International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Cross Modality Feature Fusion Framework for Diabetic Retinopathy Image Classification

[1]Preeti .Rohit. Deshmukh, [2]Vijaya. Rahul. Pawar, [3]Arun .Natha. Gaikwad
[1]E&TC, Zeal College of Engineering and Research, Pune-411041, Maharashtra, INDIA,
and *Vidya Vikas Pratisthan Institute*
of Engineering and Technology,
Solapur, Maharashtra, INDIA,
preetikadam110@gmail.com
[2]E&TC, Bharati vidyapeeth college of *Engineering for women,*
Pune-411043, Maharashtra, INDIA
Vijaya.Kashid@bharatividyapeeth.edu
[3]E&TC, Zeal College of Engineering and Research Center,
Pune-411041, Maharashtra, INDIA
arungkwd47@gmail.com

Abstract— Diabetic retinopathy (DR) is a prevalent ocular condition and a prominent contributor to vision impairment in individuals with diabetes. Consistent monitoring through fundus photography and prompt intervention represents the most efficient strategy for controlling this ailment. Given the substantial diabetic patient population and their extensive screening needs, there is a growing inclination towards harnessing computer-aidedand entirely automated methods for diagnosing DR. Over the pastyears, deep neural networks have achieved remarkable progress across a wide range of applications. Consequently, automating the diagnosis of DR and delivering tailored recommendations to DR patients underscores the significance of accurate and intricateDR classification. In this work, we have present a cross modality feature fusion based framework for diabetic retinopathy (DR) image classification. Here, cross modality means RGB image and it's green channel. Initially, we have present multi-scale multi- receptive feature extraction block to learn the local and global features from both the modalities. Further, the learned features at various scale are fused effectively with present multi-levelfeature fusion block for image classification task. We evaluated our present framework on MESSIDOR and IDRID database by comparing it to state-of-the-art (SOTA) deep learning frame-works for DR image classification. The result analysis clearly demonstrate that the present cross-modality feature fusion basedclassification framework outperforms existing SOTA frameworksin terms of various evaluation parameters.
.

Keywords- Cross Modality, Non-proliferative and proliferative diabetic retinopathy, Deep Learning, Classification

I. INTRODUCTION

Diabetic retinopathy often develops without any noticeable symptoms in its early stages. However, as the condition progresses, the symptoms like blurred or distorted vision, floaters (small dark spots), impaired color vision, fluctuating vision, loss of central vision may become apparent. In advanced stages, you may lose central vision, which is critical for tasks like reading, recognizing faces, and driving. Historically, the assessment of diabetic retinopathy (DR) grade has been conducted by considering a combination of various structural characteristics observed in color fundus images. These features encompass the presence of microaneurysms, exudates, hemorrhages, and neovascularization, among others [1]. Over the past two decades, image classification has evolved into a proficient and high-demand research area, particularly within the realms of automated medical, scientific, and educational sectors, as well as various computer vision applications. Interactive media, such as images and videos, are consistently being generated and shared on social media platforms, thanks to the

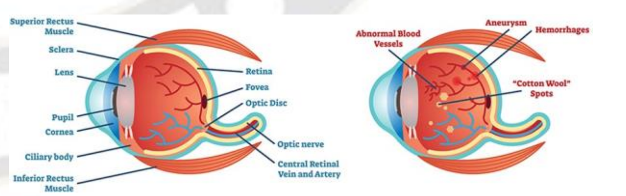

Fig. 1. Sample eyes with and without diabetic retinopathy (*left part: Healthy eye and right part: Diabetic eye*). Diabetic retinopathy is a condition that arises as a consequence of the harm inflicted by diabetes on the tiny blood vessels situated within the retina of the eye.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

proliferation of advanced data-capturing devices like smart-phones and high-speed internet connections. Consequently, extensive digital databases or repositories have been established.Likewise, within the field of healthcare, substantial medical databases have been created, fueled by advanced techniques for patient diagnosis, treatment planning, and the evaluationof treatment responses.

