International Journal of Advance Research in Science and Engineering
Volume No. 13, Issue No. 07, July 2024
www.ijarse.com
IJARSE
ISSN 2319 - 8354

Comprehensive Review on Progress in Retinal Imaging Analysis Techniques for Classifying Diabetic Retinal Disease

Rohit Verma[1], Dr. Hitesh Marwaha[2]

[1]Research Scholar, School of Computational Science, GNA University, India

[2]Associate Prof. & HOD, School of Computational Science, GNA University, India

ABSTRACT

Diabetic retinopathy (DR) is a vision impairment that occurs due to harm inflicted on the retinal vasculature, the light-sensitive membrane at the rear of the eye. With the increase in diabetes prevalence, retinopathy has become a major public health concern worldwide. Early detection and accurate classification of diabetic retinopathy can prevent a great fraction of severe vision loss. By following appropriate steps one can avoid expensive treatments like surgery, thereby lowering the healthcare costs. This literature review explores the advancements in classifying diabetic retinopathy, focusing on the deep learning (DL) approaches known for their strong image processing and analysis capabilities. Numerous deep learning models like CNNs, RNNs, and hybrid models are investigated for their effectiveness in DR classification. DL, leveraging its powerful image processing capabilities, has demonstrated significant potential in precisely identifying and classifying the various stages of diabetic retinopathy and in analyzing retinal blood vessels, which are essential for determining the disease's severity. By providing a comprehensive overview of recent advancements and identifying key research gaps, this review aims to guide future research and development in the domain of diabetic retinopathy classification and blood vessel analysis using deep learning.

Keywords: *Artificial Intelligence, CNN, Deep Learning, diabetic retinopathy, Fundus image analysis*

1. Introduction

Deep learning(DL) algorithms have significantly advanced clinical image assessment, specifically in the realm of retinal disorders. Implementation of deep neural networks in interpreting OCT scans of the human eye enables the detection and analysis of various ocular conditions such as drusen, CNV, and DME. These advanced approaches utilizing DL prove instrumental in the detailed examination of these images.

1.1 Contribution of DL in fundus scan analysis

There are basically four ways in which DL algorithms can contribute towards the diabetic retinopathy treatment, using the analysis of fundus images: image optimization, segmentation, Attribute Extraction ,classification.

- Image Optimization: The contrast and intensity levels of fundus images are generally not of excellent quality. Therefore, these images must be improved using various AI-based image optimization approaches, such as histogram equalization, contrast-limited adaptive histogram equalization (CLAHE), or average double plateau histogram equalization (ADPHE), among others. By employing these advanced algorithms, the fundus images are stretched to cover all possible intensity levels between 0 to 255.

- Segmentation: Segmentation with deep learning in diabetic retinopathy is crucial for the accurate identification of retinal structures and lesions. This increases the accuracy of disease detection and progression monitoring, allowing timely and targeted interventions. Through segmentation automation, deep learning reduces diagnostic variability and workload for clinicians. Ultimately, it contributes to improving patient outcomes through consistent and detailed analysis.
- Feature Extraction: Feature extraction is a crucial aspect in diabetic retinopathy when utilizing deep learning techniques, as it enables the automated detection of important patterns and irregularities present in images of the retina. This process serves to increase the precision of diagnosis by bringing attention to subtle characteristics that might go unnoticed by conventional approaches. Furthermore, it accelerates the examination procedure, facilitating the swift and effective screening of extensive groups of patients.
- Classification: Classification of diabetic retinal diseases is crucial to the accurate diagnosis of the severity and progression of the disease. It helps in adjusting treatment plans for each stage and ensures that patients receive appropriate interventions. Early and accurate classification can prevent visual loss by allowing medical interventions in a timely manner. In addition, it supports better patient management and long-term monitoring, improving overall results.

Real-World Applications of Deep Learning			
Image Enhancement	**Segmentation**	**Feature Extraction**	**Classification**
Contrast enhancement	Blood vessel segmentation	Feature localization	Diagnosis
Noise reduction	Optic disc detection	Abnormality detection	Grading
Sharpness improvement	Lesion segmentation	Pattern recognition	Screening
Color calibration	Macula segmentation	Texture analysis	Feature extraction
Artifact removal	Microaneurysm detection	Morphological analysis	Severity assessment
Resolution enhancement	Exudate segmentation	Vascular pattern extraction	---

figure 1. Role of DL in analyzing fundus scans for diabetic retinal detection

1.2 Diabetic retinopathy and its stages

A diabetes-related complication, diabetic retinopathy (DR) causes vision loss by damaging the blood vessels within the retina, the light-sensitive tissue situated at the back of the eye. The rising occurrence of diabetes has led to diabetic retinopathy emerging as a significant global public health issue. Timely recognition and accurate categorization of DR plays a significant role in the successful implementation of treatment strategies and in the maintenance of vision, ultimately avoid expensive treatments such as surgery, thereby lowering overall healthcare cost. In general terms, diabetic retinopathy (DR) categorizes into two types: non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Fig. 2 depicts the subcategories of NPDR along with their corresponding symptoms.

