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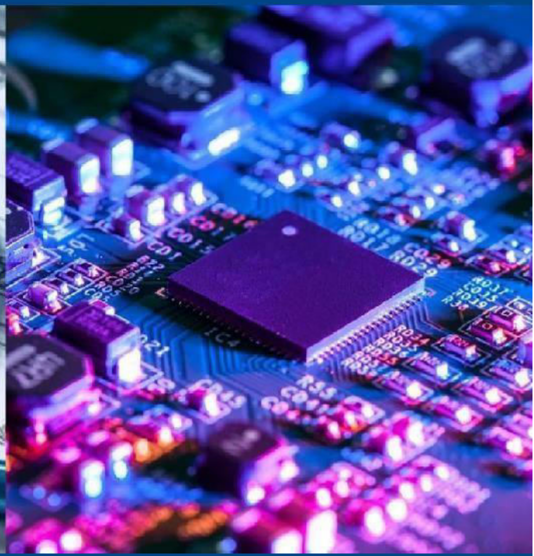

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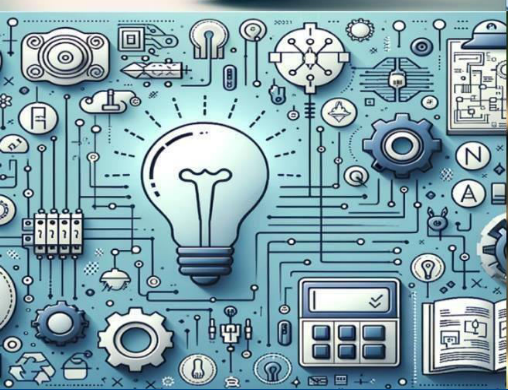

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ClaSegDR- A HYBRID DEEP LEARNING ARCHITECTURE WITH ATTENTION MECHANISMS FOR DIABETIC RETINOPATHY SEGMENATION AND CLASSIFICATION.

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ABSTRACT: Diabetic retinopathy is the adverse effect of the diabetes mellitus. This is a case in which the retinal structures are affected and results in visual impairment. Early detection can help in efficient and accurate diagnosis. The asymptomatic nature of the retinal changes makes the identification of the DR challenging. There are many existing models that were developed for either classification of DR severity or used for retinal lesions using segmentation. Most models lack the ability to perform both the tasks. In order to overcome this, hybrid models were recently introduced for both segmentation and classification tasks. Which were restricted with the challenges. The proposed model performs DR classification and lesion segmentation concurrently by utilizing the perks of MobileNet with DenseNet and U-Net. High diagnostic accuracy and enhanced interpretability are made possible by an attention-driven fusion mechanism that combines global and lesion-specific retinal information. The model outperforms existing hybrid models while ensuring interpretability, efficiency, and excellent multi-level Diabetic Retinopathy grading, achieving a segmentation Dice coefficient of 0.9501 and classification accuracy of 98.42% on the test dataset.

KEYWORDS: Diabetic Retinopathy, Deep learning, Hybrid model, Classification, Segmentation

I. INTRODUCTION

In diabetes mellitus, many complications arise apart from sugar level drops. The patients having diabetes face the most common complication of diabetic retinopathy. It mainly occurs due to the chronic hyperglycemia. Then followed by damage to the retina blood vessels that leads to serious health problems such as hemorrhages and exudates; if it persists, then this advances to neovascular issues and retinal detachment. This became the significant cause for the vision impairment and irreversible blindness.