According to the World Health Organization (WHO), in 2014, there were 422 million individuals diagnosed with diabetes, and of that number, 35% developed some form of retinopathy due to the accumulation of damage to small blood vessels in the retina [2]. Assessing diabetic neovas-cularization and macular edema in laboratory animals has posed challenges. Because most commonly used species lack a macula and fail to exhibit the characteristics seen in advanced diabetic retinopathy in human patients, especially in terms of retinal neovascularization and thickening. Figure 1 illustrates the differences between diabetic retinopathy in a healthy eye and a compromised one, featuring various types of DR lesions. Diabetic retinopathy is a medical condition that affects the

retina of the eye and can lead to vision problems, including blindness. The DR patient with high blood pressure, high hemoglobin A1c are considered at highest risk. Immediate screening with medical expertise is required to recover from the various issues [3]. Therefore, regular screening is essential for detection or DR at early stage. Generally, DR hasfour different types of lesions *i.e.,* Microaneurysms (MA), Haemorrhages (HM), soft and hard exudates [4]. The detailed explanation for each type of DR images is given below:

- **Microaneurysms (MA)** represent an initial stage in the progression of diabetic retinopathy. These are characterized by the presence of small, red, round dots on the retina, which occur due to the weakening of the blood vessel walls. Early detection and management of microaneurysms are crucial in preventing the advancement of diabetic retinopathy and preserving vision [4].
- **Hemorrhages (HM)** in the context of diabetic retinopathy are identified by the presence of larger spots on the retina. These spots typically have irregular margins and can be larger than 125 micrometers in size, which distinguishes them from microaneurysms. Recognizing and monitoring hemorrhages is important in assessing the severity of diabetic retinopathy as it progresses to more advanced stages [5].
- **Hard exudates** are a result of plasma leakage in the con-text of diabetic retinopathy. These exudates are visible as yellow spots on the retina and are caused by the leakage of plasma from damaged blood vessels. The presence of hard exudates is an important clinical sign, and their detection and management play a role in assessing and treating diabetic retinopathy [6].
- **Soft exudates**, also known as cotton wool spots, area consequence of nerve fiber swelling in the context of diabetic retinopathy. These exudates appear as white, oval-shaped areas on the retina. They are associated with localized damage to the nerve fibers and are a significant sign of retinal involvement in diabetic retinopathy. Detecting and monitoring soft exudates is crucial in managing the condition and preventing further vision impairment [7].

Microaneurysms and hemorrhages typically manifest as red lesions on the retina, while both types of exudates (hard and soft exudates) appear as bright lesions. These differences in color and appearance are significant characteristics used in diagnosing and categorizing diabetic retinopathy, aiding healthcare professionals in determining the stage and severity of the condition. Diabetic retinopathy detection typically involves identifying five distinct stages of the condition, whichare: No Diabetic Retinopathy, Mild Diabetic Retinopathy, Moderate Diabetic Retinopathy, Severe Diabetic Retinopathy and Proliferative Diabetic Retinopathy [8]. To address this issue, image classification has emerged as an effective solution,enabling efficient access to medical image data. Traditional approaches have relied on manually crafted techniques forclassifying images, but these methods prove ineffective when dealing with extensive databases. Thus in this paper, we have proposed deep learning based DR classification approach. Themajor contributions are:

1) A novel approach with cross modality (*RGB and Green channel*) feature fusion is presented for diabetic retinopathythy image classification.
2) The detailed experimental analysis with present and existing approaches is performed on MESSIDOR [9] and IDIRD [10] databases.

II. Literature Survey

The significant number of individuals diagnosed with diabetes and the high prevalence of diabetic retinopathy (DR) among them have spurred a growing demand for automated DR diagnosis systems. Over time, considerable progress has been achieved, and satisfactory results have been obtained in several sub-problems, such as vessel segmentation and lesion detection. However, it’s essential to note that these outcomes have primarily been derived from relatively small datasetsand are still a considerable distance from practical real-world applications. The choice of the most suitable treatment for patients with diabetic retinopathy can vary depending on the disease stage. For patients with no DR or mild non- proliferative diabetic retinopathy (NPDR), regular screening is typically sufficient. The sample images for various classes are provided in the Figure 2. However, for patients with moderate NPDR or more severe conditions, treatment options can range from scatter laser therapy to vitrectomy. Therefore, accurately grading the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

severity of a patient's DR is a crucial initial stepin providing them with the appropriate and timely treatment [11].

