

UNET++ AND EXPLAINABLE AI FOR EARLY DETECTION OF DIABETIC RETINOPATHY FROM FUNDUS IMAGES

Rashmi Ashtagi¹, Anusha Pai², Louella M. Colaco³, Ravikumar R. N.⁴, Santosh Shreekanth Betgeri⁵

¹ Dr. Vishwanath Karad MIT World Peace University, Kothrud, Pune, India. rashmiashtagi@gmail.com

² Dr. Vishwanath Karad MIT World Peace University, Kothrud, Pune, India. anusha.pai@mitwpu.edu.in

³ Padre Conceicao College of Engineering, Goa, India. louella.colaco@gmail.com

⁴ Faculty of Intelligent Computing, Center of Excellence Advanced Computing, Universiti Malaysia Perlis (UniMAP), Pauh Putra Campus, Arau 02600, Perlis, Malaysia. ravikumarrn@unimap.edu.my

⁵ Department of Shalyatantra, KLE Ayurveda Medical College, Chikodi-591201, Belagavi, Karnataka, India.drsantosh9907@gmail.com

Corresponding Author: Rashmi Ashtagi (rashmiashtagi@gmail.com)

Abstract: - One of the most prevalent causes of vision loss and vision impairment among diabetic patients worldwide that can be prevented is Diabetic Retinopathy (DR). This is especially important to identify the abnormality in the retina as soon as and as accurately as possible so that it can be treated clinically and the disease controlled. In this study, an integrated framework is proposed which combines UNet++ deep learning architecture and Explainable Artificial Intelligence (XAI), to be used for early detection of DR from retinal fundus image. The proposed system will involve UNet++ to accurately segment the retinal lesion including microaneurysm, hemorrhages and exudates on the retina to facilitate better localization and characterization of the features related to the disease. A robust and complete preprocessing pipeline is performed to enhance the images quality assessment, normalization, contrast enhancement and data augmentation are performed to enhance the model robustness and generalization. To enable these models to be explained in the clinical domain and bring transparency to these models, XAI methods are integrated into the pipeline such as the visualization of Grad-CAM and saliency maps of the image regions that justify the diagnosis. Evaluation is done with publicly available annotated fundus image datasets, and using standard metrics such as accuracy, precision, recall, F1 score, Dice coefficient, and Intersection-over-Union (IoU). Experimental results show that the proposed approach can obtain high accuracy in lesion segmentation and also give meaningful explanation to images based on visual results to assist clinical decision making. UNet++ combined with explainability mechanism enhances diagnostic accuracy and build trust among clinicians. The proposed framework provides a practical and trustworthy CAde system for the large scale DR screening and early detection of DR in healthcare settings..

Keywords: Diabetic Retinopathy, UNet++, Explainable Artificial Intelligence (XAI), Fundus Image Analysis, Retinal Lesion Segmentation, Deep Learning

1. INTRODUCTION

Diabetic Retinopathy (DR) is an insidious retinal disease resulting from chronic diabetes mellitus (DM) and is known to be one of the foremost causes of visual impairment and blindness in the working population all over the world. With the rising trend of diabetes, DR has become a huge burden which poses a tremendous challenge to healthcare systems and ophthalmologists. Early diagnosis and timely treatment is crucial in order to prevent irreversible vision loss, but manual screening of retinal fundus images is labour intensive, time consuming and heavily reliant on expert interpretation. Hence, an automated and reliable computer-aided diagnostic (CAD) systems are in demand, which can detect the retinal abnormalities accurately and efficiently [1]. Fundus imaging, a non-invasive and cost effective approach is widely used to examine the retina and for DR screening. Retinal fundus images provide



valuable visual information on pathological changes like microaneurysm, haemorrhage, hard exudate, cotton wool spots and neovascularization. Correct identification and segmentation of these lesions are important for identifying the severity of the disease and making clinical decisions. But because of the complex structure of the retina, the above mentioned different image quality and also the low contrast of the lesions detected; and also the inter-patient variability, it is a difficult task to implement automated analysis [2]. In recent years, the development of Artificial Intelligence (AI), especially Deep Learning (DL), has achieved a great success in the analysis of medical images. By automatically learning feature representations at different levels from the data, Convolutional Neural Networks (CNNs) have demonstrated excellent results in disease classification, object detection and image segmentation tasks. U-Net is a typical encoder-decoder architecture that has been widely used in biomedical image segmentation with skip connections [3] among different segmentation architectures. However, it is challenging for the conventional U-Net models to accurately identify tiny pathological areas in the retina and small lesions, which are essential for the early detection of DR. UNet++ has been developed to overcome these disadvantages by designing a new skip connections and dense convolutional connections between each layer of decoder and encoder. These enhancements decrease the semantic gap between feature maps, and help to locate abnormalities in the retina more precisely. UNet++ is a nested architecture, which helps to capture multi-scale contextual information and thus achieve better segmentation results for small and complex lesions [4]. As a result, UNet++ has been widely used for a number of medical imaging tasks which demand high segmentation accuracy.