In the paper [1], it was rightly pointed out that over 537 million people were living with diabetes globally in 2021, and it is also projected to rise immensely by the year 2030. Also, it is estimated that one-third of the individuals will build this over their lifetime. The progression of diabetic retinopathy in an individual's lifetime is asymptomatic in its early stages [1]. The major challenge faced is the manual detection that is a time-consuming process. Worldwide, accessibility to the specialized eye care professionals and the tools is limited, especially in the underdeveloped regions of any country. This adds up to even more prolonged treatments and diagnoses. Hence the need to find solutions is a must that are scalable, fast, and give the accurate diagnosis [2]. Over the years there have been automated systems that were developed by the ophthalmologists in the detection of the DR, although the traditional machine learning methods relied solely on the features that were handcrafted and the classifiers that used SVMs and decision trees. Machine learning models were providing the initial insights; they had a very significant limitation, which was their dependency on the manual feature extraction, and their ability to generalize was not up to the mark [3]. Then the focus shifted to the deep learning models that solved the major issues given by the machine learning models. In the area of deep learning, convolutional neural networks have become the foundational architecture for many computer vision tasks, especially in medical image analysis. These have made their way into the processes of classification and segmentation detection. They have shown exceptional skill in extracting the information. There are many models that were proven to have high reliability and accuracy in detecting the DR [4]. Even though the advancements are made available, these CNN models are only used for segmentation or classification purposes. The classification of the DR gives the predictions of the class but lacks in the detection of the lesions, such as microaneurysms, hemorrhages, or exudates, etc., which are important for decision-making purposes and the ability to localize them. Whereas segmentation models provide detailed lesions but lack the ability to classify these maps. Hence, these limit the clinical adaptability. Just like machine learning models, the deep learning models also face the challenges in clinical interpretation due to class imbalance and interpretability. This imbalance can also lead to false predictions and reduce the sensitivity of the model. Recent research has been guided in the way of hybrid models that are focused on mitigating these challenges[5]. Recent research has been guided in the way of hybrid models that are focused on mitigating these challenges. These hybrid models take the advantages of both classifiers and segmentation. These models are not only developed to localize regions within the images but also to classify accurately the severity of the disease. The major advantage of such models is that they can extract features excellently, which in turn increases the model interpretability. There were many advancements in the region of hybrid models, such as the U-Net with powerful feature extractors, which is the popular architecture to adapt the features or lesions. This model alone has been employed with many other models, like ResNet, DenseNet, or vision transformers, in order to increase the capability of the model to capture the fine details in the image [5]. Apart from this, the attention architectures or lesion-specific branches are integrated in these models that increase the overall performance of the model. These are added in the backbone of the architecture, which helps the model to selectively capture the clinically relevant regions. These hybrid models are also employed in multitasking strategies that enable prediction as well as segmentation on the same architecture. Due to this, the hybrid models are widely utilized and continuing to evolve in the field of medical image processing.

This paper introduces a hybrid model that brings together the robust feature extraction capabilities of classification architectures such as MobileNet and DenseNet with the encoder and decoder advantages of the U-Net architecture. The proposed hybrid architecture combines lesion segmentation and disease classification to overcome the difficulties in accurately and explicably detecting diabetic retinopathy. Our model utilizes both global retinal context and localized lesion details by combining segment outputs with deep features from MobileNetV2 and DenseNet121 through an attention mechanism. The model overcomes the challenges of earlier independent models by utilizing both pixel-wise and image-level supervision to accurately represent localized lesion features and overall disease severity. By combining the advantages of both individual models, our hybrid model is able to achieve both segmentation and classification tasks simultaneously. The proposed model achieved robust performance, and it is a computationally efficient solution for automatic diabetic retinal screenings.