Seepthi *et al.* [12] proposed a methodology that employs morphological operations and segmentation procedures to detect blood vessels, exudates, and microaneurysms in retinal fundus images. The retinal fundus image is divided into four sub-frames, and various features are extracted. Wavelet transformations are applied to these extracted features, followed by principal component analysis to enhance feature quality. Neural network back propagation and the one-rule classifier methods are employed to classify the images as diabetic or non-diabetic. In the work of Amin *et al.* [13], a DR model was developed to automatically differentiate retinal images into regions with exudates and non-exudates. This technique involves pre-processing, starting with lesion extraction, feature extraction, and image classification. Jiang *et al.* [14] proposed gradient-weighted class activation mapping for multi-label classification of diabetic retinopathy images. The correlation between diabetic retinopathy and its complication *i.e.,* diabetic macular edema with cross stage attention is studied in [15].

In [16], as part of simulating the diagnostic process, a novel approach is introduced. It involves the use of a two-stream binocular network designed to capture subtle correlations between the left and right eyes. This innovative design allows the model to effectively leverage information from both eyes to enhance the diagnostic capabilities, potentially leading to more accurate and robust results. The authors have introduced a two-stream model in [17]. This model employs the image itself as one input stream and also incorporates one of its individual channels as a complementary input stream. This approach aims to harness both the full image information and specific channel data to enhance the model's performance and capture a broader range of features and characteristics in the input data.

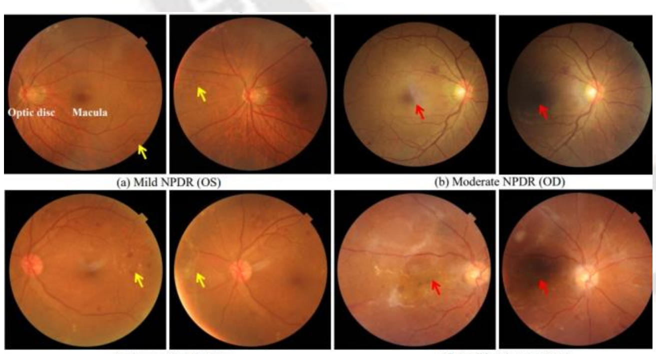

Fig. 2. Sample images for mild, moderate, severe non-proliferative and proliferative diabetic retinopathy classes. *Here, the degraded part on each retinaimage is marked with arrow. We can observe that the each class has different level of degradation.*

He *et al.* [18] introduce a novel component known as the Category Attention Block (CAB). This block is designed to delve into region-specific features that are more discriminative for each diabetic retinopathy (DR) grade. Importantly, it ensures that each category, or DR grade, is treated withequal importance, allowing the model to focus on the unique features associated with each grade for more accurate and balanced classification. Authors proposed a joint learning of multi-level tasks for diabetic retinopathy grading approach on low-resolution fundus images [19]. This approach likely involves the simultaneous learning of multiple aspects or tasksrelated to DR grading at different levels, with a focus oneffectively handling low-resolution fundus images. The goal is to improve the accuracy and robustness of DR gradingunder conditions where image quality may be limited. The framework is designed to facilitate the joint training of sub- networks involved in tasks related to image quality assessment, image enhancement, and diabetic retinopathy (DR) disease grading [20]. This unified approach allows these sub-networks to work together and learn from one another, potentially improving the overall performance of these tasks by leveraging their interdependencies. Along with two-field database, authors have proposed the cross-field transformerto capture the correspondence between two fields as well as the long-range spatial correlations within each field in [21]. Structural and angiographic optical coherence tomography based diabetic retinopathy classification approach at multiple levels is proposed in [22]. Here, to enhance the accuracy and reliability of classification, a new convolutional neural network architecture was developed. This architecture is founded on the principles of dense and continuous connections, complementedby adaptive rate dropout. These features are integrated to improve the network's performance in tasks such as image classification, making it more robust and effective in handling complex data. Adarsh *et al.* [23] employed Support Vector Machines (SVM) as a classifier for DR classification. This classification was based on utilizing features extracted from fundus images, specifically focusing on characteristics related to blood vessels and exudates. SVM is a popular machine learning algorithm known for its effectiveness in binary and multiclass classification tasks, making it a suitable choice for tasks like DR classification based on image features. These research efforts contribute to the development of effective methods for identifying and classifying different characteristics of diabetic retinopathy, which is crucial for early diagnosisand treatment.

