Traditional methods of identifying retinal diseases rely on manual observation, which is highly subjective and prone to error. This underscores the need for automated techniques that overcome the limitations of conventional methods. Automated disease identification systems must be highly accurate and possess a rapid convergence rate, making them suitable for real-time applications. Several automated techniques have been developed and successfully implemented for retinal disease identification, emphasizing the importance of each module within the system. The success of every step is crucial to ensure the overall high accuracy of the system.

2. RELATED WORK
Literature survey for visual impairment spotting using machine learning techniques reveals a rich landscape of research endeavors aimed at improving the diagnosis and management of various eye conditions. Here is a summarized survey:

In the study by Wong and Sun (2012), the authors discuss the potential of artificial intelligence, specifically deep learning, in revolutionizing diabetic retinopathy screening [2]. They highlight the importance of leveraging advanced technology to improve the efficiency and accuracy of diabetic retinopathy detection, which is crucial for early intervention and prevention of vision loss. On the other hand, Gulshan et al. (2016) present the development and validation of a deep learning algorithm specifically designed for the detection of diabetic retinopathy in retinal fundus photographs [3]. The study demonstrates the effectiveness of the deep learning algorithm in accurately identifying diabetic retinopathy, showcasing its potential as a reliable tool for screening diabetic patients and facilitating timely treatment interventions. Overall, both studies underscore the significant role of deep learning technology in enhancing diabetic retinopathy screening, offering promising prospects for improving patient outcomes and reducing the burden on healthcare systems. In the study by Li et al. (2017), the authors present a deep learning algorithm designed for the automated diagnosis of retinopathy in retinal fundus photographs [4]. The algorithm demonstrates promising results in accurately identifying retinopathy, offering potential benefits for early detection and intervention in patients with retinal diseases. Ting et al. (2017) focus on the development and validation of a deep learning system specifically tailored for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes [5]. The study highlights the robustness and generalizability of the deep learning system across diverse patient demographics, showcasing its effectiveness as a reliable tool for diabetic retinopathy screening and diagnosis. Both studies underscore

the significant advancements made in leveraging deep learning technology for the automated diagnosis of retinal diseases, particularly diabetic retinopathy. These findings hold promise for improving patient care, facilitating early detection, and reducing the burden on healthcare systems by streamlining the screening process for retinal diseases.

In the study by Zago et al. (2019), the authors propose a deep learning-based approach for the fusion of multimodal imaging data to improve the diagnosis of diabetic retinopathy [6]. By integrating information from various imaging modalities, including retinal fundus photographs and optical coherence tomography (OCT) scans, the deep learning model demonstrates enhanced diagnostic accuracy for diabetic retinopathy. This approach holds promise for leveraging complementary information from different imaging techniques to provide more comprehensive and accurate assessments of diabetic retinopathy. Ting et al. (2018) focus on the development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes [7]. The study highlights the effectiveness of transfer learning and pre-trained models in adapting deep learning algorithms to diverse patient populations. By fine-tuning pre-trained models on retinal images from multiethnic cohorts, the deep learning system achieves robust performance in diabetic retinopathy screening and diagnosis across different racial and ethnic groups. These findings underscore the importance of leveraging transfer learning and pre-trained models to improve the generalizability and reliability of deep learning-based diagnostic systems for diabetic retinopathy and other eye diseases.

Rajalakshmi et al. (2018) evaluated the performance of automated classification of diabetic retinopathy using deep learning compared to ophthalmologist-level grading [8]. The study demonstrated that deep learning algorithms achieved comparable performance to expert ophthalmologists in diagnosing diabetic retinopathy, indicating their potential as reliable screening tools for diabetic patients. De Fauw et al. (2018) introduced a clinically applicable deep learning approach for diagnosis and referral in retinal disease [9]. The study presented a deep learning model capable of accurately diagnosing various retinal diseases and recommending appropriate referrals based on retinal images. This approach holds promise for improving patient care by facilitating early detection and timely intervention for retinal conditions. Varadarajan et al. (2018) investigated the application of deep learning for predicting refractive error from retinal fundus images [10]. The study demonstrated the feasibility of using deep learning algorithms to estimate refractive error, providing potential benefits for vision screening and improving access to eye care services, particularly in resource-limited settings. Liu et al. (2018) proposed an interpretable deep learning model for predicting infant age in the first year of life using resting-state functional connectivity [11].