II. LITERATURE REVIEW

The detection and segmentation models are widely available for computer vision and image processing. Classification of diabetic retinopathy is a crucial step in early detection and diagnosis. Although there were many machine learning models that used both supervised learning and unsupervised learning to classify and segment separately. In 2019, the authors in the paper [6], the author have proposed a multi-channel CNN for automatic detection from fundus images. It leveraged the multiclass input strategy and was designed to handle variability. The evaluated dataset was EyePACS. The model gave a classification accuracy of 97.08. This model solely focuses on the classification task. In the 2020 paper [7], the authors have emphasized the need for early detection for the DR, so they saw that manual diagnosis is time-consuming from fundus images. Hence, they proposed a deep learning model, particularly CNN, that was trained to detect the severity of the fundus images, especially color images. However, the class imbalance is observed, and also the major drawback was that lesion-level interpretability was not there. In [8], the authors have proposed a segmentation model, UNet, which enhanced the connections of the encoder and decoder to get sublevel pixels of the images and create lesions. It was basically created to address the challenges that occurred in images, such as the size of the lesion and the distribution. As manually grading is a very difficult and time-consuming task. The model achieved a dice score of 0.99 and an accuracy above 99%. It was trained on the IDRiD and e-ophtha datasets, which are publicly available. Gayathri et al. [9], proposed a framework that leverages the advances of the deep learning and the machine learning techniques to enhance the diagnostic accuracy. this model uses the architecture of M-CNN—multipath convolutional neural network—to extract the features, including local and global, from the fundus images. Then these image segmentations are sent to the traditional machine learning classifier. The model is effective in terms of extraction and classification. In [10], this paper points out the research gap about the availability of skilled professionals for this task in India. The author addresses that focusing on artificial intelligence and machine learning to automate detection and grading of the DR will significantly reduce the impairment complications in the diabetic patients. In the paper [11], the proposed architecture used the multiclass segmentation framework. The model differentiated between 3 classes—exudates, microaneurysms, and hemorrhages—using a U-Net architecture that has the encoder as the EfficientNet. The architecture achieved an accuracy of 99.33% and an IoU score of 88.26%. This approach leveraged both classification and segmentation task advantages. Joddar et al. [12], proposed an architecture using a deep learning framework for binary classification using the fundus images and also the optical coherence tomography. The model classifies the images into 2 classes: No_Dr and DR. The authors focused on the model's ability to generalize and its accuracy, which demonstrated the promising results and efficient solutions. In [13], the authors proposed a deep learning framework that uses the EfficientNetB0. The model was trained on the Kaggle DR dataset. The model achieved the average accuracy even with extensive experiments. This study mainly focused on the severity levels of DR using the model. Sushith et al. [14], proposed a novel hybrid deep learning framework. Which uses the CNNs and RNNs that are connected together using an attention mechanism. It determines the progression of DR by understanding the sequential retinal images and changes over time. The CNN captures the patterns, whereas the RNN uses the attention mechanism to prioritize the relevant information. The dataset used is from Kaggle, and the accuracy obtained is 94.04%. Henge et al. [15], introduced a hybrid model that uses the advantages of both Inception and ResNet architectures. It was structured with 172 layers. It was trained on the fundus images. The model achieved the accuracy of 98.1% and outperformed the existing hybrid models. In the paper [16], a deep learning framework for classification is proposed. It was used for the severity classification for the DR and diabetic macular edema. It uses a multistage pipeline. The model achieved the accuracy of 98.1%. Musluh et al. [17], proposed a framework for classification only. It uses synthetic lesion generation, semantic segmentation, and morphological feature extraction. This model generated the artificial lesion mask to highlight the pathological regions. Later the author used these segmentation masks on other models and achieved a classification accuracy of 93.71% and a kappa score of 93.71%. Moreover, this model also provides an explanation of its predictions. Mok et al. [18], proposed a deep learning framework that uses Swin UNet for segmentation with a cross-attention-driven classification model. This model segments and then classifies the images. The cross-attention mechanism is used to enhance the ability of the model to extract the features. The model achieved the accuracy of 94.6%. This approach is an effective combo of the lesion segmentation and then classification tasks. So the existence of hybrid models is significantly increasing due to the concept of leveraging the advantages of two or more models, which, of course, increases the complexity of the model, but it also provides the multitasking architecture.

III. METHODOLOGY

A. Dataset

The APTOS 2019 Blindness Detection dataset, comprised of Gaussian-filtered retinal fundus images classified into five DR severity levels—No_DR, Mild, Moderate, Severe, and Proliferate_DR—is the source of the dataset used in this research. The dataset has been stratified and divided into training and testing subsets with an equal number of samples per class in order to ensure balanced learning and minimize the disparities between classes because the original dataset lacked segmentation masks. This transformed the dataset into a supervised format suitable for joint classification and segmentation. Through meticulous preprocessing, every image-mask pair was precisely aligned, allowing for efficient dual-task training in our proposed hybrid architecture.