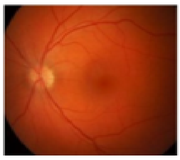
	Subcategories	Type	Observations	Images
Diabetic Retinopathy (DR)	Non-Proliferative Retinopathy	Mild	Small areas of balloon-like swelling appear in the retina's blood vessels.	
		Moderate	Some blood vessels that nourish the retina are blocked.	
		Severe	More blood vessels are blocked as a result cutting off the blood supply in the retina occurs.	
	Proliferative Retinopathy	---	It is the advanced stage where new blood vessels grow, which can leak blood, leading to severe vision problems.	

figure 2. Gradations of diabetic retinopathy Severity [1]

2. EARLIER INVESTIGATIONS

Diabetic retinopathy stands as a primary contributor to visual impairment and blindness in the adult population globally. Recent progress in medical imaging and artificial intelligence has spurred the emergence of innovative diagnostic and therapeutic strategies for this ailment. This analysis explores the most recent methodologies, with a focus on the incorporation of deep learning methods and their influence on early detection and precise categorization. Through an examination of contemporary research, the review seeks to underscore the effectiveness and constraints of these emerging technologies. Additionally, it deliberates on the potential of these strategies to improve clinical practice and patient outcomes in the management of diabetic retinopathy.

Sim et al. [2] showcased the application of Automated Retinal Image Analysis (ARIA) in telemedicine specifically for diabetic retinopathy detection. The paper presents ARIA within the telemedicine framework as a promising strategy to tackle diabetic retinopathy on a large scale, while also identifying critical requirements and challenges for its successful implementation.

Maninis, Kevis-Kokitsi, et al. [3] Introduced a Deep Retinal Image Understanding (DRIU), a comprehensive framework designed for retinal image analysis, offering simultaneous segmentation of retinal vessels and the optic disc. DRIU represents an innovative approach to segmenting retinal vessels and optic discs with a unique blend of speed and precision. It harnesses the capabilities of Convolutional Neural Networks (CNNs), which have revolutionized various aspects of computer vision, adapting them specifically for retinal image analysis. Central to DRIU's methodology is a shared base CNN network augmented with task-specific layers tailored for each segmentation task. This design optimizes both efficiency and accuracy, making DRIU a promising tool in the realm of medical image processing.

Xu Xiayu, et al., [4] introduced an enhanced approach to classify retinal arteries and veins, employing both intra-image and inter-subject normalizations. They integrated innovative features like first order and second-order image textures to enhance classification effectiveness. Their study achieved an impressive overall accuracy of 92.3% and demonstrated efficient computational performance, processing each image in approximately 5 seconds.

Zhou et al. [5] introduced a robust technique for enhancing color retinal images through adjustments in luminosity and contrast. Initially, they enhanced image luminosity using a gamma correction-based luminance gain matrix. Subsequently, contrast enhancement was achieved through CLAHE applied in the L*a*b* color space. Their method underwent rigorous validation on two extensive datasets of color retinal images. The outcomes underscored significant enhancements in image quality, particularly for images of lower initial quality, demonstrating superior improvements compared to existing methods.

Jamal, Arshad et al. [6] explored the field of Retinal Image Analysis (RIA) focusing on vessel detection. Their research involved automating the selection and analysis of retinal vessels, including measurements of diameter, standard deviation, and length. By accurately identifying and displaying these vessels on the retina, their automated approach aims to minimize diagnostic errors in fundus image analysis.

Tufail, Adnan, et al. [7] evaluates the accuracy and cost effectiveness comparison of human graders with automated diabetic retinopathy image assessment software. Studies indicated that both the Retmarker and EyeArt systems demonstrated sensitivity comparable to human graders for identifying referable retinopathy, while maintaining specificity at levels that justify their cost-effectiveness as alternatives to manual grading.