Although not directly related to ophthalmology, this study highlights the potential of interpretable deep learning models in predicting clinical outcomes from neuroimaging data, which could have implications for understanding and managing developmental disorders affecting vision. Ting et al. (2019) provided a comprehensive review of artificial intelligence and deep learning applications in ophthalmology [12]. The review highlighted the rapid advancements in deep learning techniques for various ophthalmic tasks, including disease diagnosis, image segmentation, and treatment planning. The study emphasized the transformative potential of artificial intelligence in revolutionizing ophthalmic care and improving patient outcomes. Aljohani and Aburasain (2024) proposed a hybrid framework for glaucoma detection utilizing federated machine learning and deep learning models[1]. The study introduces a novel approach that combines the strengths of federated learning, which allows training models on decentralized data sources without sharing raw data, and deep learning techniques. By leveraging this hybrid framework, the authors aim to improve the accuracy and efficiency of glaucoma detection. This approach holds promise for enhancing the diagnosis of glaucoma, a leading cause of irreversible blindness worldwide, while addressing privacy concerns associated with centralized data sharing. In their comprehensive review, Muchuchuti and Viriri (2023) provide an extensive overview of retinal disease detection using deep learning techniques [13].

The study covers a wide range of deep learning methods employed for the detection of retinal diseases, including diabetic retinopathy, age-related macular degeneration, and glaucoma, among others. Through an in-depth analysis of the current state-of-the-art approaches, the authors highlight the strengths and limitations of various deep learning models in retinal disease detection. Additionally, the review discusses the challenges and future directions in this rapidly evolving field, aiming to contribute to the advancement of automated retinal disease diagnosis through deep learning technologies. This literature survey underscores the significant progress made in visual impairment spotting using machine learning techniques and highlights ongoing efforts to address challenges and enhance the accuracy, scalability, and accessibility of automated eye disease diagnosis systems.

3. PROPOSED VISUAL IMPAIRMENT SPOTTING ARCHITECTURE

The proposed visual impairment detection process is illustrated in the Figure 1. Initially, fundus photographs of the patient's eye are collected and then processed to remove noise and background non-uniformities. This pre-processed image is then used for vessel segmentation. Ridge detection filters (such as the Canny or Sobel filter) and the minima and maxima of the Hessian matrix are employed to identify the ridges. Dijkstra's shortest path algorithm is utilized to fully connect any unconnected vessels. The resulting fully connected vascular image is then used as input for a Convolutional Neural Network (CNN) model. The input data is divided into training and testing sets and fed into the system.

During the training phase, images of eyes with Diabetic Retinopathy and Age-related Macular Degeneration are classified. The model detects the eye disease based on the features of the eye. For visualization, the processed image is then imported into Unity (using Vuforia) for 3D visualization. The target image is of a normal, defect-free eye, and the 3D model of the defective eye is superimposed over this target image. This allows the surgeon to easily localize the defective region.

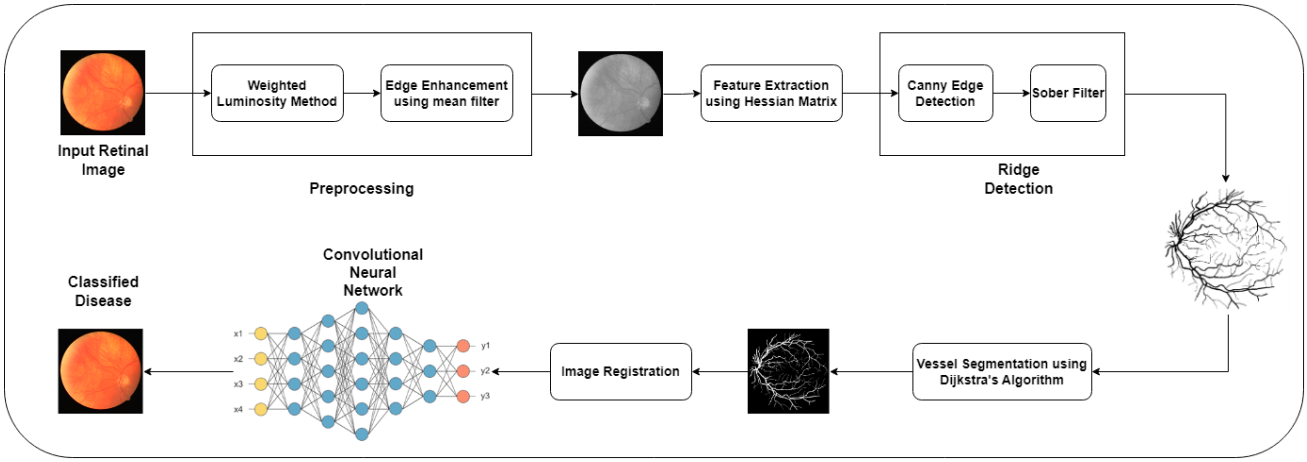

Fig 1: Architecture Diagram for Proposed Retinal Disease Classification using CNN

3.1 WEIGHTED LUMINOSITY METHOD

The retinal image is preprocessed using the weighted luminosity method[14]. This method addresses the issue of different wavelengths associated with the average method. Red has the longest wavelength among the three primary colors, while green not only has a shorter wavelength than red but also provides a more soothing effect to the eyes. Therefore, the contribution of the red color needs to be decreased, the green color's contribution increased, and the blue color's contribution adjusted to be between the two. The new equation for the grayscale image is:

$$New\ grayscale\ image = (0.3 * R) + (0.59 * G) + (0.11 * B)$$

According to this equation, red contributes 30%, green contributes 59%, and blue contributes 11%. The resulting grayscale image is depicted in Figure 2.