III. Proposed Framework

The complete overview of the proposed diabetic retinopathy image classification network is provided in Fig. 3. As one of the studies [17] proves that the green channel often provides good contrast for blood vessels in retinal images. This can be helpful in the detection of microaneurysms, hemorrhages, and other vascular abnormalities associated with diabetic retinopathy. The detailed visualization of each channel is providedin Fig. 4. From Fig. 4, it can be observed that the greenchannel often provides good contrast for blood vessels in retinal images, less

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

sensitive to hemoglobin compared to the red channel and changes in color or variations in the green channel can indicate abnormalities in the retinal tissue. To take advantages of these features, we have processed the Green channel independently with RGB image.

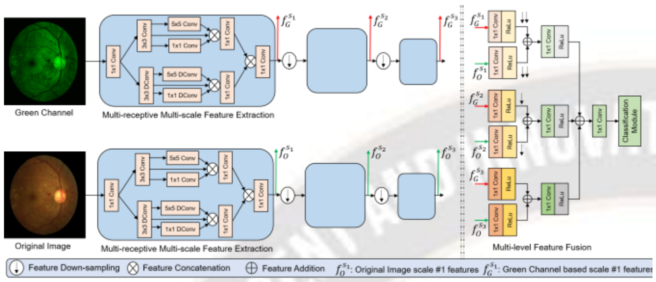

Fig. 3. Overview of the proposed network for diabetic retinopathy image classification. Initially, the RGB image is pre-processed and green channel is extracted. Further, the independent features are extracted from RGB image and green channels at various scales. Finally, the various level features are fused with proposed multi-level feature fusion block for classification.

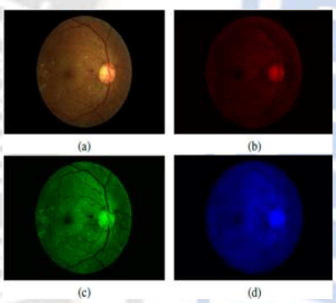

Fig. 4. Original RGB and channel-level image representation of diabetic retinopathy image

Along with the advantage of Green channel, to consider local and global level features, we have proposed multi-receptive multi-scale feature extraction block. The proposed block is defined as:

$$f_G^{si} = C_1\{fmr, fms\};\ i \in 1,2,3 \quad (1)$$

where, C_1 is convolution operation with 1×1 kernel size, {.} indicates concatenation operation, f_{mr} and f_{ms} are the multi receptive and multi-scale features respectively. These features are extracted as:

$$f_{ms} = C_1\{C_3(f), C_5(C_3(f)), C_1(C_3(f))\} \quad (2)$$

$$f_{mr} = C_1\{DC_3(f), DC_5(DC_3(f)), DC_1(DC_3(f))\} \quad (3)$$

where, Cs and DC_s are the convolution and dilated convolution operations with s × s kernel size, respectively and f is the input feature after passing through C_1.

After repeating the above operation three times (s_i; i ∈ 1, 2,3) at different scales, which likely involves a process of feature extraction or refinement, the resulting features that incorporate both global and local channel information are fused with the proposed multi-level feature fusion block. The iterative processing and incorporation of both global and local information at different levels aim to enhance the model's ability to make accurate and robust classifications. Therefore, all the features from green channel (f_G^{s1}, f_G^{s2}, f_G^{s3}) and RGB image (f_O^{s1},f_O^{s2}, f_O^{s3}) fused with the proposed multi-level feature fusion block. Initially, the RGB and green channel features are scale level are merged as:

$$fs_1 = C_1 (f_G^{s1})+C_1(f_O^{s1}) \quad (4)$$

$$fs_2 = C_1(f_G^{s2})+C_1(f_O^{s2}) \quad (5)$$

$$fs_3 = C_1(f_G^{s3})+C_1(f_O^{s3}) \quad (6)$$

where, C1 represents convolution operation with 1 × 1 kernel size followed by ReLu activation function. Further, these features are merged as:

$$f = C_1 [C_1(f^{s1}) +C1(\downarrow(f^{s2})) +C1(\downarrow\downarrow(f^{s3}))] \quad (7)$$

where, ↓ and ↓↓ indicate down-sampling operation with factor of 2 and 4, respectively. The resulting features that incorporate both global and local information at different levels. These feature are flatten to 1-dimensional layer. Further, fully connected layers are used for classification.