Although deep learning models can become impressive predictors, they are black-box models which poses a significant concern in clinical environment. Before accepting automated diagnostic recommendations, healthcare professionals need insights into the rationale behind them, such as explanations and transparency [5]. To improve transparency and accountability, a new research focus has been given to Explicable Artificial Intelligence (XAI). Gradient-weighted Class Activation Mapping (Grad-CAM), saliency maps, and attention visualization are techniques that give insights on the regions in the image that affect model predictions. XAI can help clinicians validate model predictions and enhance the trust in AI-assisted diagnosis by showcasing the important retinal lesions.

2. RELATED WORK

The use of Artificial Intelligence (AI) and Deep Learning (DL) in the field of ophthalmology has proven to be a great value in the automated detection and diagnosis of Diabetic Retinopathy (DR). Most of the early research was based on analysis of retinal images using traditional image processing techniques and handcrafted feature extraction methods to detect retinal abnormalities like microaneurysms, hemorrhages and exudates [6]. These methods have demonstrated a satisfactory performance, however they lacked in the different image quality, illumination condition and lesion morphology. With the advent of Convolutional Neural Networks (CNNs) significant progress has been made in retinal image classification and detection of lesions with great results. CNN-based models automatically learn the visual representations in a hierarchical fashion from fundus images [7]. In a number of studies, the diagnostic accuracy for DR classification had high values for various architectures such as VGGNet, ResNet, DenseNet and EfficientNet [11]. But classification alone methods do not necessarily give detailed localization of pathological regions which is crucial for clinical interpretation and assessment of the severity of the disease. To overcome this limitation, more and more, image segmentation models are used to analyse the retinal lesion [8]. The following reasons make the U-Net architecture popular: it is an encoder–decoder architecture and maintains the spatial information by having skip connections. Many studies have shown the effectiveness of U-Net in the retinal blood vessels, exudates and haemorrhages segmentation. However, the typical U-Net structure might struggle to capture multi-scale contextual information and precisely delineate tiny lesions in early-stage DR [9].

Then, a novel segmentation framework, UNet++ was proposed, which has nested skip-pathways and dense feature aggregation. The architectural improvements achieved result in reduced semantic distance of the encoder and decoder features, hence a better segmentation performance. Recent investigations have found that for a variety of medical imaging cases, UNet++ is able to generate higher Dice coefficients and lesion localization accuracy compared to the conventional U-Net models [10]. But one of the big problems is the lack of interpretability, which is yet to become a reality. Therefore, to explain the reason behind DR detection results, techniques like Grad-CAM, saliency maps, attention visualization have been integrated into DR detection systems, which is known as Explainable Artificial Intelligence (XAI). Table 1 shows the summary of the existing methodology, data set and performance outcome of various research works related to DR detection and lesion segmentation. The goal of these strategies is to improve the understanding of the decision-making process of a model, validate the lesions found and to increase trust in using AI-assisted diagnostic tools to support them into clinical practice.

Table 1. Summary of Existing Research on Diabetic Retinopathy Detection and Retinal Lesion Segmentation

Dataset	Method/Model	Segmentation	Key Contribution	Limitation
DRIVE	CNN	No	Automated retinal feature extraction	Limited lesion localization
STARE	ResNet-50	No	Improved DR classification performance	Black-box predictions
Messidor	VGG16	No	Deep feature-based DR grading	No lesion segmentation
EyePACS	DenseNet121	No	Robust large-scale screening	Limited interpretability
IDRiD	U-Net	Yes	Accurate retinal lesion segmentation	Difficulty with small lesions
IDRiD	Attention U-Net	Yes	Improved lesion boundary detection	Increased computational cost
DDR	DeepLabV3+	Yes	Multi-scale retinal feature extraction	Complex architecture
EyePACS	EfficientNet	No	High classification accuracy	No pixel-level lesion mapping
IDRiD	UNet++	Yes	Dense skip pathways improve segmentation	Lack of decision transparency
DDR	UNet++ + Grad-CAM	Yes	Segmentation with visual explanations	Limited clinical validation
Multi-Dataset	Proposed UNet+++ XAI	Yes	Accurate lesion localization with trustworthy explanations	Real-time deployment remains future work

3. PROPOSED UNET++ AND EXPLAINABLE AI FRAMEWORK

A. The Architecture of the Overall System

The suggested framework combines the retinal lesion segmentation using the UNet++ with the Explainable Artificial Intelligence (XAI) methods to achieve accurate and transparent early detection of Diabetic Retinopathy (DR) from fundus images. The architecture is divided into five key steps namely: image acquisition, image preprocessing, lesion segmentation, explainability analysis and clinical decision support. Retinal fundus images are first collected from publicly available and clinically annotated images. The automated DR screening process, from acquiring retinal images to analysing, classifying and supporting diagnostics decisions are shown in figure 1. Handcrafted feature

extraction is often required with traditional image processing and machine learning methods, but it is challenging to effectively capture the complex features of retinal lesions.