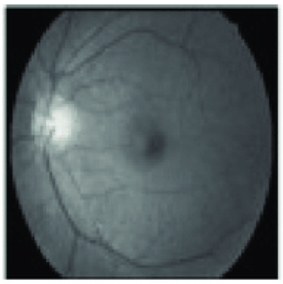

Fig 2: Grayscale conversion

3.2 EDGE ENHANCEMENT USING IMAGE FILTERS

Image filters are employed to reduce noise and enhance edges in an image. There are two types of noise that can affect an image: speckle noise and salt-and-pepper noise. Speckle noise occurs during image acquisition, while salt-and-pepper noise, characterized by sporadic white and black pixels, results from sudden disturbances in an image signal. Enhancing the edges of an image aids in feature detection for a model. The mean filter is commonly used to blur an image to remove noise [15]. This process involves calculating the mean of the pixel values within an n×nn \times nn×n kernel. The pixel intensity of the center element is then replaced by this mean value, which helps eliminate some of the noise and smooths the edges of the image.

3.3 FEATURE DETECTION USING HESSIAN MATRIX

The first step involves detecting distinctive points in an image, specifically along the ridges, which are unambiguous locations. We use the Hessian feature detector for this purpose [16]. The next step is to describe the area around each detected point. The detector outputs a vector that characterizes the surrounding area of each point. If two points have similar surroundings, their vectors will be correlated. The final step is to identify the ridges.

3.3.1 Hessian feature detector

An image is scaled to a size defined by the scale parameterσ. Let $H\sigma$ denote the Hessian matrix at a specific image location in level σ and e.g. $\partial xx = \partial^2 I \partial^2 x^2$ denoting the second order derivative of the image II along the xx-axis. We can use the normalized determinant response of the Hessian to detect image features (blobs and notches) by searching for maxima in each image location across scale.

$$\sigma^4.det(H\sigma) = \sigma^4.(\partial xx.\partial yy - \partial^2 xy)$$

The output after Pre-processing is shown in figure 3.

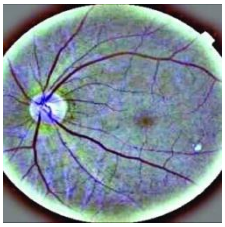

Fig 3: Pre-processed fundus of eye

3.4 RIDGE DETECTION

Figure 4 illustrates ridge detection in a fundus image. In digital image processing, ridges are defined as the set of curves of a smooth function of two variables. These points are less precise than local maxima of the function in at least one dimension, resembling geographical ridges. Ridges are detected by first applying the Canny edge detection algorithm, followed by the Sobel filter.

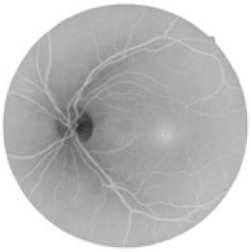

Fig 4: Ridge detection in eye vessels

3.5 CANNY EDGE DETECTION

Canny edge detection is a technique used to extract useful structural information from various visual objects, significantly reducing the amount of data to be processed [17]. It has been widely applied in numerous computer vision systems. Canny discovered that the requirements for edge detection across different vision systems are quite similar, making it possible to implement a universal edge detection solution for various applications. The general criteria for effective edge detection are as follows:

1. Detection of edges with a low error rate, ensuring that as many edges as possible are accurately captured from the image.
2. Accurate localization of detected edge points, ensuring they align with the center of the actual edge.
3. Each edge in the image should be marked only once, and image noise should not create false edges where possible.

The output is shown in Figure 5.

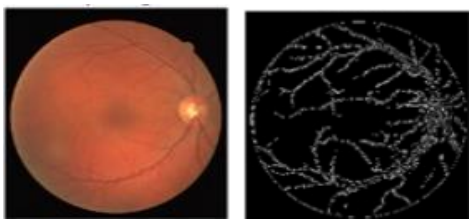

Fig 5: Canny edge detection

3.6 SOBEL FILTER

The Sobel operator, also known as the Sobel–Feldman operator or Sobel filter, is used in image processing and computer vision, particularly for edge detection [18]. It highlights edges in an image by computing an approximation of the gradient of the image intensity function. At each point in the image, the Sobel–Feldman operator outputs either the gradient vector or the norm of this vector. It works by convolving the image with a small, separable, and integer-valued filter in both the horizontal and vertical directions, making it relatively inexpensive in terms of computation. However, the gradient approximation it produces is relatively crude, especially for high-frequency variations in the image.

