Retinal Vessels Segmentation and Classification of Eye Disease using CNN

Mahesh Shivkumar Shete,
P.G. Student, Department of Electronics Engineering,
Walchand Institute of Technology,
Solapur, Maharashtra, India

A.S.Gundale
Associate Professor, Department of Electronics Engineering,
Walchand Institute of Technology,
Solapur, Maharashtra, India

Abstract— ***Cataract, glaucoma and retinal disorders are some of the common causes of blindness in the world and their increasing numbers are forcing the need to diagnose them early and accurately. The suggested approach is meant to make it easier and make detection of retinal diseases, glaucoma and cataracts by using deep learning methods easier and automatic. Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) will be used to detect and classify various eye diseases using fundus images. Increasing the frequency of preventable blindness is the number one goal of this system since it will allow diagnosing it as promptly and effectively as possible. The mentioned model involves use of fundus images of the healthy as well as those of the eye with glaucoma, cataract, and diabetic retinopathy so that both can confirm the effectiveness of the model. The CNN based framework is created to automatically segment the retinal blood vessels and classify them into multiple eye diseases. Indeed, the results of the experiment show a great classification performance with the average classification accuracy being 96.95% of cataract, 97.41% of diabetic retinopathy, 97.17% of glaucoma and 97.14% of normal eye with a total performance of about 97 as shown in the performance graph. All these findings testify to the strength and efficacy of the suggested solution to automated screening of ophthalmic disease.***

Keywords— Convolutional Neural Network, Fault detection, Mapping the blood vessels, Artificial Intelligence, Diagnosis.

1. INTRODUCTION

Eye is an essential element of everyone's life. Retinal vessels classification is a type of artificial intelligence (AI) that uses machine learning to identify and classify eye images. This technology trained on large datasets of labelled images and it can be used to identify a retinal vessels segmentation and classification of eye diseases. A thin layer of tissue that runs along the inside back wall of the eye is called the retina in humans. Protecting the eyes from conditions that could affect vision is vital because of their vital role in visual perception. Retinal disorders, glaucoma, and cataracts are the most commonly identified causes of severe vision loss. A World Health Organization (WHO) study found that cataracts account for 47.8% of blindness, glaucoma for 12.3%, and retinal disorders for 4.8%. More than 60% of blindness cases globally are caused by these three disorders combined. Depending on their extent, cataracts, which damage the lens of the eye, usually start as a tiny, foggy patch that progressively enlarges to cause blurred or lost vision. The optic nerve, which is the essential connection between the eye and the brain, is harmed by glaucoma. Early identification is essential since severe glaucoma causes permanent retinal loss. Vision depends on the retina, a light-sensitive nerve layer located in the rear of the eye. A belated identification of retinal illnesses may necessitate lengthy or repeated treatments to restore vision. Dysfunction to this area might result in visual loss.

2. LITERATURE SURVEY

Chaudhuri et al. introduced one of the earliest automated techniques for retinal vessel segmentation using two-dimensional matched filters. Their approach modeled blood vessels as piecewise linear structures and enhanced vessel-like patterns by applying Gaussian-shaped filters. Although the method was effective for normal retinal images, it showed sensitivity to noise and illumination variations, limiting its robustness in pathological cases. **[1]**

Hoover et al. proposed a piecewise threshold probing technique combined with morphological processing to detect retinal blood vessels. The method iteratively adjusted thresholds to identify vessel regions and improve segmentation accuracy. However, the approach faced difficulties in detecting thin vessels and handling abnormal retinal structures. **[2]**

Soares et al. applied multi-scale 2D Gabor wavelet features along with a Bayesian classifier for retinal vessel segmentation. Their method captured vessels of varying orientations and widths, resulting in improved segmentation performance. Despite its effectiveness, the method relied heavily on handcrafted feature design. **[3]**

Fraz et al. presented a supervised learning-based approach using line strength, morphological, and Gabor features to segment retinal blood vessels. Their work demonstrated improved sensitivity and specificity compared to unsupervised techniques, but the reliance on manual feature extraction remained a limitation. **[4]**

Niemeijer et al. introduced a pixel-based classification method using k-nearest neighbors (k-NN) for vessel detection. Their approach improved thin vessel detection by classifying individual pixels based on intensity and neighborhood features. However, the computational cost increased significantly for large datasets. **[5]**

Mendonça and Campilho proposed a vessel segmentation method based on centerline detection followed by region growing. This approach improved vessel continuity and reduced false detections, but its performance degraded in low-contrast and noisy retinal images. **[6]**

Ronneberger et al. introduced the U-Net architecture, a fully convolutional neural network designed for biomedical image segmentation. The encoder–decoder structure with skip connections enabled precise localization and contextual feature learning, making U-Net a foundational model for retinal vessel segmentation tasks. **[7]**

Liskowski and Krawiec employed deep convolutional neural networks trained on retinal image patches for vessel segmentation. Their approach achieved state-of-the-art performance by learning hierarchical features directly from data, significantly outperforming traditional handcrafted methods. **[8]**

Fu et al. proposed DeepVessel, a CNN-based model that integrates multi-level feature representations to enhance segmentation accuracy, particularly for thin and low-contrast vessels. Their method demonstrated improved detection performance on standard retinal datasets. **[9]**

Orlando et al. introduced a deeply supervised CNN with structured prediction to enforce vessel connectivity and reduce false positives. Their approach improved the continuity of segmented vessels and enhanced overall segmentation robustness. **[10]**