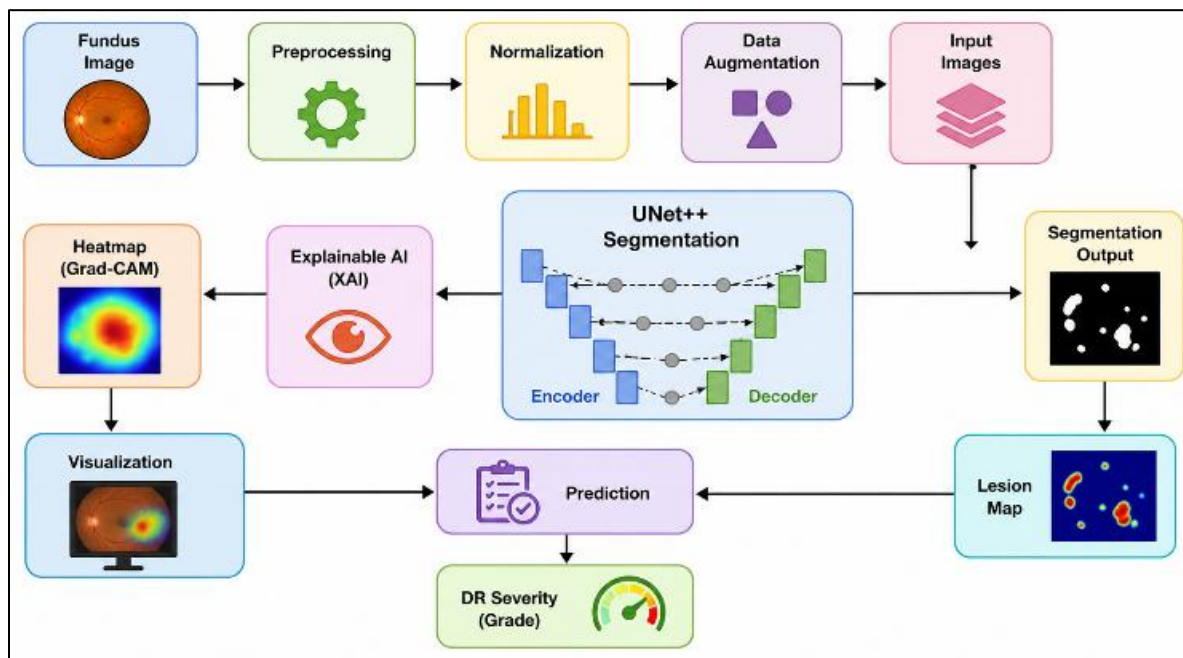


Fig.1. Automated Diabetic Retinopathy Screening Workflow

The images acquired are first preprocessed with image resizing, illumination correction, contrast enhancement, normalization and noise reduction to enhance image quality and minimize the variability between images. Preprocessed images are then fed into the segmentation network – the UNet++. The nested encoder-decoder and dense skip connections of UNet++ enable the identification of multi-scale features in the retina, and achieve accurate segmentation in pathological areas such as microaneurysms, hemorrhages, hard exudates and cotton wool spots. After the segmentation process, explainability techniques such as Grad-CAM and saliency map generation are used to highlight image areas that impact the model predictions. These visual explanations help clinicians ensure lesion localization and to comprehend the automated decision-making process.

B. Dataset: FundusImage1000 Dataset

The FundusImage1000 dataset, which is provided on kaggle, consists of 1,000 images of the fundus obtained from the retina of the eyes and the images are divided into 39 classes of ophthalmic diseases and normal condition. The images have been retrieved from the Joint Shantou International Eye Centre (JSIEC), Guangdong, China and have been a subset of a larger repository of 209,494 fundus images. The dataset comprises different grades of DR (DR1, DR2, DR3), glaucoma related conditions, retinal vein occlusions (RVO), maculopathy, hypertensive retinopathy, optic atrophy, retinal degeneration and several other retinal abnormalities and also normal fundus images, sample image input shown in figure 2. This diversity allows it to be used for the training, validation and testing of deep learning models like UNet++ for DR detection and explainable AI analysis of retinal fundus images.