IV.TRAINING DETAILS

A. Databases

MESSIDOR [9]: The MESSIDOR database is a publicly available dataset that contains 1,200 retinal images captured from patients with diabetic retinopathy. This dataset is a valuable resource for researchers and medical professionals working on the diagnosis and management of diabetic retinopathy. It provides a substantial collection of retinal images, which can be used for various purposes, including the development and evaluation of algorithms and models for the detection and classification of diabetic retinopathy.

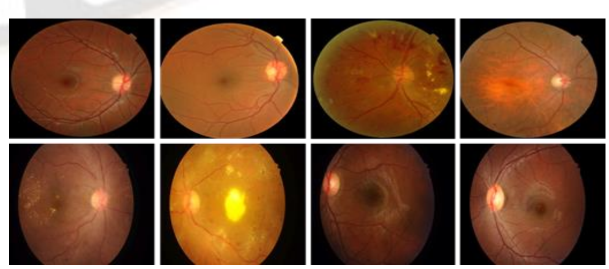

Fig. 5. Sample images from MESSIDOR [9] (first row) and IDRID [10] (second row) database used for classification.

The division of the retinal images in the MESSIDOR database is done into four groups based on the severity of diabetic retinopathy is as: Group 1: 546 images, Group 2: 153 images, Group 3: 247 images and Group 4: 254 images. Each of these groups likely represents different stages or severity levels of diabetic retinopathy, ranging from mild to severe. The specifications of retinopathy grading are based on number of micro-aneurysms, hemorrhage, and the sign of neovascularization. The images in which the above abnormalities are absent are considered as normal images. For experimental analysis of the proposed and existing network, we have divided the total 1200 images as 900 training and 300 testing splits.

IDRID [10]: The Indian Diabetic Retinopathy Image Dataset (IDRiD) is a significant database representing an Indian population, specifically tailored for diabetic retinopathy research. This dataset is valuable because it includes retinal images from individuals in India, making it relevant for the study of diabetic retinopathy. Such region-specific datasets are essential for ensuring that the research and diagnostic tools are applicable and effective for the unique characteristics of the Indian population. This database has 413 and 103 training and testing images respectively. The ground truth labels for diabetic retinopathy and diabetic macular edema severity grade is also provided for training and testing analysis.

B. Implementation Details

All the images are resized to 256 256 for training the proposed network. While training the proposed network on IDRID [10] database, we have performed the data augmentation like horizontal and vertical flipping as number of training images are less. We train the network on Google Colab with batch size of 16 and learning rate 0.00002.

V. RESULT ANALYSIS

The effectiveness of the proposed and existing architectures is analyzed on testing splits of MESSIDOR [9] and IDRID [10] database. The parameters like Accuracy, Sensitivity and Specificity are calculated in terms of True Positive (TP), True Negative (TN), False Positive (FP), and Flase Negative (FN).

TABLE I
CLASSIFICATION ACCURACY ANALYSIS OF DIABETIC RETINOPATHY ON MESSIDOR [9] DATABASE.

Method	Accuracy	Sensitivity	Specificity
VGG-19 [24]	78.67%	81.37%	90.74%
ResNet [25]	80.01%	83.18%	91.35%
GoogleNet [26]	80.25%	84.59%	92.18%
InceptionNet [27]	81.12%	85.31%	92.87%
Proposed	**83.33%**	**86.67%**	**94.44%**

TABLE II
CLASSIFICATION ACCURACY ANALYSIS OF DIABETIC RETINOPATHY ON IDRID [10] DATABASE.

Method	Accuracy	Sensitivity	Specificity
VGG-19 [24]	84.79%	89.09%	78.69%
ResNet [25]	85.22%	90.36%	79.26%
GoogleNet [26]	85.99%	91.79%	79.89%
InceptionNet [27]	86.35%	91.54%	80.01%
Proposed	**87.56%**	**92.61%**	**80.81%**

Mathematical expression are given below:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (9)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (10)$$