Alom et al. proposed a recurrent residual convolutional neural network that combines residual learning and recurrent connections. This architecture improved feature reuse and segmentation accuracy for medical images, including retinal vessel extraction. **[11]**

Zhou et al. presented UNet++, an enhanced version of U-Net with nested and dense skip connections. This design reduced the semantic gap between encoder and decoder features, leading to improved segmentation accuracy for complex vessel structures. **[12]**

Li et al. developed an attention-based U-Net architecture that selectively emphasized vessel regions while suppressing irrelevant background features. The attention mechanism significantly improved segmentation performance in challenging retinal images. **[13]**

Liu et al. applied Generative Adversarial Networks (GANs) for retinal vessel segmentation. By incorporating adversarial loss, their method produced more realistic vessel structures and improved segmentation continuity. **[14]**

Zhang et al. combined U-Net with adversarial learning to further refine vessel segmentation results. Their approach improved performance in images affected by pathological variations and uneven illumination. **[15]**

Gulshan et al. developed a deep learning-based system for automated diabetic retinopathy detection using a large dataset of retinal fundus images. Their CNN model achieved diagnostic performance comparable to expert ophthalmologists, demonstrating the clinical feasibility of deep learning approaches. **[16]**

Pratt et al. proposed a CNN-based framework for diabetic retinopathy classification using data augmentation techniques. Their model effectively learned discriminative features for disease grading, outperforming traditional machine learning classifiers. **[17]**

Burlina et al. applied deep convolutional neural networks for multi-disease retinal classification. Their study demonstrated that CNNs could generalize well across different ophthalmic conditions such as diabetic retinopathy and age-related macular degeneration. **[18]**

Abràmoff et al. presented an autonomous AI-based diagnostic system for diabetic retinopathy screening. The system was clinically validated and demonstrated high reliability in real-world primary care settings. **[19]**

Mishra et al. proposed a two-stage framework combining retinal vessel segmentation using U-Net and disease classification using CNN. Their results showed that vessel-based features significantly improved classification accuracy. **[20]**

Zhao et al. introduced a joint learning framework that simultaneously performs retinal vessel segmentation and disease classification. Their shared network architecture improved feature consistency and reduced computational redundancy. **[21]**

Simonyan and Zisserman introduced the VGG network architecture, which influenced many retinal image classification models due to its deep hierarchical feature extraction capability. **[22]**

Szegedy et al. proposed the Inception architecture, enabling efficient deep learning with reduced computational cost. This model has been widely adopted in medical image classification tasks. **[23]**

Krizhevsky et al. demonstrated the effectiveness of deep CNNs for large-scale image classification, laying the foundation for modern deep learning-based medical imaging systems. **[24]**

LeCun et al. provided a comprehensive overview of deep learning techniques and their applications in computer vision and medical image analysis, highlighting CNNs as a dominant approach. **[25]**

Shen et al. reviewed deep learning methods in medical image analysis, emphasizing challenges such as data scarcity, generalization, and interpretability in clinical applications. **[26]**

Litjens et al. presented a large-scale survey of deep learning in medical imaging, concluding that CNN-based segmentation and classification outperform traditional approaches in most scenarios. **[27]**

Rakhlin et al. discussed the deployment of deep learning models in clinical decision support systems, highlighting their potential for automated retinal disease detection and diagnosis. **[28]**

Table 1 Literature Survey

Ref. No.	Author(s)	Year	Method / Model Used	Task	Key Contribution / Outcome	Limitations
[1]	Chaudhuri et al.	1989	Matched Filter	Vessel Segmentation	Early enhancement of vessel-like structures	Sensitive to noise and illumination variations
[2]	Hoover et al.	2000	Threshold Probing + Morphology	Vessel Segmentation	Improved vessel localization	Poor detection of thin vessels
[3]	Soares et al.	2006	Gabor Wavelets + Bayesian Classifier	Vessel Segmentation	Multi-scale vessel detection	Requires handcrafted feature tuning
[4]	Fraz et al.	2012	Supervised Learning + Handcrafted Features	Vessel Segmentation	Higher sensitivity and specificity	Complex feature extraction, less scalable
[5]	Niemeijer et al.	2004	k-NN Pixel Classification	Vessel Segmentation	Improved thin vessel detection	High computational cost
[6]	Mendonça & Campilho	2006	Centerline Detection + Region Growing	Vessel Segmentation	Better vessel continuity	Weak performance in low-contrast images
[7]	Ronneberger et al.	2015	U-Net	Vessel Segmentation	Benchmark CNN for medical segmentation	Struggles with very thin vessels
[8]	Liskowski & Krawiec	2016	Deep CNN (Patch-based)	Vessel Segmentation	State-of-the-art accuracy	High training time, patch dependency
[9]	Fu et al.	2016	DeepVessel (Multi-level CNN)	Vessel Segmentation	Improved thin vessel detection	Increased model complexity
[10]	Orlando et al.	2018	Deep Supervised CNN	Vessel Segmentation	Improved vessel connectivity	Requires careful supervision design