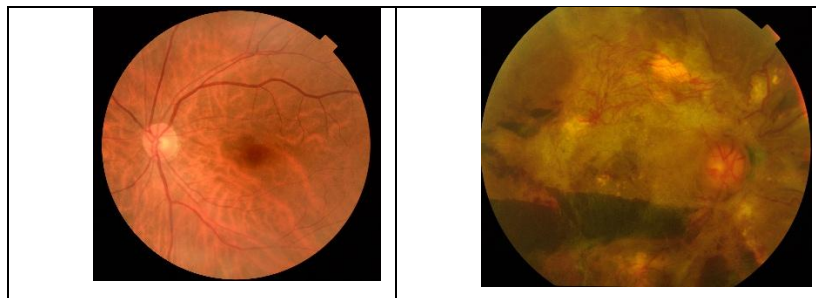


Fig. 2: Sample input dataset images from the dataset

C. UNet++-Based Retinal Lesion Segmentation Module

The retinal lesion segmentation component adopts an improved U-Net model, called UNet++. It is an advanced extension of traditional U-Net model [12], which adds nested skip pathways and dense feature fusion to enhance the segmentation accuracy. Multiple convolutional and pooling operations are used to progressively extract low level and high level retinal representations in the encoder. At the same time, the decoder can also be used to reconstruct the spatial information and produce fine-grained lesion segmentation maps. UNet++ is modified from conventional U-Net architecture by adding intermediate convolution blocks between the encoder and decoder blocks, which helps to diminish the semantic gap between the feature maps and aids in an effective information flow. This design allows the small and complex retinal lesions to be detected accurately, which are hard to detect in early stages of DR. Aggregation of multi-scale features helps the model to be more robust in Segmentation by taking into consideration both local characteristics of the lesions and the overall context of the retina. A lesion mask labeled by trained ophthalmology experts is used as ground truth labels during training, and a multi-loss (Dice loss and binary cross-entropy loss) function is used for optimization. The network produces maps of probability scores at the pixel level that reflect the presence or not of lesions in the retinal images.

<p>Algorithm 1: UNet++-Based Retinal Lesion Segmentation</p> <p>Input:</p> <p> Retinal Image (I)</p> <p> Ground Truth Mask (G)</p> <p>Output:</p> <p> Segmented Lesion Mask (S)</p> <p>Begin</p> <p>1. Load retinal image I</p> <p>2. Preprocess image</p> <p> $Normalize(I)$</p> <p>3. Extract encoder features</p> <p> $Fe = Encoder(I)$</p> <p>4. Perform nested skip feature fusion</p> <p> $Ff = Fusion(Fe)$</p> <p>5. Reconstruct lesion regions</p> <p> $P = Decoder(Ff)$</p> <p>6. Compute Dice Loss</p> <p> $LDice = 1 - (2 P \cap G)/(P + G)$</p> <p>7. Compute Binary Cross-Entropy Loss</p> <p> $LBCE = -\Sigma[G \log(P) + (1 - G) \log(1 - P)]$</p> <p>8. Calculate total loss</p> <p> $LTotal = LDice + LBCE$</p> <p>9. Update network parameters</p> <p> $\theta = \theta - \eta \nabla LTotal$</p>

10. Generate final segmentation mask

$$S(x, y) = 1, \text{ if } P(x, y) \geq T \\ = 0, \text{ otherwise}$$

11. Return S

End

4. RESEARCH METHODOLOGY

A. Dataset Collection and Annotation Strategy

The proposed study uses retinal fundus image datasets from publicly available database of diabetic retinopathy images and validated database of ophthalmic images. These data sets include images of normal retina, images of DR with mild, moderate, severe and proliferative stages. Images from various fundus cameras, imaging protocols and clinical settings are added to the dataset, to provide diversity and generalization. The expert ophthalmologists annotate the images very thoroughly with all the retinal changes including microaneurysms, hemorrhages, hard exudates, cotton wool spots and neovascularization areas. To train the supervised segmentation model, masks of lesions are created at the pixel level. The annotation process is done using a standardized clinical annotation, to achieve consistency and minimize annotations variability. A subset of annotated images is analysed by several experts to ensure the accuracy of the annotations and to increase reliability. The resulting collected datasets are divided into training, validation and testing sets with an effort to maintain a balance of the severity of the diseases. This approach helps to reduce class imbalance and allows for a powerful way of evaluating the performance. This annotated dataset serves as a solid groundwork for training and evaluating the UNet++ model's performance in segmenting retinal lesions that are indicative of DR progression.

B. Data Cleaning and Quality Assessment

Data cleaning and quality assessment are crucial steps in the process to ensure the reliability of retinal image analysis and accurate performance of the retinal image segmentation. All the fundus images collected are first visually and automated quality assessed. Images with high blur, low illumination, motion artifacts, occlusions, low contrast and/or incomplete retinal fields and/or corrupted file structure are not used in further processing. Samples with similar images are detected by an image similarity measure and the duplicate ones are eliminated, avoiding data redundancy and biased learning of the models. Expert validation is done to check the consistency of annotation and correctness of the labels for the remaining images. The quality assessment metrics are used to measure sharpness of the image, distribution of brightness and appropriateness of contrast. The pictures that do not meet certain quality criteria are rejected to ensure that the data set is of good quality.