Standard Sobel operators, for a 3×33 \times 33×3 neighborhood, compute a simple central gradient estimate as the vector sum of a pair of orthogonal vectors. Each orthogonal vector is a directional derivative estimate multiplied by a unit vector indicating the direction of the derivative. The vector sum of these simple gradient estimates results in a vector sum of the eight directional derivative vectors. A convolution mask, which is usually much smaller than the actual image, is slid over an area of the input image. It changes the pixel's value and then shifts one pixel to the right, continuing this process until it reaches the end of a row. The output of the Sobel operator is shown in Figure 6.

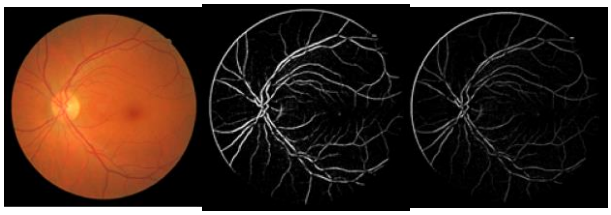

Fig 6: Sobel filter output

3.7 SEGMENTING VESSELS

Vessel segmentation is performed using multi-scale ridge detection. The output from the previous step is a grayscale image with a maximum response to vessels. To obtain the vessel centerline, pixels around the vessel centerline must be suppressed. This is achieved by scanning the image along the direction of the gradient and setting any pixel that is not a local maximum to zero. The vessels are then segmented from the image. After segmentation, the vessels appear as shown in Figure 7.

The result of image segmentation is either a set of segments that collectively cover the entire image or a set of contours extracted from the image (see Figure 8). Following this step, the image is converted to a binary image. Dijkstra's single-source shortest path algorithm is then used to determine the shortest path from one vein to another, resulting in a fully connected vascular tree [19].

Fig 7: Vessel Segmentation

Fig 8: Image after segmenting vessels

3.8 IMAGE REGISTRATION

Image registration is an image processing technique used to align multiple scenes into a single, integrated image. It addresses issues such as image rotation, scale, and skew, which commonly occur when overlaying images.

4. VISUAL IMPAIRMENT SPOTTING USING CONVOLUTIONAL NEURAL NETWORK

A CNN is a type of Deep Learning algorithm designed to process images [20-21]. It can take an input image, assign importance (learnable weights and biases) to various aspects or objects within the image, and distinguish between them.

Compared to other classification algorithms, CNNs typically require less pre-processing. In traditional methods, filters are manually engineered, whereas CNNs have the capability to learn these filters or characteristics through training. The CNN model outline is depicted in Figure 9.

The first layer in a CNN is typically a convolutional layer, responsible for extracting features from the input image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input data. It involves a mathematical operation that combines the image matrix with a filter or kernel.

- An image matrix of dimension $(h\ x\ w\ x\ d)$
- A filter $(f_h\ x\ f_w\ x\ d)$
- Outputs a volume dimension $(h - f_h + 1)\ x\ (w - f_w + 1)\ x\ 1$

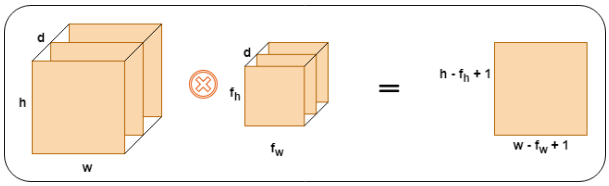

Fig 9: Image matrix multiplies kernel or filter matrix

Convolving an image with various filters enables operations like edge detection, blur, and sharpening. Pooling layers further aid in reducing the number of parameters, particularly when dealing with large images. Spatial pooling, also known as subsampling or downsampling, decreases the dimensionality of each feature map while retaining critical information. The process involves flattening the matrix into a vector, which is then fed into a fully connected layer, similar to a traditional neural network. In Figure 10, the feature map matrix is transformed into a vector format (x1, x2, x3, …). Through fully connected layers, these features are integrated to construct a model. The fully connected vascular tree is inputted into a CNN and trained to identify defects. The accuracy of prediction relies on appropriate weights and biases. The process of adjusting these weights and biases from the computer file is referred to as training the Neural Network. Each iteration of the training process involves the following steps: calculating the predicted output (ŷ) known as feedforward, and adjusting the weights and biases known as backpropagation.