Fu, Huazhu et al. [8] introduced the EyeQ dataset derived from the EyePACS dataset, featuring a comprehensive three-tier quality grading system (Good', Usable', and `Reject'). This dataset offers substantial benefits including its extensive scale, diverse grading levels, and incorporation of multiple imaging modalities. Additionally, they proposed the Multiple Color-space Fusion Network (MCF-Net) designed for the classification of retinal image quality. MCF-Net innovatively integrates various color spaces to enhance the accuracy and robustness of quality

Sarki, Rubina, et al. [9] investigated an automated classification system for diabetic eye diseases (DED) under two conditions: (i) mild multi-class DED and (ii) general multi-class DED. Their study involved testing the model across multiple datasets that were meticulously annotated by an ophthalmologist. The research utilized the top two pretrained convolutional neural network (CNN) models originally trained on ImageNet. The VGG16 model achieved an impressive 88.3% accuracy for general multi-class classification and 85.95% for mild multi-class classification, demonstrating robust performance in automated diagnosis of diabetic eye diseases.

Vujosevic and colleagues [10] highlighted the critical role of healthcare accessibility, quality, and affordability in preventing blindness among populations vulnerable to diabetic retinopathy. They emphasized that integrating automated analysis of retinal images with telemedicine could greatly enhance the delivery of diabetes eye care. This approach promises to offer real-time automated assessments that are tailored to individual needs, thereby potentially revolutionizing the management and early detection of diabetic retinopathy.

Ref. No	Approach	Dataset	Observations	Efficiency Assessment
[11] Das Sraddha (2021) et al.	- Segmentation of fundus images using adaptive histogram equalization and morphological opening to improve and remove falsely segmented areas. - Novel deep learning architecture consisting of a two-way classification CNN model: -One utilizing a mix of squeeze, excitation, and bottleneck layers. - The second with conv. and pooling layer approach. -Classification is accepted only if both networks produce a unanimous result.	DRIVE dataset for testing the proposed segmentation algorithm.	Effectiveness of segmentation directly impacts classification accuracy. Poor segmentation could lead to incorrect classification results due to feature extraction from non-DR pixels.	Comparison metrics include Precision, Specificity, and Accuracy. Average: Precision 96.1%, Specificity 97.6%, Accuracy 97.4%
[12] Veena et al. (2021)	Two Novel CNN techniques for the segregation of the optic disc (OD) and optic cup (OC) to identify glaucoma.	DRISHTI GS database, consisting of more than 100 retinal scans gathered from the Arvind Eye Hospital.	Model can be affected by the learning rate, Its low and high value can affect the model performance greatly.	Optic disk segmentation Training Data Accuracy: 98.76% Test Data Accuracy :99.01% Optic Cup Segmentation Training Data Accuracy: 97.13% Testing Data Accuracy: 97.98%
[13] Butt Mohsin et al. (2022)	Hybrid model CNN for feature extraction and various classifiers (including SVM and ANN) for classification.	Asia Pacific Tele Ophthalmology Society (APTOS) containing 3662 fundus images received from The Aravind Eye Hospital in India	Data synthesis and cleansing techniques are needed to get rid of artifacts and noise.	Convolution Neural Network (CNN) for feature selection followed by Support Vector Machine (SVM) classifier accomplishes the maximum average accuracy of 97.80% in case of binary classification & 89.29% for multiclass classification.
[14] J Ramya et al. (2022)	hybrid approach combining CNN with Binary Local Search Optimization (BLSO) and Particle Swarm Optimization (PSO) algorithms	Retinopathy Online Challenge (ROC) with 200 images, ARA400 Dataset from Aravind Eye Hospital, containing 400 fundus images	Utilization of more CNN layers, increases the computational complexities.	- SVM classifiers: Sensitivity: 89.37%, Specificity: 84.09%, Accuracy: 83.27% -MMS: Sensitivity: 90.46%, Specificity: 84.25%, Accuracy: 85.74%