B. Existing models

Numerous hybrid frameworks for the study of Diabetic Macular Edema (DME) and Diabetic Retinopathy (DR) have been developed as a result of the latest developments in deep learning. One such model combines an AlexNet-DQN classifier optimized by ExpGD STFA with GD STFA-enhanced SwinUNet for lesion segmentation [16]. Although it captures lesion-level information well, scalability is limited by high processing cost and reliance on the IDRiD dataset. Another model uses a Swin-T classifier with cross-attention and a cross-learning approach that combines fundus images with lesion maps generated by Swin U-Net [18]. This enhances feature richness, but its complex architecture and dependence on pre-trained segmentation limit applicability in a variety of contexts. For better interpretability, a third strategy concentrates on generating artificial lesion masks and extracting morphological characteristics. It has difficulties because of bias in synthetic data and a more sophisticated pipeline, even though it generates visual explanations that are therapeutically relevant. Strong outcomes have also been demonstrated using a robust multi-stage pipeline that incorporates DeepLabV3 (Xception backbone) with features from EfficientNet-B0 and SqueezeNet [19]. The model MTNet jointly performed the segmentation and the classification tasks. The architecture involves the UNet, which is used for segmentation purposes. This is built upon the CSP_UNet, which is the backbone of the segmentation. Then this branch is connected to the binary classifier branch [20].However, its actual deployment practically in real-world scenarios is hindered by its reliance on numerous deep models and carefully curated datasets. Finally, a thorough analysis of DR models emphasizes the benefits of multi-task learning while pointing out its drawbacks, including its lack

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of clinical scalability, poor explainability, and restricted demographic coverage. Our suggested framework was developed as an answer to those constraints, which together bring out the need for a unified, interpretable, and effective model that may provide excellent diagnostic performance without compromising generalizability or development readiness.

C. Proposed model

For automated diabetic retinopathy (DR) detection, the model proposed is a hybrid deep learning framework that combines lesion segmentation and disease categorization into one, seamless end-to-end system. An RGB retinal fundus image that has been scaled to 224×224×3 pixels serve as the model's input. It is processed through one auxiliary pathway and two parallel branches. Both visual interpretability and lesion-specific features for classification are provided by the first branch, an encoder–decoder segmentation network inspired by U-Net that records fine lesion details and creates a 224×224×1 lesion probability map.ementary high-level features.

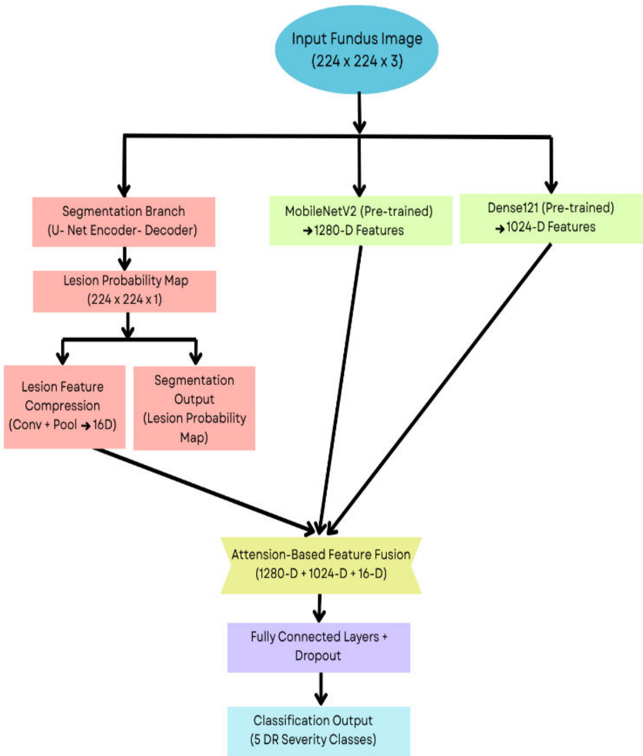


Fig1- Proposed model architecture

DenseNet121 captures larger structural context, while MobileNetV2 captures texture-rich local patterns. To create a compact 16-dimensional representation, the segmentation branch's lesion mask is subjected to feature compression using convolution and pooling. An attention-based fusion mechanism is then used to integrate these three feature sources: MobileNetV2 (1280-D), DenseNet121 (1024-D), and compressed lesion features (16-D). Depending on the situation, this mechanism adaptively allocates emphasis to lesion-specific or global data.The probability distribution across the five DR severity categories—No_DR, Mild, Moderate, Severe, and Proliferative_DR—is produced by a final softmax layer after the fused vector has been run through fully connected layers with dropout regularization. The model is well suited for clinical decision-making because of its dual-task design, which allows it to provide interpretable lesion localization in addition to better accuracy in DR severity classification. The approach's unique feature is its lesion-aware classification technique, which ensures both diagnostic accuracy and transparency by directly incorporating segmentation output into the classification process through adaptive attention fusion.