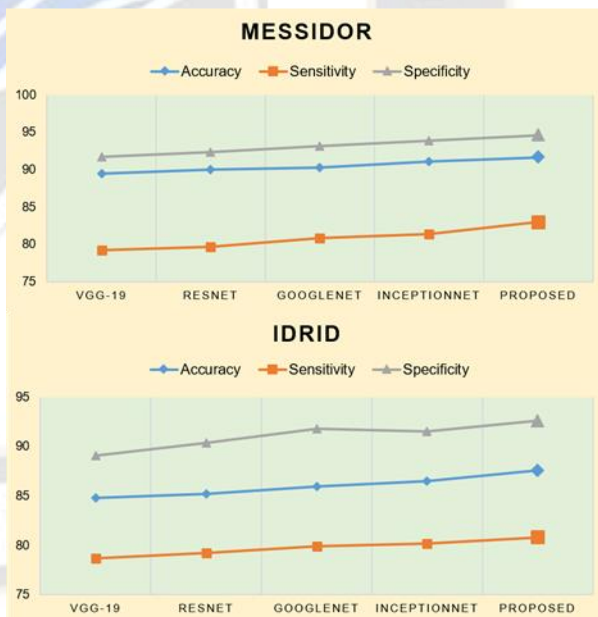

Fig. 6. Analysis with Accuracy, Sensitivity and Specificity on MESSIDOR [9] (*top graph*) and IDRID [10] (*bottom graph*).

VI. CONCLUSION

In the present research work a cross modality feature fusion network for diabetic retinopathy image classification is implemented. To efficiently extract information from different modalities, the present work employs a cross-channel feature fusion mechanism. This mechanism is implemented through a cross channel attention module, which is integrated with two stream model. This approach allows the model to focus on and gather information from various channels, signifi cantly improving its performance and accuracy in an image classification task. The empirical results shows an analysis with respect to performance parameters, Accuracy (83.33%), Sensitivity (86.67%), and Specificity (94.44%) on MESSIDOR database and Accuracy (87.56%), Sensitivity (92.61%), and Specificity (80.81%) on IDRID database. The present work attains 85.45% average accuracy which is significantly better as compared to an existing state-of-the-art deep learning architectures for DR image classification.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

ACKNOWLEDGMENTS

The authors truly appreciate Mr. Rohit Deshmukh for their invaluable help, guidance. Authors express gratitude to Dr. Shirbahadurkar sir, Dr. Kate sir and Mr. Unde sir, for providing the necessary facilities as well as his kind support and encouragement.

REFERENCES

[1] C.-H. Hua, K. Kim, T. Huynh-The, J. I. You, S.-Y. Yu, T. Le-Tien, S.-H. Bae, and S. Lee, "Convolutional network with twofold feature augmentation for diabetic retinopathy recognition from multi-modal images," IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 7, pp. 2686–2697, 2020.

[2] D. Ophthalmoscopy and E. Levels, "International clinical diabetic retinopathy disease severity scale detailed table," 2002.

[3] J. W. Yau, S. L. Rogers, R. Kawasaki, E. L. Lamoureux, J. W. Kowalski, T. Bek, S.-J. Chen, J. M. Dekker, A. Fletcher, J. Grauslund et al., "Global prevalence and major risk factors of diabetic retinopathy," Diabetes care, vol. 35, no. 3, pp. 556–564, 2012.

[4] M. Dubow, A. Pinhas, N. Shah, R. F. Cooper, A. Gan, R. C. Gentile, V. Hendrix, Y. N. Sulai, J. Carroll, T. Y. Chui et al., "Classification of human retinal microaneurysms using adaptive optics scanning light ophthalmoscope fluorescein angiography," Investigative ophthalmology & visual science, vol. 55, no. 3, pp. 1299–1309, 2014.

[5] N. Murugesan, T. ¨ Ustunkaya, and E. P. Feener, "Thrombosis and hemorrhage in diabetic retinopathy: a perspective from an inflammatory standpoint," in Seminars in thrombosis and hemostasis. Thieme Medical Publishers, 2015, pp. 659–664.

[6] J. Amin, M. Sharif, M. Yasmin et al., "A review on recent developments for detection of diabetic retinopathy," Scientifica, vol. 2016, 2016.

[7] P. Vora and S. Shrestha, "Detecting diabetic retinopathy using embedded computer vision," Applied Sciences, vol. 10, no. 20, p. 7274, 2020.

[8] S. Mamtora, Y. Wong, D. Bell, T. Sandinha et al., "Bilateral birdshot retinochoroiditis and retinal astrocytoma," Case Reports in Ophthalmo logical Medicine, vol. 2017, 2017.