			Optimization techniques required	RF: Sensitivity: 93.54%, Specificity: 88.47%, Accuracy: 92.30% CNN: Sensitivity: 91.23%, Specificity: 89.30%, Accuracy: 94.65% Hybrid CNN BLSO PSO: Sensitivity: 98.56%, Specificity: 92.54%, Accuracy: 97.20% Comparison of Methods on ARA400 Dataset: - SVM classifiers: Sensitivity: 89.24%, Specificity: 84.56%, Accuracy: 84.12%
[15] Law Kumar Singh et al. (2022)	Combination of nature-inspired computing algorithms (Blackhole Cataclysmic Selection (BCS), Bat Algorithm (BA), Particle Swarm Optimization (PSO)) along with machine learning(ML) classifiers A novel two-layer approaches used to develop a significantly reduced feature set	REFUGE and ORIGA datasets Containing having fundus images	Dataset is limited.	Dataset is reduced by 50% Method provides significance accuracy with fewest features.
[16] Tin Tin Khaing et al. (2022)	Fully automatic hybrid method for Optic Disk (OD) localization (HLM). Self-operating OD localization and segmentation Approach, custom crafted for mobile camera fundus images	MHT, STARE, MEX, MHM, DIARETDB0, DIARETDB1, ROP	challenging nature of segmenting the optic disk (OD) in the ROP dataset	HLM achieves an mean localization precision of 98%. Average precision: 92.64% Average recall: 82.38% for OD segmentation.
[17] P. Muthukannan et al. (2022)	Optimization of a convolutional neural network (CNN) using the Firefly Population Optimization Algorithm (FPOA) for the recognition of Various ocular disorders.	ODIR dataset of fundus images	Challenges of the study may include the specific characteristics of the ODIR dataset.	Performance: accuracy: 98.30%, precision: 95.27% recall: 95.21% specificity: 98.28% F1 score: 93.3%.
[18] Al Gburi et al.	Combination of Shannon entropy (SE)	RIM-ONE	These methods can be complex	The Golden Eagle method was shown to

International Journal of Advance Research in Science and Engineering
Volume No. 13, Issue No. 07, July 2024
www.ijarse.com
IJARSE
ISSN 2319 - 8354

(2022)	method for preprocessing and the Golden Eagle optimization method for optical disk segmentation in retina images. The divided methods include SVM, decision tree, geometrically active contour methods, Radon transform, and thresholding.		and time consuming.	have higher accuracy and lower error rates compared to Bayesian methods, decision tree, SVM, and geometrically active contour algorithms. Combination of methods optimized SVM & Decision Tree by 7.06% and 5.87%
[19] Mesut Tog˘ ac¸ar et al. (2022)	Decision support system, leveraging CNN models and metaheuristic methods for the classification and feature selection of retinal OCT images	UCSD dataset, Duke dataset, age-related macular degeneration (AMD)	using more than one CNN model, increases time and reduces efficiency	For dataset 1: Overall Accuracy:99.60% For dataset 2: Overall Accuracy: 99.89% For dataset 3: Overall Accuracy: 97.49%
[20] Gupta Indresh Kumar et al. (2022)	Mayfly optimization with kernel extreme learning machine (MFO KELM) model is employed for classification to accurately classify the input images.	ARIA Dataset and STARE Dataset	Using hybrid DL-based classification, detection rate can be further optimize.	The ODCNN-RFIC approach has peak classification outputs with Sensitivity : 0.9778 Specificity: 0.9888, Accuracy: 0.9882
[21] Reddy et al. (2022)	Hybrid DLCNN MGWO VW Model. DSAM and DDAM to understand both disease-specific and disease-contextualized features. MGWO VW	Indian diabetic retinopathy Image Dataset (IDRiD)	Meta-heuristic optimal attribute selection algorithms is recommended for further betterment	Training Accuracy: - CANet: 80% - SUNet: 86% - DLCNN MGWO VW: 95%
[22] Agrawal, Ranjana, et al. (2022)	Modified U-Net approach incorporating both squeeze and excitation alongside attention gates (AG) were used to extract the boundary and vessel features.	HVDROPDB-BV and HVDROPDBRIDGE	Thick and thin vessels were considered as single class, which affected the dice score. Future work will focus on identifying the tortuosity and dilation parameters of blood vessels	Testing Data Sensitivity: 96% specificity: 89%.
[23] Xiangjie Leng et al. (2023)	The approach involves evaluating the Diagnostic reliability of DL in detecting age-	Various photos like OCT visuals, FPs, OPTOS ultra widefield retinal scans, and OCT	Publication bias was assessed using Deeks funnel plot, indicating the	Performance metrics included sensitivity, specificity, positive likelihood ratio (PLR), negative likelihood