IV. RESULTS

From the Fig. 2 it is evident that the proposed architecture is successfully classifying and segmenting the images by predicting the predicted mask for the input image, which demonstrates the ability of the architecture to detect the DR severity. The input fundus images are taken as is, from the dataset, in which it was observed that few of the images were too much zoomed in, or not fully showing the oval shape of the eye.

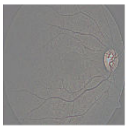
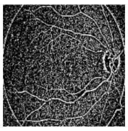
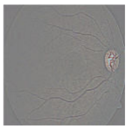
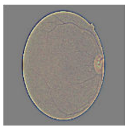
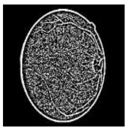
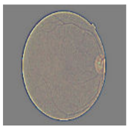
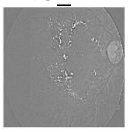
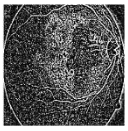
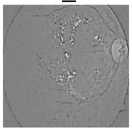
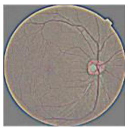
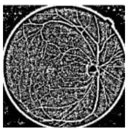
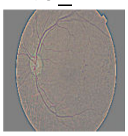
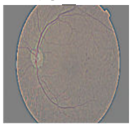
Model	Input image	Predicted mask	Predicted class
AlexNet - DNQ -UNet	 NO_DR		 NO_DR
Swin U-Net+ Dual Input Classification	 NO_DR		 NO_DR
U-Net + FusionClassifier	 Severe		 Severe
Unet++ DenseNet121	 NO_DR		 NO_DR
Proposed model	 Mild_DR		 Mild_DR

Fig. 2 - Sample results from all the model. (a) Input image, (b) Predicted Ground truth mask, (c) Predicted class

In comparison with the other existing models, as it is mentioned in Table 1, the AlexNet-DQN-UNet, Swin U-Net with dual input, and UNet++ with DenseNet121 predicted the image as NO_DR, indicating potential under-detection. The U-Net + FusionClassifier, correctly identified more advanced stages—such as Severe and Proliferative DR, respectively—showing their strength in late-stage detection. Even with the zoomed in images or not fully shown oval shape of the image, the architecture propsed is able to capture the patterns to do the assigned tasks perfectly.

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Table 1- Classification evaluation metric

Models	Accuracy	Precision	Recall	F1-Score
AlexNet -DNQ -UNet	59.06	61.83	59.0	58.22
Swin U-Net+ Dual Input Classification	20.87	4.35	20.8	7.20
U-Net + FusionClassifier	97.64	97.71	97.6	97.64
Unet++ DenseNet121	98.03	98.01	98.07	98.03
Proposed model	98.42	98.39	98.4	98.40

In Table 1, it is evident that the proposed model achieved the highest classification accuracy, precision, recall, and F1 score, since, the classification model is using dual classification architectures that is MobileNet and DenseNet that had individual advantages, which when combined together has stronger classification results compared to the existing architectures used for classification task. This strongly indicates that the proposed architectures classification task is able to generalize better compared to the existing models.

Table 2- Segmentation evaluation metrics

Models	Mean Dice Coefficient	Mean IoU
AlexNet -DNQ -Unet	97.66	95.43
Swin U-Net+ Dual Input Classification	97.19	94.54
U-Net + FusionClassifier	92.00.	85.28
Unet++ DenseNet121	87.55	77.91
Proposed model	97.36	94.85

In Table 2. proposed model has demonstrated competingly strong performance getting its results near to the Exisiting architecture by [16] whose Dice score achieved is 0.9766 and IoU is 0.9543. This shows that the proposed model excelled in the classification task and maintained the ability to segment quite high in the segmentation task.