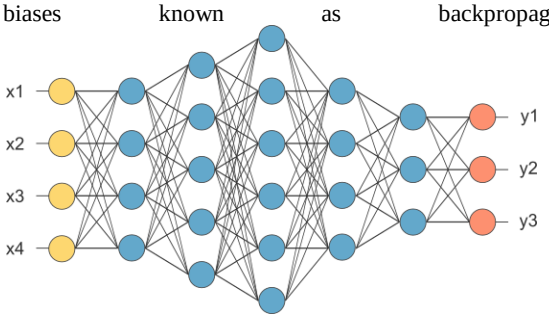

Fig 10: Fully connected layer

The architecture comprises stacking convolutional layers with small 3×3 filters followed by a max-pooling layer as illustrated in figure 11. These layers are grouped into blocks, which can be repeated, with the number of filters increasing within each block (e.g., 32, 64, 128, 256 for the first four blocks). Padding is applied to the convolutional layers to maintain the height and width shapes of the output feature maps matching the inputs. Each layer utilizes the ReLU activation function and the He weight initialization, both considered best practices. Stochastic gradient descent is used for optimization, starting with a conservative learning rate of 0.001 and a momentum of 0.9.

The task involves binary classification, requiring the prediction of either 0 or 1. Hence, the output layer consists of 1 node with a sigmoid activation function, optimized using the binary cross-entropy loss function. The number of steps for the train and test iterators must be specified, representing the number of batches in one epoch. This is determined by the total number of images in the train and test directories divided by the batch size (64). The model is trained for 20 epochs to evaluate its learning capabilities. The CNN, trained with disease dataset, automatically generates features. Increasing the number of convolutional layers can potentially enhance accuracy. In this system, three convolutional layers and two pooling layers are utilized.

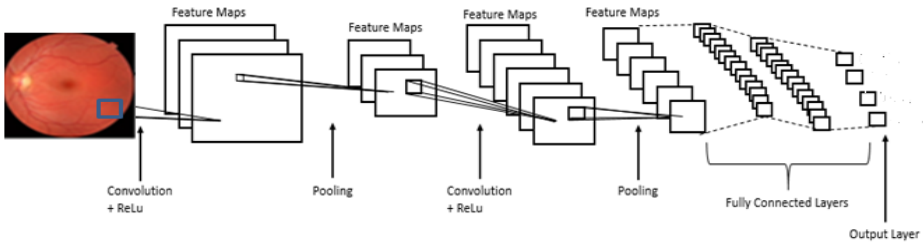

Fig 11: Complete CNN Architecture

5. EXPERIMENTAL RESULTS

The proposed research involved training and assessing the performance of the model using a dataset comprising around 3,200 retinal fundus images sourced from Kaggle. This dataset encompasses a broad spectrum of 46 distinct conditions related to retinal health. The primary objective in this study was to develop and refine a model capable of accurately detecting and classifying these conditions. While the dataset contained images representing 46 different conditions, the focus narrowed down to detecting 25 specific conditions. The rationale behind this focus lies in the recognition of the diverse range of diseases commonly encountered in clinical practice. Rather than concentrating solely on individual diseases, our approach aimed at creating a more comprehensive and versatile model capable of screening for multiple conditions simultaneously. This shift in focus represents a departure from earlier methodologies, which often centered on targeting specific diseases in isolation.

By adopting a broader perspective and encompassing a wider array of conditions, the research contributes to the development of general-purpose models for retinal screening. These models hold the potential to enhance diagnostic capabilities in clinical settings, offering a more holistic approach to identifying and managing retinal pathologies. The proposed model demonstrates proficiency in classifying five specific classes of diseases, namely age-related macular degeneration (ARMD), central retinal vein occlusion (CRVO), optic disc center (ODC), diabetic retinopathy (DR), and branch retinal vein occlusion (BRVO). This capability underscores the versatility and utility of our model in accurately identifying and categorizing these distinct pathological conditions affecting the retina. Ridge detection is accomplished using the Hessian matrix, where maxima and minima filters are employed to precisely identify vessels. The output of this process is depicted in Figure 12.

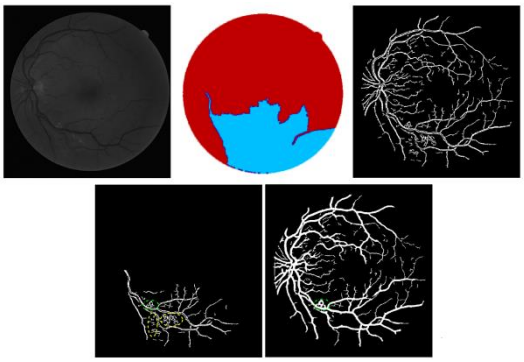

Fig 12: Ridge detection using Hessian matrix

Additionally, the input image undergoes morphological transformation, followed by the detection of image contours using a predefined threshold, as illustrated in Figure 13. Glaucoma classification is performed using convolutional neural networks. The model summary is presented in figure 14. The diameter of the glaucomic eye is greater than the normal person's eye. The Fovea length of patient eye found using our proposed model is shown in figure 15. The fovea region is highlighted as shown in figure 16. The accuracy of detecting Glaucoma is presented in figure 17.