	related macular degeneration (AMD). Utilization of the QUA DAS 2 tools for checking bias risk	pictures combined with FP scans. Data from 778,052 various images were analyzed.	possibility of bias if the funnel shape is asymmetrical or P<0.05. - The heterogeneity was evaluated, wherein I2 exceeding 25%, 50%, and 75% represent low, medium, and high heterogeneity, respectively.	ratio (NLR), and diagnostic odds ratio (DOR), all accompanied by a 95% Confidence Interval (CI). Meta-analyses and further analyses were conducted using MetaDisc 1.4 and Review Manager 5.4.1.
[24] Rohit Thanki et al. (2023)	A 2-fold cross-validation method is proposed here. It utilized the SqueezeNet model to gather deep features from fundus pictures. These features were then fed into six different classifiers: K nearest neighbors (KNN), decision tree, SVM, naive bayes, random forest (RF), and logistic regression (LR).	DRISTHI GS dataset containing 101 retinal images. 70 glaucomatous images and 31 normal images	For best results, dataset can be populated with more images.	kNN: Accuracy = 0.598 Decision Tree: Accuracy = 0.558 SVM: Accuracy = 0.661 Naive Bayes: Accuracy = 0.697 Logistic Regression: Accuracy = 0.610
[25] Neha Sengar et al. (2023)	A framework called EyeDeep-Net, a deep neural network designed for the fully automatic diagnosis of fundus diseases that can be used for multiclass diagnosis.	Retinal Fundus Multi Disease Image Dataset (RFMiD) Containing 3200 retinal pictures.	Implementation of advanced classification methods with the large dataset	validation Accuracy: 82.13% testing Accuracy: 76.04%
[26] Ishika Giroti et al. (2023)	Efficient Net model	APTOS dataset from Kaggle	---	accuracy in the range of 87-95%. SVM, KNN,LDA, RF, & RRF were outshined by RRF, which achieved an accuracy of 86%.
[27] Al-ahmadi et al. (2024)	Applying ResNet-101, DenseNet121, InceptionResNetV2, and EfficientNetB0 models to automatically monitor the stages of diabetic retinopathy.	A repository of 56,839 fundus images from EyePACS for model training and validation	For further improvement, future research could focus on ensemble methods.	DenseNet-121 secured the best accuracy of 0.87, followed by Inception-ResNetV2 with 0.86, ResNet-101 with 0.82, and EfficientNetB0 with 0.73

[28] Xu et al. (2024)	hybrid NN model EfficientNet and Swin Transformer	APTOS	The method has deficiencies related to identifying different lesion types and degrees.	Through integrating local and global features, the model achieves enhanced prediction accuracy

3. Conclusion

Recent years have seen significant developments in the field of fundus image analysis for classification, driven by the growing prevalence of retinopathy and the need for early and accurate diagnosis. The literature reveals a diverse array of techniques and methodologies, ranging from traditional image processing and machine learning approaches to more sophisticated deep learning models. The advent of deep learning revolutionized fundus image analysis. Convolutional Neural Networks (CNNs), in particular, emerged as powerful tools capable of automatically learning hierarchical features directly from raw pixel data. State-of-the-art architectures like ResNet, U-Net have shown remarkable success in disease classification, segmentation, and synthesis of retinal images. Despite the progress, several challenges remain in the field. Future research should focus on creating more robust and generalizable models, possibly through the use of transfer learning and domain adaptation techniques.

REFERENCES

[1] Yasin, S.; Iqbal, N.; Ali, T.; Draz, U.; Alqahtani, A.; Irfan, M.; Rehman, A.; Glowacz, A.; Alqhtani, S.; Proniewska, K.; et al. Severity Grading and Early Retinopathy Lesion Detection through Hybrid Inception-ResNet Architecture. Sensors 2021, 21, 6933. [CrossRef] [PubMed]

[2] Sim, Dawn A., et al. "Automated retinal image analysis for “diabetic retinopathy” in telemedicine." Current diabetes reports 15 (2015): 1-9.

[3] Maninis, Kevis-Kokitsi, et al. "Deep retinal image understanding." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part II 19. Springer International Publishing, 2016.

[4]Xu, Xiayu, et al. "An improved arteriovenous classification method for the early diagnostics of various diseases in retinal image." Computer methods and programs in biomedicine 141 (2017): 3-9.

[5]Zhou, Mei, et al. "Color retinal image enhancement based on luminosity and contrast adjustment." IEEE Transactions on Biomedical engineering 65.3 (2017): 521-527.

[6]Jamal, Arshad, et al. "Retinal imaging analysis based on vessel detection." Microscopy research and technique 80.7 (2017): 799-811.

[7]Tufail, Adnan, et al. "Automated “diabetic retinopathy” image assessment software: diagnostic accuracy and cost-effectiveness compared with human graders." Ophthalmology 124.3 (2017): 343-351.