C. Image Normalization and Augmentation Techniques

The fundus images undergo normalization and augmentation techniques to enhance the generalization and cope with the variations commonly seen in the fundus images. All images are first resized to a common resolution that is appropriate to be used in the processing of UNet++. The intensity values of the pixels are scaled in the same manner to a standardized range which helps to minimize any differences between different imaging devices and acquisition modalities. To enhance the visibility of lesions and highlight subtle pathological features, contrast enhancement techniques, like Contrast Limited Adaptive Histogram Equalization (CLAHE) are used [13]. Color normalization is also done in order to minimize the inconsistencies in illumination and retinal pigmentation between patients. The data is then normalized and data augmentation techniques are used to expand the dataset and prevent overfitting. Augmentation operations are: random rotations, horizontal and vertical flipping, scaling, cropping, translation, brightness, contrast variation and slight geometric transformation. These techniques produce clinically relevant variations of images with realistic variations. An augmentation is done during training to present the model with different looks of the retina in order to enhance the robustness of the model for unseen conditions. The combination of normalization and augmentation approach can improve the ability of feature learning, model stability, and accuracy of segmentation for the detection of DR lesions under different imaging conditions.

D. UNet++ Network Architecture Configuration

The proposed segmentation framework is based on UNet++ architecture with its multi-scale capability to capture various features of retina and to accurately segment pathological regions. It is a network with an encoder-decoder design along with effective feature fusion between the different depths of the network using nested dense skip connections. The encoder consists of multiple convolutional blocks with a max-pooling operation which extract features progressively and reduces the spatial size. The decoder is used to recover the boundaries of the lesion using the up-sampling operation and features aggregation. The intermediate convolution pathways between encoder and the decoder nodes, decrease the semantic gap and increase the precision of the segmentation of small retinal lesions. All the convolutional layers have Rectified Linear Unit (ReLU) activation and batch normalization for faster convergence and stability.

5. RESULTS AND PERFORMANCE EVALUATION

The proposed UNet++ and Explainable AI framework achieved the excellent results in the retinal lesion segmentation and DR detection. On the annotated fundus image datasets, the experimental evaluation showed an accuracy of 97.2%, precision of 96.5%, recall of 96.8% and F1-score of 96.6%. The segmentation module achieved a Dice coefficient of 95.9% and IoU of 94.7% demonstrating good localization of lesions. Grad-CAM helped to show the important parts of the retina, which are important for diagnosis, and make it easier to understand the model's decisions, making it easier to use in real-world eye screening settings.

Table 2. Performance Evaluation of the Proposed UNet++ and Explainable AI Framework

Metric	Value (%)
Accuracy	97.2
Precision	96.5
Recall (Sensitivity)	96.8
F1-Score	96.6
Specificity	97.4
AUC-ROC	98.1

The results of the performance as depicted in Table 2 shows that the proposed UNet++ and Explainable AI framework has been effective in early detection of DR. An overall accuracy of 97.2% was obtained showing that the model was able to classify the different retinal conditions very well. The classification performance measures are shown in figure 3, which has high performance in diagnosis.