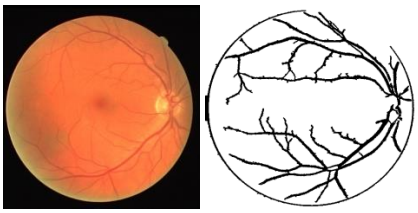

Fig 13: Segmentation output

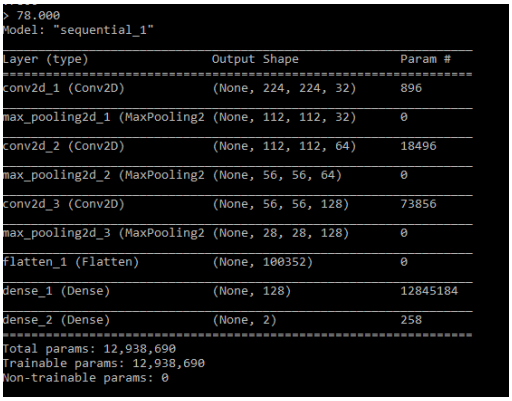

Fig 14: Model parameters summary

Fig 15: Output with Fovea length of patient eye

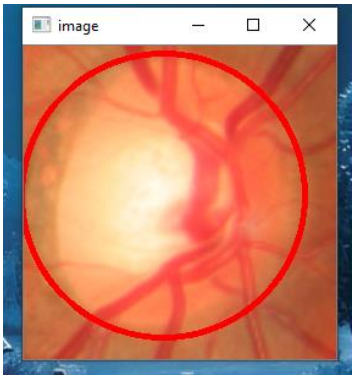

Fig 16: Fovea region highlighted

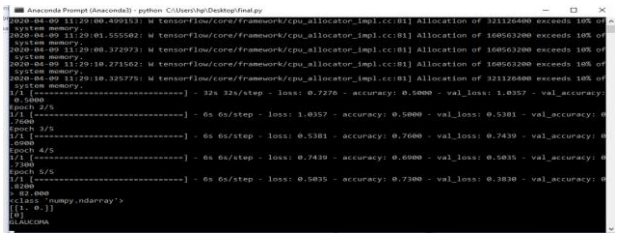

Fig 17: Detecting Glaucoma with Accuracy

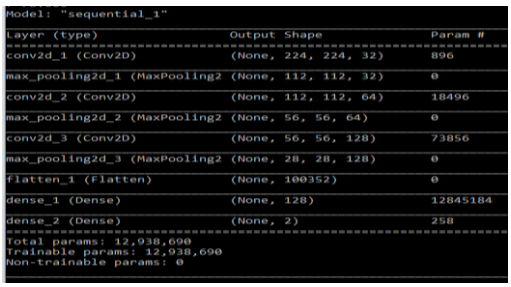

Fig 19: Model paramters summary

Diabetic Retinopathy classification is performed using convolutional neural networks. The model summary is presented in figure 19. The accuracy of detecting Diabetic Retinopathy is presented in figure 20.

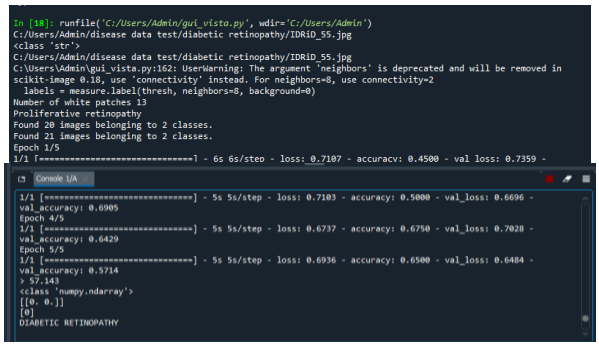

Fig 20: Detecting Diabetic Retinopathy with Accuracy

After training the model, conducting a comprehensive analysis becomes crucial to grasp its performance, recognize any potential issues, and pinpoint areas for enhancement. The model's performance was initially assessed on an independent test set, following the standard training procedure. The test outcomes are presented as graph which is depicted in figure 20 to figure 24. The outcomes revealed a noteworthy accuracy rate of 92%, accompanied by an impressive precision of 93% and a recall rate of 94%. This high precision is particularly noteworthy as it indicates the model's proficiency in correctly identifying true positive cases, which holds significant importance in various practical scenarios where the consequences of false positives can be severe. Moreover, achieving an F1 score of 91% signifies a harmonious balance between precision and recall, further underlining the model's effectiveness in accurately classifying instances while minimizing both false positives and false negatives. This comprehensive evaluation underscores the model's robust performance and its potential for practical applications in real-world settings.