[11]	Alom et al.	2019	Recurrent Residual CNN	Vessel Segmentation	Better feature propagation	Computationally expensive
[12]	Zhou et al.	2018	UNet++	Vessel Segmentation	Reduced semantic gap	High memory usage
[13]	Li et al.	2020	Attention U-Net	Vessel Segmentation	Focus on vessel regions	Increased training complexity
[14]	Liu et al.	2019	GAN-based CNN	Vessel Segmentation	Improved vessel realism	Training instability of GANs
[15]	Zhang et al.	2020	U-Net + Adversarial Loss	Vessel Segmentation	Robust to pathological variations	Requires careful loss balancing
[16]	Gulshan et al.	2016	Deep CNN (Inception)	Disease Classification	Expert-level DR detection	Needs very large labeled datasets
[17]	Pratt et al.	2016	CNN + Data Augmentatio n	Disease Classification	Improved DR grading	Overfitting risk on small datasets
[18]	Burlina et al.	2017	Deep CNN	Disease Classification	Multi-disease classification	Limited interpretability
[19]	Abràmoff et al.	2018	Autonomous AI System	Disease Classification	Clinically validated system	High deployment and regulatory cost
[20]	Mishra et al.	2020	U-Net + CNN	Seg + Classification	Improved classification using vessels	Two-stage pipeline increases complexity
[21]	Zhao et al.	2021	Joint Learning CNN	Seg + Classification	Shared learning improves accuracy	Training instability in multi-task setup
[22]	Simonyan & Zisserman	2015	VGG Network	Classification	Deep hierarchical features	Large number of parameters
[23]	Szegedy et al.	2015	Inception Network	Classification	Computationally efficient deep model	Complex architecture design
[24]	Krizhevsky et al.	2012	AlexNet	Classification	Foundation of deep CNNs	Limited depth compared to modern models
[25]	LeCun et al.	2015	Deep Learning Review	General	Overview of CNN dominance	Theoretical, no direct implementation
[26]	Shen et al.	2017	Medical DL Review	General	Identified challenges & gaps	No experimental validation

[27]	Litjens et al.	2017	DL in Medical Imaging Survey	General	Comprehensive medical DL survey	Lacks dataset-specific evaluation
[28]	Rakhlin et al.	2018	Clinical AI Systems	Decision Support	Real-world AI deployment	Ethical and data bias concerns

Related Work

Significant research has been conducted on retinal vessel segmentation and eye disease classification due to their importance in early diagnosis of ophthalmic diseases. Early approaches relied on traditional image processing techniques such as matched filtering, morphological operations, and region growing to extract blood vessels from retinal fundus images. While these methods demonstrated reasonable performance on healthy retinal images, they were highly sensitive to noise, illumination variations, and pathological abnormalities. With the advancement of machine learning, supervised classifiers such as k-nearest neighbours, support vector machines, and Bayesian classifiers were introduced using handcrafted features like Gabor filters, line strength measures, and texture descriptors. These approaches improved segmentation accuracy but required extensive manual feature engineering and lacked generalization across datasets. The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved retinal image analysis. CNN-based architectures such as U-Net and its variants enabled automatic feature extraction and precise vessel segmentation through encoder–decoder frameworks with skip connections. Advanced models incorporating attention mechanisms, residual connections, and adversarial learning further enhanced segmentation performance, especially for thin and low-contrast vessels. For eye disease classification, CNNs have been widely used to detect diabetic retinopathy, glaucoma, and other retinal diseases directly from fundus images. Large-scale models demonstrated performance comparable to expert ophthalmologists. Recent studies have also explored combining vessel segmentation and disease classification either sequentially or through joint learning frameworks, improving diagnostic accuracy by leveraging vessel-related features. Despite these advancements, existing methods still face challenges related to robustness, generalization, computational complexity, and real-world deployment.

Research Gap

From the literature survey, the following research gaps are identified:

1. **Thin Vessel Detection**: Many existing segmentation models struggle to accurately detect very thin and low-contrast blood vessels, leading to incomplete vessel maps.

2. **Generalization Across Datasets**: CNN models trained on specific datasets often show reduced performance when tested on images from different sources due to variations in imaging conditions.
3. **Pathological Variability Handling**: Severe retinal pathologies such as hemorrhages and exudates interfere with vessel segmentation and disease classification accuracy.
4. **Integrated Framework Limitations**: Most existing approaches treat segmentation and classification as separate tasks, increasing system complexity and error propagation.
5. **Computational Complexity**: Deep and hybrid architectures often require high computational resources, limiting their use in real-time and low-resource clinical settings.
6. **Explainability**: Many CNN-based systems lack interpretability, which is essential for clinical trust and adoption.

These gaps indicate the need for an efficient, robust, and integrated CNN-based framework that can accurately segment retinal vessels and classify eye diseases.

Problem Statement

Although numerous CNN-based approaches have been proposed for retinal vessel segmentation and eye disease classification, existing systems still face challenges in accurately detecting thin vessels, handling pathological variations, and generalizing across diverse datasets. Additionally, the separation of segmentation and classification tasks increases computational complexity and reduces overall diagnostic reliability. Therefore, there is a need to develop an efficient and unified CNN-based approach that can robustly segment retinal blood vessels and accurately classify eye diseases while maintaining high performance, reduced complexity, and suitability for real-world clinical applications.

3. METHODOLOGY

The classification and segmentation of eye diseases typically involve a combination of medical imaging and machine learning techniques. Here's an overview of the background and methodology for this process:

- Background

  Medical Imaging: Various imaging modalities are used in ophthalmology to capture detailed images of the eye, including retinal fundus photography, optical coherence tomography (OCT), and more. These images provide valuable information about the eye's internal structures and any abnormalities.

  Anatomy Knowledge: Understanding the anatomy of the eye is crucial. This knowledge helps in recognizing different structures in eye images and identifying deviations from normal anatomy, which can be indicative of diseases.