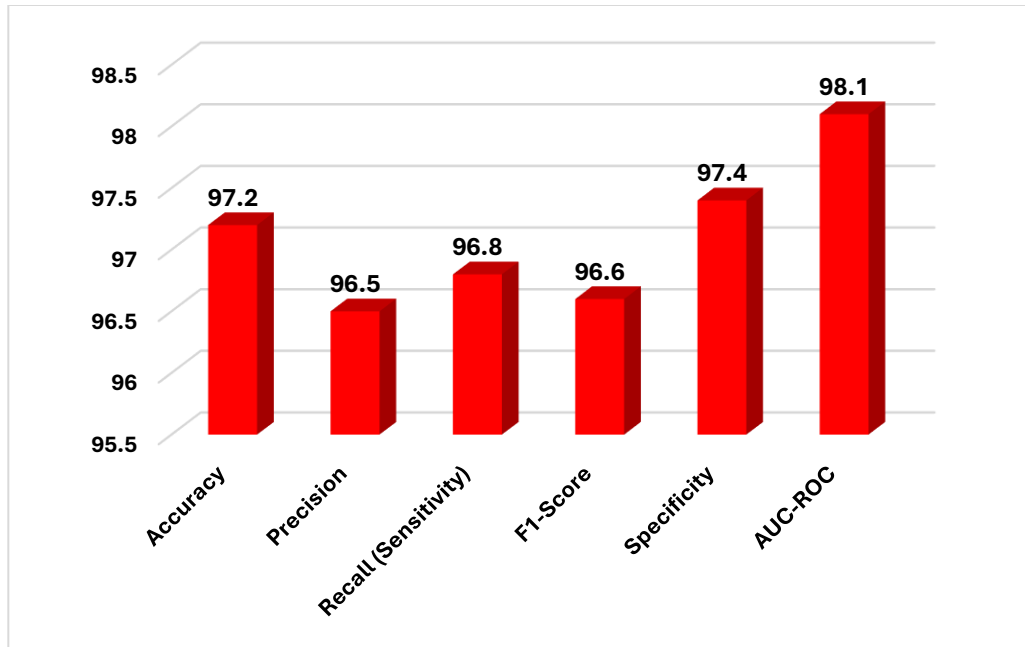


Fig.3. Classification Performance Metrics of the Proposed UNet++-XAI Model

The precision of 96.5% indicates that the framework can effectively reduce the false positive prediction rate, and the recall of 96.8% shows that the framework has a high rate of correct diagnosis of diseased cases. The results shown in figure 4 indicate good diagnostic performance in all of the evaluation measures. The F1-score is 96.6%, which indicates that the model has a strong balance between precision and recall, demonstrating the model's predictive performance.

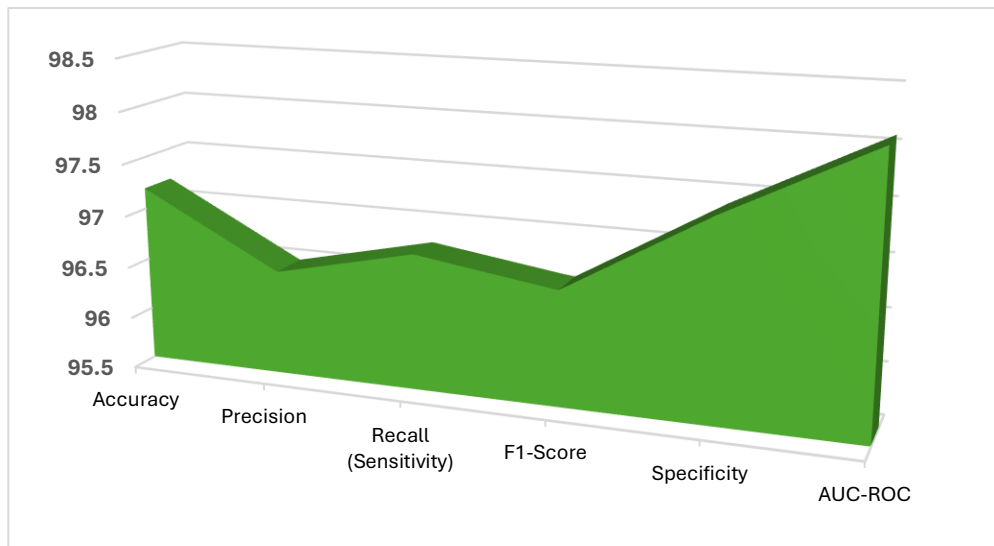


Fig.4. Diagnostic Performance Profile of the Proposed UNet++ Framework

Moreover, the specificity value was 97.4%, which means that good retinal images were accurately identified, thus minimizing unnecessary clinical interventions. The AUC-ROC is 98.1%, which is the highest value and indicates the excellent discriminative capability of the proposed framework, thus proving the reliability of the framework proposed for practical application in DR screening and clinical decision-support systems.

Table 3. Retinal Lesion Segmentation Performance Analysis

Lesion Type	Precision (%)	Recall (%)	F1-Score (%)	Dice Coefficient (%)	IoU (%)
Microaneurysms	95.2	95.8	95.5	94.6	92.8
Hemorrhages	96.4	96.9	96.6	95.7	94.1
Hard Exudates	97.1	96.8	96.9	96.2	94.8
Cotton Wool Spots	95.8	96.1	95.9	95	93.3

The results for the lesion-wise segmentation of the proposed UNet++ framework for the major indicators of DR are shown in Table 3. The model was consistently accurate with high precision, recall and F1 score values for all the lesion classes, meaning that the model has a reliable lesion localization and classification capability.