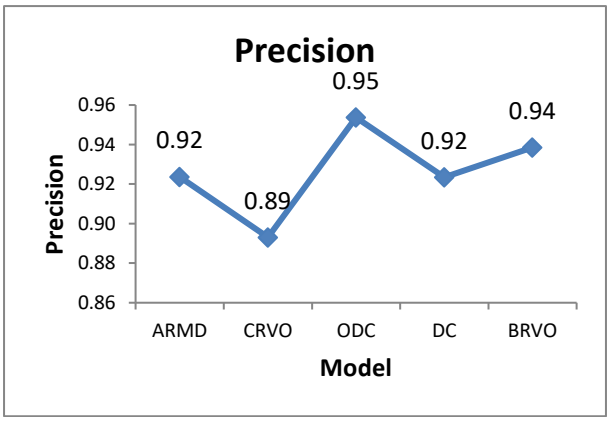

Fig 21: Comparison of Precision values

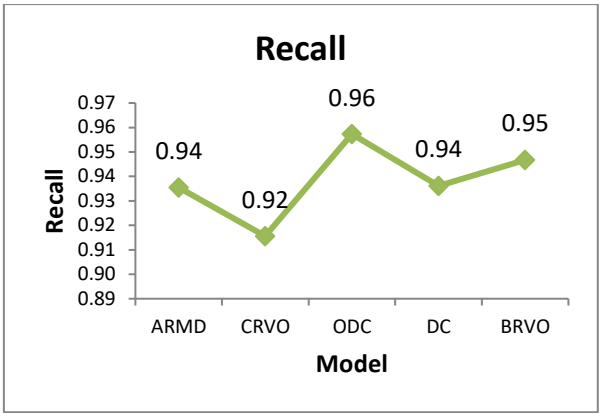

Fig 22: Comparison of Recall values

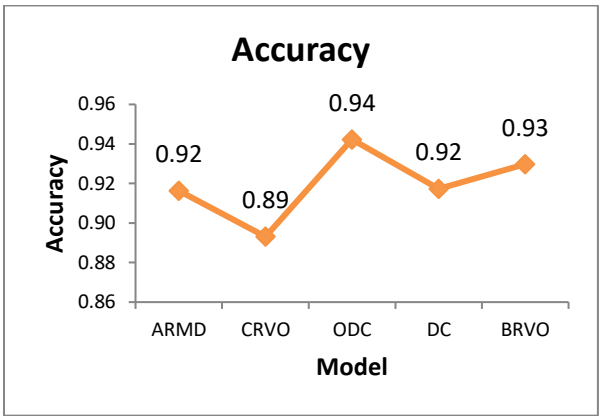

Fig 23: Comparison of Accuracy

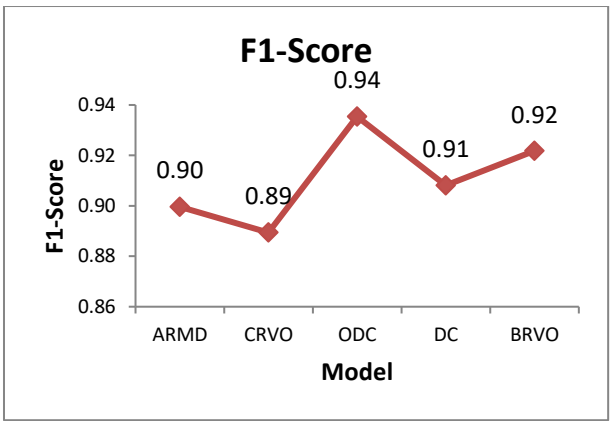

Fig 24: Comparison of F1 score

6. CONCLUSION

In conclusion, the research has demonstrated the efficacy of the proposed model in classifying retinal diseases with high accuracy, precision, and recall rates. By leveraging a diverse dataset and employing advanced techniques, the developed model is capable of identifying five key classes of retinal diseases: age-related macular degeneration (ARMD), central retinal vein occlusion (CRVO), optic disc center (ODC), diabetic retinopathy (DR), and branch retinal vein occlusion (BRVO). Through thorough analysis, the robustness and reliability of the proposed model showcases its potential for practical implementation in clinical settings. Moving forward, there are several avenues for future research and development in this domain. Firstly, enhancing the model's performance by

incorporating additional data sources and refining the training process could further improve its accuracy and generalizability. Additionally, exploring novel techniques such as transfer learning and ensemble methods may provide opportunities to optimize model performance and address specific challenges in retinal disease classification.