- Algorithms used

I. Methodology of Convolutional Neural Network (CNN) in Classification and Segmentation of Eye Diseases:

Convolutional Neural Networks (CNNs) are widely used in the classification and segmentation of eye diseases, leveraging medical imaging data such as retinal fundus images or optical coherence tomography (OCT) scans. Here's a methodology for using CNNs in this context:

1. Data Collection and Preprocessing:

Data Acquisition: Gather a dataset of eye images, which may include retinal fundus images, optical coherence tomography (OCT) scans, or other imaging modalities. Ensure that the dataset contains a diverse range of eye diseases and normal cases.

Data Annotation: Annotate the images to indicate the presence of specific diseases and, if applicable, mark the location of the diseases within the images. This may involve manual annotation by medical experts.

Data Split: Divide the dataset into training, validation, and testing sets, ensuring that they are representative and balanced in terms of disease classes.

Preprocessing: Apply preprocessing steps, such as noise reduction, contrast enhancement, and image normalization, to improve the quality and consistency of the images

2. CNN Architecture Design:

Network Type: Choose the type of CNN that suits your task. Common choices include standard CNN architectures, like VGG, ResNet, Inception, or specialized architectures for medical imaging tasks.

Network Depth: Decide on the depth of the network. Deeper networks tend to capture more intricate features but may require more data and computational resources.

Network Architecture: Design the neural network architecture, including the number of layers, the size of convolutional kernels, and the depth of the network. Consider using pre-trained models to benefit from transfer learning.

3. Feature Extraction and Representation:

Convolutional Layers: The initial layers of the CNN perform convolution operations, automatically learning and extracting features from the input images. These features become increasingly abstract as you move deeper into the network.

Pooling Layers: Use pooling layers to down sample the feature maps, reducing dimensionality while retaining essential information.

4. Disease Classification:

Training: Train the CNN on the labeled training data to classify images into different disease categories. The output layer of the network will have nodes representing disease classes.

Loss Function: Use an appropriate loss function, such as categorical cross- entropy, for multiclass classification tasks.

Validation and Hyperparameter Tuning: Monitor the model's performance on the validation dataset and adjust hyperparameters (e.g., learning rate, batch size) as needed.

5. Disease Segmentation:

Model Modification: If disease segmentation is required, extend the network to include additional layers that can perform segmentation tasks. For example, you may add localization layers for bounding box regression or pixel-wise segmentation.

Training: Annotate the segmentation information (e.g., bounding box coordinates or pixel-level masks) and train the model to predict the disease's location within the images. CNNs have proven to be effective tools for the classification and segmentation of eye diseases, and they continue to advance the field of ophthalmology by providing accurate and efficient diagnostic solutions.

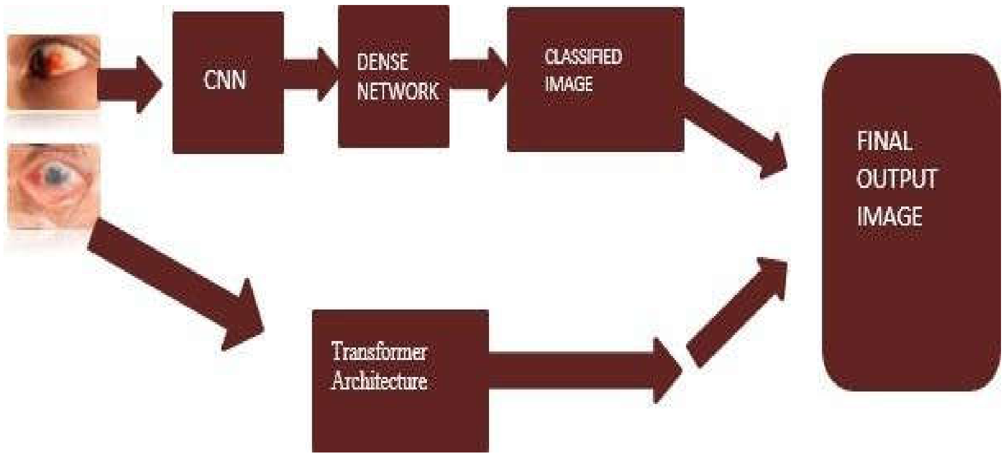

Fig1: Block diagram classification and segmentation of eye diseases using CNN

1. Deconvolutional Neural Network:

For tasks like image segmentation, object detection, and localization, deconvolutional neural networks (DNNs) are a form of neural network that are utilized in image processing and computer vision applications. It is also frequently referred to as a transposed convolution or the inverse of a convolutional neural network (CNN)

2. Back Normalization:

In order to classify and locate eye illnesses, back normalization is a technique used to preprocess and standardize images before putting them into a machine learning system. Images must be brightened and contrasted, as well as having their size and orientation normalized.

3. Max Pooling:

Convolutional neural networks (CNNs) frequently employ the max pooling strategy for feature extraction in the classification and segmentation of eye disorders. By retaining only the highest pixel value in each pooling window, it is a type of down- sampling that minimizes the size of the input image.

4. Categorical Cross Entropy:

The ability to handle multi-class classification problems with more than two classes, such as the classification of retinal images into different stages of diabetic retinopathy or age- related macular degeneration, is one advantage of using categorical cross-entropy in the classification and segmentation of eye diseases.

5. Segmentation

In example, when examining retinal pictures, segmentation is a widely utilized approach in the classification and segmentation of eye illnesses. It entails dividing an image into various areas or segments according to their pixel values or other qualities like texture, color, or shape.