V. CONCLUSION

The study introduces a novel hybrid deep learning framework that the advantages of both segmentation and classification models. The architecture used has also leveraged the benefits of attention mechanism, which enables the model to get deeper insights and capturing the intricate patterns to do a supervised classification and segmentation. In this work, an integrated deep learning solution is presented which utilizes a single pipeline to both identify retinal lesions and assess the severity of the condition. The model provides clear visual cues to enhance clinical reasoning and produces reliable

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predictions by utilizing complementing information from several backbones and directing their interaction through attention. With a classification accuracy of 99.21% and a Dice coefficient of 0.9736, our findings demonstrate that our dual-branch model greatly enhances both diagnostic accuracy and lesion-level interpretability. This certifies the proposed model as an entirely automated DR analysis solution. This work has proved that the parallel hybridization of models can significantly increase the capabilities of any model. In areas with limited resources, like Medical, the combination of severity categorization with interpretable lesion maps improves clinician trust and facilitates decision-making. In conclusion, the automated analysis of diabetic retinopathy using the proposed architecture has significantly shown results surpassing the existing architectures with similar intension in achieving both segmentation and classification. Hence, this study, provides a solid, comprehensible, and clinically feasible framework that connects segmentation and classification, thereby establishing the foundation for further advancements in related areas.

VI. FUTURE SCOPE

Despite its incomparable performance, the architecture has some drawbacks. As the segmentation masks were annotated using the unsupervised learning algorithm, there is high chances of subjectivity involved, and in return might not scale well to larger datasets. In addition, just one dataset was utilised for both training and verification, which would restrict the architecture's applicability to different demographics or imaging scenarios. To improve scalability and generalizability, further research can improve our findings by implementing domain adaptation strategies, automated lesion labelling, and testing across multi-institutional datasets.

REFERENCES

[1] Si-Yu Gui, Xin-Chen Wang, Jian-Chao Qiao, Si-Yu Lin, Qian-Qian Wang, Meng-Yue Zhang, Yue-Yang Xu, Zhi-Hao Huang, Li-Ming Tao, Cheng-Yang Hu, Fang-Biao Tao, Zheng-Xuan Jiang and Dong-Wei Liu, "Association of retinopathy with risk of all-cause and specific-cause mortality in the National Health and Nutrition Examination Survey, 2005 to 2008," Frontiers in Public Health, vol. 11, 2023.

[2] Gopal S.Pillai, Bhibuti Sinha, Sheeba C.S, Manabjyoti Barman, Alok Sen, S.Natarajan, Merin Dickson, Anjana Abhilash, Sumit K U, Samruddhi Dhani, Ashid Salim, Shamlin Joyal, Manjisa Choudhury, Aniket Kumar, Deepthi K G, Jamil Ahmed and Poonam Jangid, "Assessing Visual Acuity, Impact Of Ocular And," Dental and Medical Sciences, vol. 23, no. 12, pp. 22-31, 2024.

[3] Pooja Bidwai, Shilpa Gite, Kishore Pahuja and Ketan Kotecha, "A Systematic Literature Review on Diabetic Retinopathy Using an Artificial Intelligence Approach," Big Data and Cognitive Computing, vol. 6, no. 4, 2022.

[4] Nazeef Ul Haq, Talha Waheed, Kashif Ishaq, Muhammad Awais Hassan, Nurhizam Safie, Nur Fazidah Elias and Muhammad Shoaib, "Computationally efficient deep learning models for diabetic retinopathy detection: a systematic literature review," Artificial Intelligence Review, vol. 57, 2024.

[5] Richa Vij and Sakshi Arora, "A hybrid evolutionary weighted ensemble of deep transfer learning models for retinal vessel segmentation and diabetic retinopathy detection," Computers and Electrical Engineering, vol. 115, 2024.