[8] Fu, Huazhu, et al. "Evaluation of retinal image quality assessment networks in different color-spaces." Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part I 22. Springer International Publishing, 2019.

[9]Sarki, Rubina, et al. "Automated detection of mild and multi-class diabetic eye diseases using deep learning." Health Information Science and Systems 8.1 (2020): 32.

[10] Vujosevic, Stela, et al. "Screening for “diabetic retinopathy”: new perspectives and challenges." The Lancet Diabetes & Endocrinology 8.4 (2020): 337-347.

[11] Das, S., Kharbanda, K., Suchetha, M., Raman, R. and Dhas, E., 2021. Deep learning architecture based on segmented fundus image features for classification of “diabetic retinopathy”. Biomedical Signal Processing and Control, 68, p.102600.

[12]Veena, H. N., A. Muruganandham, and T. Senthil Kumaran. "A novel optic disc and optic cup segmentation technique to diagnose glaucoma using deep learning convolutional neural network over retinal fundus images." Journal of King Saud University-Computer and Information Sciences 34.8 (2022): 6187-6198.

[13] Butt, Muhammad Mohsin, et al. "“diabetic retinopathy” Detection from Fundus Images of the Eye Using Hybrid Deep Learning Features." Diagnostics 12.7 (2022): 1607.

[14]Ramya, J., M. P. Rajakumar, and B. Uma Maheswari. "Deep CNN with hybrid binary local search and particle swarm optimizer for exudates classification from fundus images." Journal of Digital Imaging 35.1 (2022): 56-67.

[15]Singh, Law Kumar, et al. "Collaboration of features optimization techniques for the effective diagnosis of glaucoma in retinal fundus images." Advances in Engineering Software 173 (2022): 103283.

[16] Khaing, Tin Tin, et al. "Vessel-based hybrid optic disk segmentation applied to mobile phone camera retinal images." Medical & Biological Engineering & Computing (2022): 1-17.

[17] Muthukannan, P. "Optimized convolution neural network based multiple eye disease detection." Computers in Biology and Medicine 146 (2022): 105648.

[18]Al-Gburi, Zahraa Dawood Salman, and Sefer Kurnaz. "Optical disk segmentation in human retina images with golden eagle optimizer." Optik 271 (2022): 170103.

[19]Toğaçar, Mesut, Burhan Ergen, and Vedat Tümen. "Use of dominant activations obtained by processing OCT images with the CNNs and slime mold method in retinal disease detection." Biocybernetics and Biomedical Engineering 42.2 (2022): 646-666.

[20] Gupta, Indresh Kumar, Abha Choubey, and Siddhartha Choubey. "Mayfly optimization with deep learning enabled retinal fundus image classification model." Computers and Electrical Engineering 102 (2022): 108176.

[21] Reddy, V. Purna Chandra, and Kiran Kumar Gurrala. "Joint DR-DME classification using deep learning-CNN based modified grey-wolf optimizer with variable weights." Biomedical Signal Processing and Control 73 (2022): 103439.

[22] Agrawal, Ranjana, et al. "Deep dive in retinal fundus image segmentation using deep learning for retinopathy of prematurity." Multimedia Tools and Applications 81.8 (2022): 11441-11460.

[23] Leng X, Shi R, Wu Y, Zhu S, Cai X, Lu X, et al. (2023) Deep learning for detection of age-related macular degeneration: A systematic review and meta-analysis of diagnostic test accuracy studies. PLoS ONE 18(4): e0284060

[24] Thanki, Rohit et al. "A deep neural network and machine learning approach for retinal fundus image classification." Healthcare Analytics 3 (2023): 100140.

[25]Sengar, Neha, et al. "EyeDeep-Net: A multi-class diagnosis of retinal diseases using deep neural network." Neural Computing and Applications (2023): 1-21.

[26] Ishika Giroti et al. "“diabetic retinopathy” Detection & Classification using Efficient Net Model" 2023 International Conference on Artificial Intelligence and Applications (ICAIA) Alliance Technology Conference (ATCON-1), Bangalore, India, 2023, pp. 1-6

[27] Al-ahmadi et al. “Classification of “diabetic retinopathy” by Deep Learning”, International Journal of Online and Biomedical Engineering (iJOE), iJOE | Vol. 20 No. 1 (2024)

[28] Xu H, Shao X, Fang D and Huang F (2024) “A hybrid neural network approach for classifying “diabetic retinopathy” subtypes”, Front. Med. 10:1293019.