[9] E. Decenci` ere, X. Zhang, G. Cazuguel, B. Lay, B. Cochener, C. Trone, P. Gain, R. Ordonez, P. Massin, A. Erginay et al., "Feedback on a publicly distributed image database: the messidor database," Image Analysis & Stereology, vol. 33, no. 3, pp. 231–234, 2014. Sahasrabuddhe,

[10] P. Porwal, S. Pachade, R. Kamble, M. Kokare, G. Deshmukh, V. and F. Meriaudeau, "Indian diabetic retinopathy image dataset (idrid)," 2018. [Online]. Available: https://dx.doi.org/10.21227/H25W98.

[11] S. Resnikoff, W. Felch, T.-M. Gauthier, and B. Spivey, "The number of ophthalmologists in practice and training worldwide: a growing gap despite more than 200 000 practitioners," British Journal of Ophthal mology, vol. 96, no. 6, pp. 783–787, 2012.

[12] D. K. Prasad, L. Vibha, and K. Venugopal, "Early detection of diabetic retinopathy from digital retinal fundus images," in 2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS). IEEE, 2015, pp. 240–245.

[13] J. Amin, M. Sharif, M. Yasmin, H. Ali, and S. L. Fernandes, "A method for the detection and classification of diabetic retinopathy using structural predictors of bright lesions," Journal of Computational Science, vol. 19, pp. 153–164, 2017.

[14] H. Jiang, J. Xu, R. Shi, K. Yang, D. Zhang, M. Gao, H. Ma, and W. Qian, "A multi-label deep learning model with interpretable grad-cam for diabetic retinopathy classification," in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2020, pp. 1560–1563.

[15] X. Li, X. Hu, L. Yu, L. Zhu, C.-W. Fu, and P.-A. Heng, "Canet: cross disease attention network for joint diabetic retinopathy and diabetic macular edema grading," IEEE transactions on medical imaging, vol. 39, no. 5, pp. 1483–1493, 2019.

[16] P. Qian, Z. Zhao, C. Chen, Z. Zeng, and X. Li, “Two eyes are better than one: Exploiting binocular correlation for diabetic retinopathy severity grading,” in 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2021, pp. 2115–2118.

[17] Z. Xia, Q. Jiang, W. Li, H. Hu, C. Zhu, and Z. Zou, “A two-stream chan nel cross enhancement network for diabetic retinopathy classification,” in 2023 International Joint Conference on Neural Networks (IJCNN). IEEE, 2023, pp. 01–07.

[18] A. He, T. Li, N. Li, K. Wang, and H. Fu, “Cabnet: Category attention block for imbalanced diabetic retinopathy grading,” IEEE Transactions on Medical Imaging, vol. 40, no. 1, pp. 143–153, 2020.

[19] X. Wang, M. Xu, J. Zhang, L. Jiang, L. Li, M. He, N. ang, H. Liu, and Z. Wang, “Joint learning of multi-level tasks for diabetic retinopathy grading on low-resolution fundus images,” IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 5, pp. 2216–2227, 2021.

[20] Q. Hou, P. Cao, L. Jia, L. Chen, J. Yang, and O. R. Zaiane, “Image quality assessment guided collaborative learning of image enhancement and classification for diabetic retinopathy grading,” IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 3, pp. 1455–1466, 2022.

[21] J. Hou, J. Xu, F. Xiao, R.-W. Zhao, Y. Zhang, H. Zou, L. Lu, W. Xue, and R. Feng, “Cross-field transformer for diabetic retinopathy grading on two-field fundus images,” in 2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). IEEE, 2022, pp. 985–990.

[22] P. Zang, L. Gao, T. T. Hormel, J. Wang, Q. You, T. S. Hwang, and Y. Jia, “Dcardnet: diabetic retinopathy classification at multiple levels based on structural and angiographic optical coherence tomography,” IEEE Transactions on Biomedical Engineering, vol. 68, no. 6, pp. 1859 1870, 2020.

[23] P. Adarsh and D. Jeyakumari, “Multiclass svm-based automated di agnosis of diabetic retinopathy,” in 2013 International Conference on Communication and Signal Processing. IEEE, 2013, pp. 206–210.

[24] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” arXiv preprint arXiv:1409.1556, 2014.

[25] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[26] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 1–9.

[27] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the inception architecture for computer vision,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 2818–2826