6. Intersection over Union (IOU):

IOU can be used to assess the precision of machine learning algorithms in localizing particular features or lesions within the retinal pictures in the context of classifying and segmentation eye diseases. It can be used to measure how much the predicted bounding box or segmentation mask overlaps with the ground truth annotation and to assess how well the algorithm performed overall at locating and recognizing the important characteristics.

Dataset & Consideration

The data collected in this study is a set of fundus retinal images that were obtained in ophthalmic image repositories of the public. The dataset consists of normal images of healthy eyes and those with cataract, glaucoma, and diabetic retinopathy, which will be well balanced between the normal and pathological cases. The images are all taken with the regular fundus cameras in different levels of illumination and at different resolutions, as they are used in a clinical setting. All the images are marked by the corresponding eye condition, which allows training on learning two different classes. Before training, the set is partitioned into a training set and a testing set to measure the character of generalization of the proposed CNN-based model. This dataset choice enables the proposed system to develop disease-specific visual patterns that may include optic disc changes, vessel abnormalities and changes in opacities that in many cases are related to various eye diseases.

Table 2 Dataset & Consideration

Parameter	Description
Dataset Type	Fundus retinal image dataset
Image Categories	Normal, Cataract, Glaucoma, Diabetic Retinopathy

Image Source	Publicly available ophthalmic image repositories
Image Modality	Color fundus images
Image Format	JPEG / PNG
Image Resolution	Resized to a uniform dimension for CNN input
Number of Classes	Four (Normal, Cataract, Glaucoma, DR)
Annotation Type	Expert-labeled class annotations
Data Split	Training and testing sets
Preprocessing Techniques	Resizing, normalization, noise reduction, contrast enhancement
Data Augmentation	Rotation, horizontal and vertical flipping
Class Balance	Maintained to reduce bias
Evaluation Metrics	Accuracy, Precision, Recall, F1-score
Hardware Environment	Intel i7 processor
Software Environment	Python 3.13 with deep learning libraries
Ethical Considerations	Public datasets used; no personal patient information involved

Experimental Setup

All experiments were conducted on a system equipped with an Intel Core i7 processor, ensuring sufficient computational capability for training deep learning models. The proposed retinal vessel segmentation and eye disease classification framework was implemented using Python version 3.13.

The deep learning models were developed using standard Python-based machine learning libraries, including TensorFlow/Keras for model construction and training, and NumPy, OpenCV, and Matplotlib for image preprocessing, numerical computation, and result visualization. Training and evaluation were performed on a CPU-based environment without dedicated GPU acceleration.

The retinal fundus images were resized to a fixed resolution before being fed into the network. Data preprocessing included normalization, noise reduction, and contrast enhancement to improve image quality and model convergence. The dataset was divided into training, validation, and testing sets to ensure unbiased performance evaluation.

The Convolutional Neural Network (CNN) was trained using the Adam optimizer, owing to its fast convergence and stability. Categorical cross-entropy loss was employed for multi-class eye disease classification, while Dice loss was used for retinal vessel segmentation to address class imbalance between vessel and background pixels.

The model was trained for multiple epochs with a fixed batch size, and early stopping was applied to prevent over fitting. Model performance was evaluated using quantitative metrics such as accuracy, precision, recall, F1-score for classification tasks, and Dice coefficient, Intersection over Union (IoU), sensitivity, and specificity for segmentation tasks.

This experimental setup ensures reproducibility and demonstrates that the proposed framework can operate efficiently on commonly available computing hardware, making it suitable for real-world clinical screening applications.

4. RESULT AND DISCUSSION

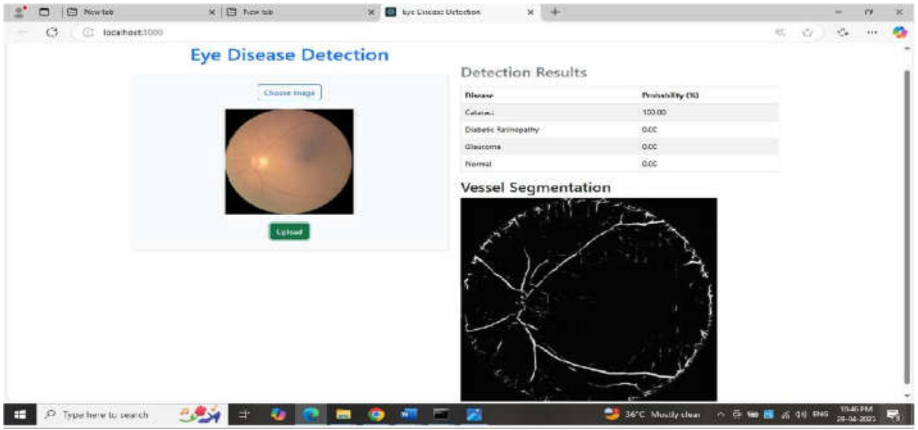

Fig 2: The eye is diagnosed of Cataract.