Furthermore, extending the scope of the model to encompass a broader range of retinal conditions and incorporating longitudinal data for monitoring disease progression could enhance its utility in clinical practice. Moreover, integrating the model into existing healthcare systems and conducting real-world validation studies would be essential steps towards translating the research findings into practical applications that benefit patients and healthcare providers alike. Overall, continued research and innovation in this field hold the potential to significantly impact the diagnosis and management of retinal diseases, ultimately improving patient outcomes and quality of care.

7. REFERENCES

[1] Aljohani A, Aburasain RY (2024). A hybrid framework for glaucoma detection through federated machine learning and deep learning models. BMC Med Inform Decis Mak. 2024 May 2;24(1):115. doi: 10.1186/s12911-024-02518-y. PMID: 38698412; PMCID: PMC11064392.

[2] Wong, T. Y., & Sun, J. (2012). Artificial intelligence with deep learning technology looks into diabetic retinopathy screening. JAMA, 308(21), 2185-2186.

[3] Gulshan, V., et al. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402-2410.

[4] Li, Z., et al. (2017). Deep learning algorithm for automated diagnosis of retinopathy in retinal fundus photographs. Ophthalmology, 124(7), 962-969.

[5] Ting, D. S., et al. (2017). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA, 318(22), 2211-2223.

[6] Zago, G., et al. (2019). Deep learning-based multimodal imaging data fusion for diabetic retinopathy diagnosis. IEEE Journal of Biomedical and Health Informatics, 23(4), 1613-1623.

[7] Ting, D. S., et al. (2018). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA, 318(22), 2211-2223.

[8] Rajalakshmi, R., et al. (2018). Performance of automated classification of diabetic retinopathy using deep learning with ophthalmologist-level graded diabetic retinopathy. Jama Ophthalmology, 136(9), 1022-1029.

[9] De Fauw, J., et al. (2018). Clinically applicable deep learning for diagnosis and referral in retinal disease. Nature Medicine, 24(9), 1342-1350.

[10] Varadarajan, A. V., et al. (2018). Deep learning for predicting refractive error from retinal fundus images. Investigative Ophthalmology & Visual Science, 59(7), 2861-2868.

[11] Liu, Y., et al. (2018). An interpretable deep learning model for accurate prediction of infant age in the first year of life using resting-state functional connectivity. NeuroImage, 178, 649-660.

[12] Ting, D. S., et al. (2019). Artificial intelligence and deep learning in ophthalmology. British Journal of Ophthalmology, 103(2), 167-175.

[13] Muchuchuti, S.; Viriri, S.(2023) Retinal Disease Detection Using Deep Learning Techniques: A Comprehensive Review. J. Imaging 2023, 9, 84. https://doi.org/10.3390/jimaging9040084

[14] Y. Gao, X. Xiong, D. Xu, X. Zhu and Y. Fan, "Luminance weighted color constancy," *2022 IEEE 16th International Conference on Solid-State & Integrated Circuit Technology (ICSICT)*, Nangjing, China, 2022, pp. 1-3, doi: 10.1109/ICSICT55466.2022.9963324. keywords: {Integrated circuit technology;Image color analysis;Brightness;Lighting;Prediction algorithms;Image restoration;Light sources},

[15] Hiary, Hazem, Rawan Zaghloul, Aryaf Al-Adwan, and Moh'D. B. Al-Zoubi. "Image contrast enhancement using geometric mean filter." Signal, Image and Video Processing 11 (2017): 833-840.

[16] Xiao, Bin, Ge Ou, Han Tang, Xiuli Bi, and Weisheng Li. "Multi-focus image fusion by hessian matrix based decomposition." IEEE Transactions on Multimedia 22, no. 2 (2019): 285-297.

[17] Sekehravani, Ehsan Akbari, Eduard Babulak, and Mehdi Masoodi. "Implementing canny edge detection algorithm for noisy image." Bulletin of Electrical Engineering and Informatics 9, no. 4 (2020): 1404-1410.

[18] Sanida, Theodora, Argyrios Sideris, and Minas Dasygenis. "A heterogeneous implementation of the Sobel edge detection filter using OpenCL." In 2020 9th International Conference on Modern Circuits and Systems Technologies (MOCAST), pp. 1-4. IEEE, 2020.

[19] Al-Jarrah, Rami, Mohammad Al-Jarrah, and Hubert Roth. "A novel edge detection algorithm for mobile robot path planning." Journal of Robotics 2018 (2018).

[20] Sarvamangala, D. R., and Raghavendra V. Kulkarni. "Convolutional neural networks in medical image understanding: a survey." Evolutionary intelligence 15, no. 1 (2022): 1-22.

[21] Solís-Pérez, J. E., et al. "Blood vessel detection based on fractional Hessian matrix with non-singular Mittag–Leffler Gaussian kernel." Biomedical Signal Processing and Control 54 (2019): 101584.