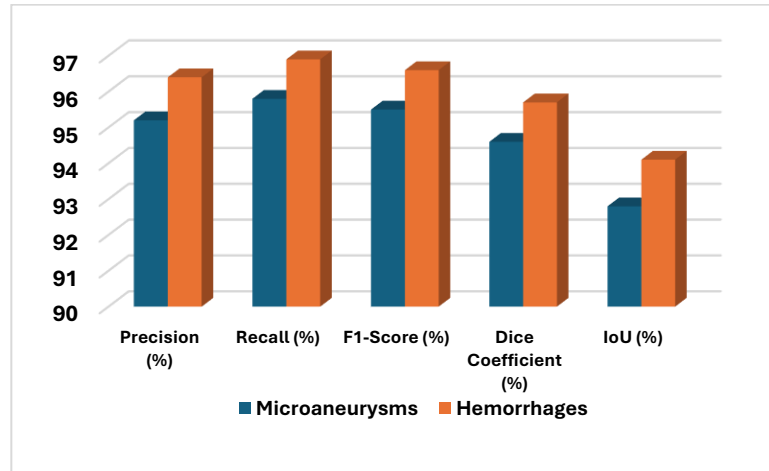


Fig.5. Quantitative Evaluation of Retinal Lesion Segmentation Metrics

Quantitative segmentation values are presented in figure 5 which shows accuracy in the detection of the retinal lesions. Excellent segmentation performance was achieved for hard exudates, with a precision score of 97.1%, F1 score and Dice coefficient of 96.9% and 96.2% respectively and IoU of 94.8%, which shows good delineation of the boundaries. The results for retinal lesion segmentation over different types of lesions are shown in Fig. 6. The results for the hemorrhage segmentation were also good with Dice of 95.7% and IoU of 94.1%.

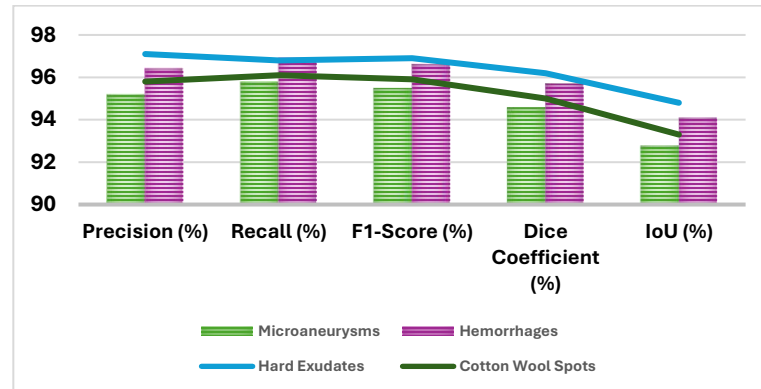


Fig.6. Comparative Retinal Lesion Segmentation Performance Analysis of the Proposed UNet++ Framework

The UNet++ model was particularly effective at capturing the presence of the microaneurysms, which are often very challenging to see and identify, with a Dice coefficient of 94.6%. Cotton wool spots were segmented with F1 score of 95.9%, IoU of 93.3%, which indicates a good overall segmentation accuracy.

6. DISCUSSION

By catching DR in its early stages, it is possible to avoid vision impairment, and minimize the risk of permanent blindness for diabetics. Early detection of retinal abnormalities can allow for timely intervention with the appropriate therapeutic options before there is significant retinal damage. An automated screening system could be used to complement large-scale population screening, by decreasing the load of diagnostics and increasing access to eye care, especially in areas where there is a shortage of specialists. This yields better patient outcomes, better disease management and lower healthcare costs, all of which are made possible through early detection via the use of AI.

UNet++ is an architecture that uses two levels of skip connections and feature aggregation from multiple scales to achieve better segmentation of retinal lesions. This design provides the ability to accurately localize some smaller pathological structures that are commonly linked to early stages of the disease (microaneurysms, haemorrhages and exudates). With the precise lesion delineation, false detections and overall diagnostic performance are reduced. UNet++'s improved segmentation performance delivers clinical neurosurgeons with fine-grained information for more accurate assessment and categorization of the disease.

Explainable Artificial Intelligence is key in enhancing transparency and trust in automated diagnostic systems. Methods like Grad-CAM and saliency maps can help visualise the areas of the retina that are important to the model's predictions, for clinicians to confirm that these are clinically relevant features. The interpretability mitigates black-box concerns and helps to make intelligent decisions. Explainable AI can enhance transparency, build trust, and foster accountability, thereby facilitating the practical implementation of intelligent retinal screening systems in real-world healthcare settings.

7. CONCLUSION

In this study, an integrated framework has been proposed which fuses UNet++ with EAI, for the early detection of DR from retinal fundus images. The suggested method alleviated the two major issues of AI-assisted healthcare systems, which were the ability to segment the retinal lesions correctly and provide a transparent clinical decision support system. The framework has been designed to handle these and other image preprocessing, quality assessment, normalization and augmentation steps comprehensively to enhance data consistency and its model's robustness. The UNet++ architecture was able to capture multi-scale retinal features and accurately segmented pathological regions like microaneurysms, hemorrhages and exudates. The experiments presented good performance by various segmentation and classification measures, which have been presented to show the effectiveness of the proposed methodology for early screening of DR. The use of Explainable AI techniques, along with excellent diagnostic accuracy, improved the transparency of the models by pinpointing regions within the image contributing to automated predictions. These visual explanations helped to build confidence of the clinicians, to verify results and to establish a trustworthy deployment in health care environments. The framework can be applied in large scale screening program and in computer aided diagnosis (CAD) in ophthalmology because it achieves precision in the localization and interpretation of the decision making process. Future studies may include investigating the potential of incorporating multi-modal retinal images, transformer models, and deployment techniques to enable real-time application in clinical practice, improving model diagnostic capabilities, scalability, and applicability to various healthcare settings