[6] M. Mohsin Butt, Ghazanfar Latif, D.N.F. Awang Iskandar, Jaafar Alghazo and Adil H. Khan, "Multi-channel Convolutions Neural Network Based Diabetic Retinopathy Detection from Fundus Images," Procedia Computer Science, vol. 163, pp. 283-291, 2019.

[7] Wejdan L. Alyoubi, Wafaa M. Shalash and Maysoon F. Abulkhair, "Diabetic retinopathy detection through deep learning techniques: A review," Informatics in Medicine Unlocked, vol. 20, 2020.

[8] Nitigya Sambyal, Poonam Saini, Rupali Syal and Varun Gupta, "Modified U-Net architecture for semantic segmentation of diabetic retinopathy images," Biocybernetics and Biomedical Engineering, vol. 40, pp. 1094-1109, 2020.

[9] S. Gayathri, Varun P. Gopi and P. Palanisamy, "Diabetic retinopathy classification based on multipath CNN and machine learning classifiers," Physical and Engineering Sciences in Medicine, vol. 44, pp. 639-653, 2021.

[10] Naveenkumar, M., Srithar, S., Maheswaran, T., Sivapriya, K., Brinda and B.M, "Diabetic Retinopathy Disease Classification Using EfficientNet-B3," in Innovative Data Communication Technologies and Application, 2022.

[11] N Padmasini, G.K Krithika, P Lithiga and S.J Akshaya, "Automatic Detection And Segmentation Of Retinal Manifestations Due To Diabetic Retinopathy," in International Conference on Signal Processing, Computation,

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Electronics, Power and Telecommunication (IConSCEPT), Karaikal, India, 2023.

[12] Sayani Joddar, Aarushi Verma, Pranav Mamgain, Sushruta Mishra, Zabiha Khan and Rajeev Sobti , "Diabetic Retinopathy Determination Using Deep Learning Approach," in Innovative Computing and Communications, 2024.

[13] Lakshay Arora, Sunil K. Singh, Sudhakar Kumar, Hardik Gupta, Wadee Alhalabi, Varsha Arya, Shavi Bansal, Kwok Tai Chui and Brij B. Gupta, "Ensemble deep learning and EfficientNet for accurate diagnosis of diabetic retinopathy," vol. 14, 2024.

[14] Mishmala Sushith, A. Sathiya, V. Kalaipoonguzhali and V. Sathya, "A hybrid deep learning framework for early detection of diabetic retinopathy using retinal fundus images," Scientific Reports, vol. 15, 2025.

[15] S. K. Henge, N. R. Viraati, M. Alhussein, A. S. Kushwaha, K. Aurangzeb and R. Singh, "Detection of Diabetic Retinopathy Using a Multi-Decision Inception-ResNet-Blended Hybrid Model," IEEE Access, vol. 13, pp. 8988-9005, 2025.

[16] A. S. Sabeena and M. K. Jeyakumar, "A hybrid model for diabetic retinopathy and diabetic macular edema severity grade classification," International Journal of Diabetes in Developing Countries, 2025.

[17] Saif Khalid Musluh, Ammar M. Okran, Saddam Abdulwahab, Domenec Puig and Hatem A. Rashwan , "Advanced Diabetic Retinopathy Classification: Integrating Pathological Indicators Segmentation and Morphological Feature Analysis," Ophthalmic Medical Image Analysis, vol. 15188, pp. 104-114, 2024.

[18] Dahyun Mok, Junghyun Bum, Le Duc Tai and Hyunseung Choo, "Cross Feature Fusion of Fundus Image and Generated Lesion Map for Referable Diabetic Retinopathy Classification," in Proceedings of the Asian Conference on Computer Vision, 2024.

[19] Meher Boulaabi, Takwa Ben Aïcha Gader, Afef Kacem Echi and Sameh Mbarek, "Advanced Segmentation of Diabetic Retinopathy Lesions Using DeepLabv3+," [Online]. Available: https://arxiv.org/html/2504.17306v1. [Accessed 05 07 2025].

[20] Ruochen Liu, Song Gao, Hengsheng Zhang, Simin Wang, Lun Zhou and Jiaming Liu, "A combined diagnosis algorithm of vessel segmentation and diabetic retinopathy for retinal images.," PLoS One, 2022.

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