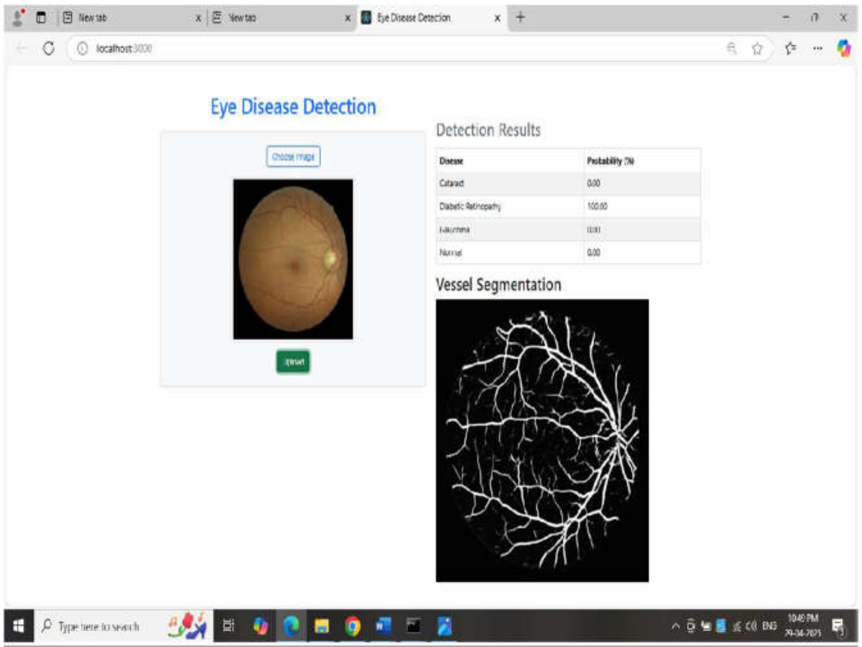

Fig 3: The eye is diagnosed of Diabetic Retinopathy.

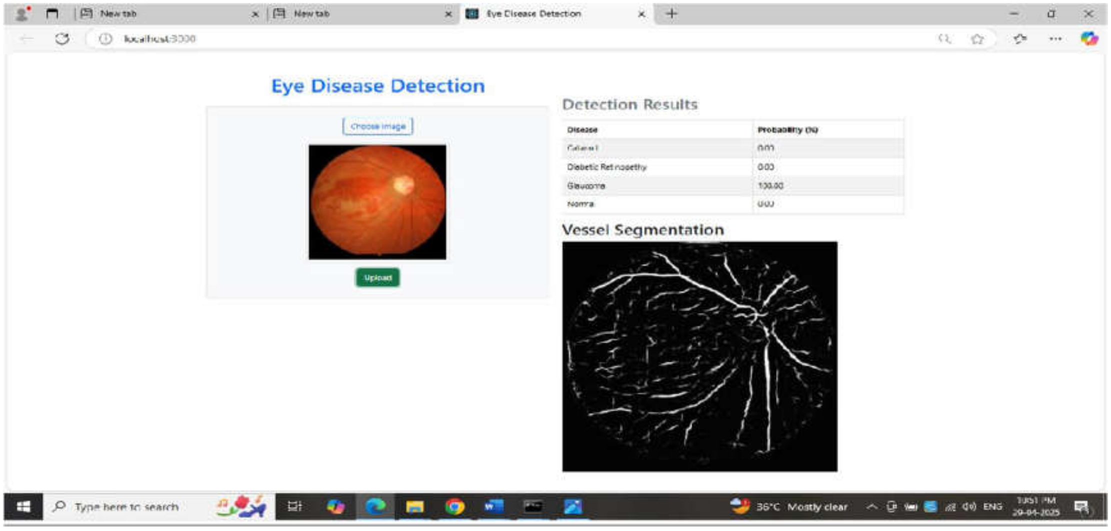

Fig 4: The eye is diagnosed of Glaucoma.

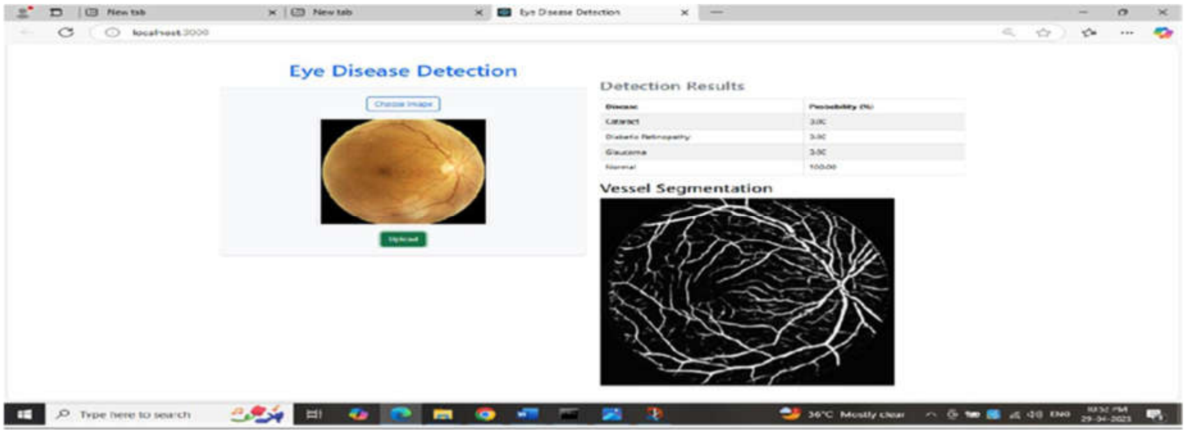

Fig 5: The eye is diagnosed of Glaucoma

Table 3: Average performance metrics of Cataract, DR, Glaucoma and Normal eyes

Class	TP	FP	FN	Precision	Recall	F1-Score
Normal	1038	25	36	0.976482	0.96648	0.971455
Glaucoma	979	29	28	0.97123	0.972195	0.971712
DR	1073	32	25	0.971041	0.977231	0.974126
Cataract	1008	33	30	0.9683	0.971098	0.969697