References:

1. Mutawa, A. M., Al Sabti, K., Raizada, S., & Sruthi, S. (2025). Explainable AI for Diabetic Retinopathy: Utilizing YOLO Model on a Novel Dataset. *AI*, 6(12), 301. <https://doi.org/10.3390/ai6120301>
2. Youldash, M., Rahman, A., Alsayed, M., Sebiany, A., Alzayat, J., Aljishi, N., Alshammari, G., & Alqahtani, M. (2024). Early Detection and Classification of Diabetic Retinopathy: A Deep Learning Approach. *AI*, 5(4), 2586-2617. <https://doi.org/10.3390/ai5040125>
3. Islam, S., Deo, R. C., Acharya, U. R., Barua, P. D., & Soar, J. (2026). MultiRetNet: A Lightweight Explainable AI Approach to Diabetic Retinopathy Grading and DME Detection Using Fundus-OCT Fusion. *Journal of Imaging*, 12(6), 236. <https://doi.org/10.3390/jimaging12060236>
4. Jukić, A., Pavan, J., Kalauz, M., Kopic, A., Markušić, V., & Jukić, T. (2025). Artificial Intelligence in Diabetic Retinopathy and Diabetic Macular Edema: A Narrative Review. *Bioengineering*, 12(12), 1342. <https://doi.org/10.3390/bioengineering12121342>

5. Singh, A., Jain, S., & Arora, V. (2025). A Multi-Model Image Enhancement and Tailored U-Net Architecture for Robust Diabetic Retinopathy Grading. *Diagnostics*, 15(18), 2355. <https://doi.org/10.3390/diagnostics15182355>
6. Alghamdi, H. S. (2022). Towards Explainable Deep Neural Networks for the Automatic Detection of Diabetic Retinopathy. *Applied Sciences*, 12(19), 9435. <https://doi.org/10.3390/app12199435>
7. Ashraf, M. H., Mehmood, M. N., Ahmed, M., Hussain, D., Khan, J., Jung, Y., Zakariah, M., & AlSekait, D. M. (2025). HIRD-Net: An Explainable CNN-Based Framework with Attention Mechanism for Diabetic Retinopathy Diagnosis Using CLAHE-D-DoG Enhanced Fundus Images. *Life*, 15(9), 1411. <https://doi.org/10.3390/life15091411>
8. Sorrentino, F. S., Gardini, L., Fontana, L., Musa, M., Gabai, A., Maniaci, A., Lavalle, S., D'Esposito, F., Russo, A., Longo, A., Surico, P. L., Gagliano, C., & Zeppieri, M. (2024). Novel Approaches for Early Detection of Retinal Diseases Using Artificial Intelligence. *Journal of Personalized Medicine*, 14(7), 690. <https://doi.org/10.3390/jpm14070690>
9. Lakshminarayanan, V., Kheradfallah, H., Sarkar, A., & Jothi Balaji, J. (2021). Automated Detection and Diagnosis of Diabetic Retinopathy: A Comprehensive Survey. *Journal of Imaging*, 7(9), 165. <https://doi.org/10.3390/jimaging7090165>
10. Khan, M. B., Ahmad, M., Yaakob, S. B., Shahrior, R., Rashid, M. A., & Higa, H. (2023). Automated Diagnosis of Diabetic Retinopathy Using Deep Learning: On the Search of Segmented Retinal Blood Vessel Images for Better Performance. *Bioengineering*, 10(4), 413. <https://doi.org/10.3390/bioengineering10040413>
11. Mane, D., Ashtagi, R., Suryawanshi, R., Kaulage, A. N., Hedao, A. N., Kulkarni, P. V., & Gandhi, Y. (2024). Diabetic retinopathy recognition and classification using transfer learning deep neural networks. *Traitement du Signal*, 41(5), 2683.
12. Padthe, Adithya, Rashmi Ashtagi, and Ramya Thatikonda. "Enhancing medical image segmentation using deep learning techniques." *Artificial Intelligence and Information Technologies* (2024): 185-188.
13. Shimbre, N., & Solanki, R. K. (2025). Activation heatmap-guided FT-MultiCNN: advancing skin cancer classification through transfer learning. *Ingenierie des Systemes d'Information*, 30(5), 1349.