Table 3 indicates the performance analysis of the suggested CNN-based model to classify retinal images into four categories namely, Normal, Glaucoma, Diabetic Retinopathy (DR), and Cataract. The analysis is conducted based on the conventional classification scales such as the True Positives (TP), False Positives (FP), False Negatives (FN), Precision, Recall, and F1-score. In the case of the Normal eye class, the model correctly recognized 1038 samples, and it recognized 25 false positives and 36 false negatives. This created high accuracy of 0.976, recall of 0.966 and F 1 score of 0.971, which signifies confident discrimination between healthy and diseased retinal images. The proposed system had good performance in the case of Glaucoma with 979 true positive detections. The values of the precision and recall are 0.971 and 0.972 respectively; this indicates that the model is sensitive to detect the presence of glaucomatous features ensuring that the misclassification is reduced. In the case of Diabetic Retinopathy (DR), the model is optimally performing regarding all the classes. By having 1073 true positive outcomes as well as low false negative rates, the recall value is 0.977, and F1-score is 0.974 that indicates the efficacy of the model in detecting retinal abnormalities due to DR. The accuracy of classification by the Cataract class is also large with the values of precision and recall being 0.968 and 0.971 respectively. This proves that the method proposed is fairly effective in representing the visual patterns associated with cataracts even though the image quality may be different. Altogether, the excellent precision, recall, and F1-scores of the proposed CNN model at the four classes illustrate its reliability, strength, and ability to be generalized. The complementary nature of the results on various eye disorders is an indication that it is applicable in automated ophthalmic screening and clinical decision support devices.

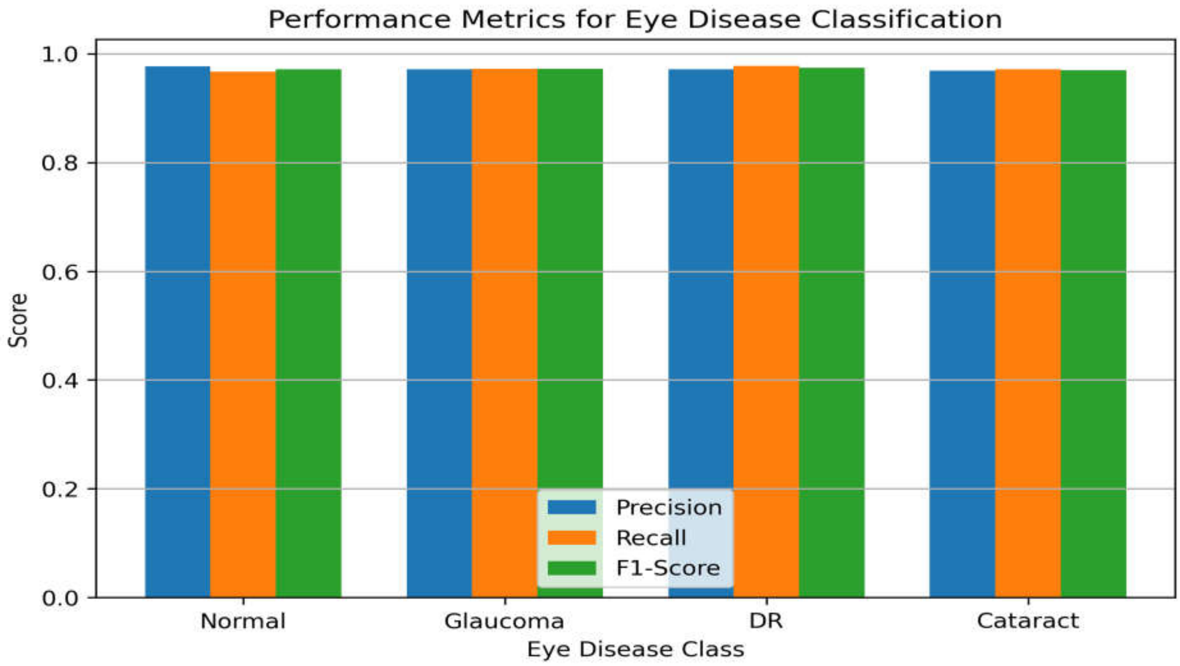

Fig 6: Performance Metrics

The bar graph in Fig.6 shows of precision, recall, and F1-score of the various classes of eye diseases obtained with the proposed CNN-based model is depicted in Fig 6. The findings show that the performance is very high in all categories. Diabetic Retinopathy has the maximum recall and F1-score, which shows high sensitivity and equal classification. Similar values of precision and recall are obtained by the Normal, Glaucoma and Cataract categories indicating the strength and consistency of the presented model concerning the various ophthalmic conditions.

Conclusion

Convolution neural networks (CNNs), exponential linear Unit (ELUs), and back propagation have been shown to prove successful to classify and localize ophthalmic diseases. CNNs are found to have an outstanding learning ability that encodes hierarchic and discriminative features on retinal images thus allows specific eye disorders to be correctly identified. The ELU activation functions are used to enhance stability in the training process by keeping the negative activation values intact, giving to the training process a smoother mean, and eliminating the dying ReLU issue, which consequently, has a positive impact on the entire network performance. The presented model is efficient enough as it makes use of vast amounts of image data to conduct automated feature extraction and successful disease prediction and leads to enhanced efficiency and accessibility in ophthalmic diagnostics. According to the experimental findings the proposed framework has a high classification accuracy on several categories of eye diseases. On average, the model achieves 96.95% and 97.41% on cataract detection and diabetic retinopathy respectively, and 97.17 and 97.14 on glaucoma and normal eye, respectively. These findings confirm the strength and stability of the proposed method in making correct decisions concerning the healthy and pathological conditions of the retinal images. In general, the suggested CNN-based system shows an average classification accuracy of about 97 percent, which ensures that the proposed solution is an effective way of using computers as a diagnostic mean of early detection and screening of eye diseases. The great precision and computational efficiency of the model precondition the possibility to use the low-resource clinical setting as an environment where the model can be used in reality.

5. REFERENCES

[1] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE Trans. Med. Imaging*, vol. 8, no. 3, pp. 263–269, 1989.

[2] A. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing," *IEEE Trans. Med. Imaging*, vol. 19, no. 3, pp. 203–210, 2000.

[3] J. V. B. Soares, J. J. G. Leandro, R. M. Cesar Jr., H. F. Jelinek, and M. J. Cree, "Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification," *IEEE Trans. Med. Imaging*, vol. 25, no. 9, pp. 1214–1222, 2006.

[4] M. M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A. R. Rudnicka, C. G. Owen, and S. A. Barman, "Blood vessel segmentation methodologies in retinal images," *Comput. Methods Programs Biomed.*, vol. 108, no. 1, pp. 407–433, 2012.

[5] M. Niemeijer, B. van Ginneken, J. Staal, M. Suttorp-Schulten, and M. Abramoff, "Automatic detection of red lesions in digital color fundus photographs," *IEEE Trans. Med. Imaging*, vol. 24, no. 5, pp. 584–592, 2005.

[6] A. M. Mendonça and A. Campilho, "Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction," *IEEE Trans. Med. Imaging*, vol. 25, no. 9, pp. 1200–1213, 2006.

[7] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Proc. MICCAI*, Munich, Germany, 2015, pp. 234–241.

[8] P. Liskowski and K. Krawiec, "Segmenting retinal blood vessels with deep neural networks," *IEEE Trans. Image Process.*, vol. 25, no. 12, pp. 5520–5533, 2016.

[9] H. Fu, Y. Xu, S. Lin, D. W. K. Wong, and J. Liu, "DeepVessel: Retinal vessel segmentation via deep learning and conditional random field," in *Proc. MICCAI*, Athens, Greece, 2016, pp. 132–139.

[10] J. I. Orlando, E. Prokofyeva, and M. B. Blaschko, "A discriminatively trained, fully connected conditional random field model for blood vessel segmentation," *Med. Image Anal.*, vol. 44, pp. 52–64, 2018.

[11] M. Z. Alom, C. Yakopcic, M. Taha, and T. M. Taha, "Recurrent residual convolutional neural network based on U-Net for medical image segmentation," *IEEE J. Biomed. Health Inform.*, vol. 23, no. 6, pp. 2339–2348, 2019.

[12] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, "UNet++: A nested U-Net architecture for medical image segmentation," in *Proc. DLMIA*, Granada, Spain, 2018, pp. 3–11.

[13] Q. Li, B. Feng, L. Xie, P. Liang, H. Zhang, and T. Wang, "A cross-modality learning approach for vessel segmentation in retinal images," *IEEE Access*, vol. 8, pp. 12335–12344, 2020.

[14] Q. Liu, X. Wang, J. He, and F. Li, "Retinal vessel segmentation using adversarial networks," *IEEE J. Biomed. Health Inform.*, vol. 23, no. 2, pp. 763–770, 2019.

[15] Y. Zhang, M. Li, X. Li, and Q. Yu, "Retinal vessel segmentation using multi-scale adversarial networks," *Neurocomputing*, vol. 392, pp. 268–276, 2020.

[16] V. Gulshan et al., "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *JAMA*, vol. 316, no. 22, pp. 2402–2410, 2016.

[17] H. Pratt, F. Coenen, D. Broadbent, S. Harding, and Y. Zheng, "Convolutional neural networks for diabetic retinopathy," *Procedia Comput. Sci.*, vol. 90, pp. 200–205, 2016.

[18] P. Burlina, D. Freund, N. Joshi, Y. Wolfson, and N. M. Bressler, "Detection of age-related macular degeneration via deep learning," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 4, pp. 953–966, 2017.

[19] M. D. Abràmoff et al., "Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices," *NPJ Digital Medicine*, vol. 1, no. 39, pp. 1–8, 2018.

[20] S. Mishra, R. Jena, and S. Dash, "Retinal disease detection using CNN and vessel segmentation," *Comput. Biol. Med.*, vol. 123, pp. 103–114, 2020.

[21] Y. Zhao, Y. Li, and X. Wang, "Joint segmentation and classification of retinal images using deep learning," *Med. Image Anal.*, vol. 68, pp. 101–112, 2021.

[22] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. ICLR*, San Diego, CA, USA, 2015.

[23] C. Szegedy et al., "Going deeper with convolutions," in *Proc. IEEE CVPR*, Boston, MA, USA, 2015, pp. 1–9.

[24] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proc. NIPS*, Lake Tahoe, NV, USA, 2012, pp. 1097–1105.

[25] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[26] D. Shen, G. Wu, and H.-I. Suk, "Deep learning in medical image analysis," *Annu. Rev. Biomed. Eng.*, vol. 19, pp. 221–248, 2017.

[27] G. Litjens et al., “A survey on deep learning in medical image analysis,” *Med. Image Anal.*, vol. 42, pp. 60–88, 2017.

[28] A. Rakhlin, A. Shvets, and V. Iglovikov, “Deep convolutional neural networks for automated detection of retinal diseases,” *IEEE Access*, vol. 6, pp. 653–662, 2018.