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EYE DISEASE DETECTION AND CLASSIFICATION USING DEEP LEARNING: METHODS, CHALLENGES, AND ADVANCES

[1]Pankaj Pateriya, [2]Neha Yadav, [3]Arpita Bhatia

[1,2,3]Assistant Professor,

[1,2,3]Department of Computer Science and Engineering,

[1,2,3]IPS Academy, Institute of Engineering & Science, Indore, M.P., India.

Abstract: The use of machine learning (ML) and deep learning (DL) models for the automated diagnosis of eye diseases has gained significant traction in recent years. Common conditions such as glaucoma, cataracts, diabetic retinopathy, myopia, and age-related macular degeneration can lead to severe visual impairment if not detected early. Early diagnosis is critical for effective treatment and preventing long-term damage. Therefore, thorough analysis and early identification of symptoms are highly recommended. This paper presents a comprehensive review of ML and DL models developed for detecting and classifying eye diseases, highlighting their strengths, limitations, and associated challenges. Recognizing these diseases typically requires extensive medical expertise, making automated systems particularly valuable. The objective of this study is to provide a foundation for identifying the most robust and adaptable solutions in this domain. Specifically, the research focuses on deep learning architectures such as VGG16, ResNet, and Inception. The general workflow involves collecting publicly available eye disease datasets, applying preprocessing techniques to ensure experimental consistency, and training models to recognize disease patterns rather than overfitting to specific data segments. With the success of DL in image classification and object recognition, the field is shifting away from traditional handcrafted feature extraction methods. A promising approach involves leveraging pre-trained deep convolutional neural networks (CNNs) for feature representation, followed by classifiers such as Support Vector Machines (SVMs) or Multilayer Perceptrons (MLPs). Studies have shown that CNN-based methods, trained on large-scale annotated datasets, can effectively perform eye disease classification even when applied to smaller, domain-specific datasets.

***Index Terms* - Eye diseases, Machine learning, deep learning, Convolutional Neural Networks, VGG16, ResNet.**

INTRODUCTION

Machine learning (ML), artificial intelligence (AI), and deep learning (DL) have significantly shaped the technological landscape of the 21st century. These computational techniques have proven effective in diagnosing various eye disorders with high precision. Early detection of ophthalmic diseases is essential to prevent further complications and vision loss. Traditionally, diagnosis relies on clinical observation, which can be time-consuming and susceptible to human error. Integrating AI and ML into clinical workflows can help minimize these limitations and provide timely and accurate diagnostic support.

AI comprises several branches that simulate human behavior and cognition, including narrow, general, and super intelligence. Components such as intelligent sensing, robotics, natural language processing, and both algorithmic and intuitive learning play vital roles in medical applications. ML algorithms, particularly in medical imaging, reading, and speech/writing recognition, have shown promise in identifying the underlying causes of ocular diseases.

The advancement of DL and traditional ML techniques has motivated their application in ophthalmology. This field has emerged as a leader in adopting AI technologies, particularly for analyzing ophthalmic images to enable rapid disease diagnosis. These systems are capable of identifying conditions such as diabetic retinopathy (DR), glaucoma, and other complex ocular pathologies, even in the absence of specialized medical personnel.

The human eye is a delicate and complex organ prone to numerous diseases. Neglecting these conditions can result in severe consequences, including irreversible blindness. While some eye diseases may be mild, others can progress and cause permanent damage if left untreated. Notably, many of these conditions begin early in life and worsen with age, emphasizing the need for ongoing monitoring and early intervention. Common eye diseases include:

Diabetic Retinopathy (DR)DR results from prolonged hyperglycemia, with plasma glucose levels exceeding 7.0 mmol/L. The World Health Organization (WHO) notes that high blood sugar damages blood vessels, nerves, and organs such as the eyes. When retinal vessels are compromised, DR develops. According to Abramoff et al., DR is a leading cause of vision loss in adults.

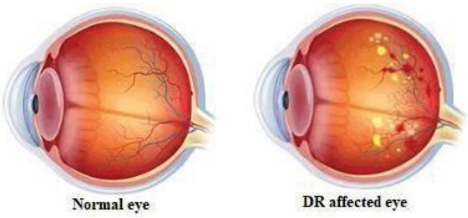

Figure 1: Fundus image affected by DR.

Age-Related Macular Degeneration (AMD)
AMD is a major cause of blindness, affecting around 55% of legally blind individuals in the U.S. It typically occurs in individuals

Figure 2: Age-Related Macular Degeneration

Glaucoma: Glaucoma is a prevalent eye disease that can cause harm to the optic nerve of the eye. The high intraocular pressure here will cause blindness to the eye due to optic nerve damage of the eye. Figure 3 displays the impact of glaucoma on the fundus of the human eye [7].

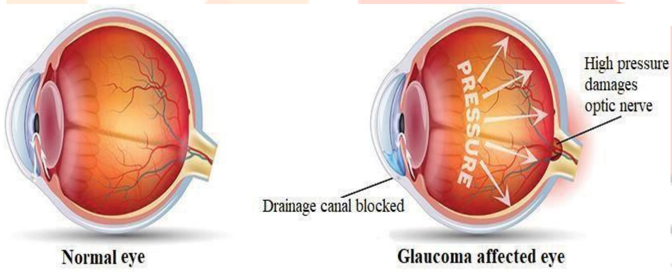

Figure 3. Human eye fundus affected by glaucoma.

I. CONVOLUTIONAL NEURAL NETWORK AND DEEP LEARNING

CNNs are deep neural networks widely employed in DL to analyze visual data. Three layers make up CNN: the fully connected (FC) layer, the pooling layer, and the convolutional layer. The convolutional layer is the first layer, and the FC layer is the last. The convolutional layer of the CNN becomes more complex than the FC layer. When dots are joined in a specific manner, the result is a feature map, also known as a convolved feature. Unlike the convolutional layer, the pooling layer reduces the number of input parameters, resulting in some information loss. On the plus side, this layer makes the CNN more efficient and straightforward. CNN categorizes images in the FC layer based on the features of the previous levels. In this context, "fully connected" means that all inputs or nodes of the prior layer are linked to all activation units or nodes in the following layer [11].

Figure 4 below shows the basic eye disease classification process using deep learning, consisting of the following steps: data collection, pre-processing, feature extraction, and classification. The data collection gathers a diverse and well-annotated dataset of retinal images containing various eye diseases, such as glaucoma, diabetic retinopathy, and macular degeneration. Pre-processing plays a crucial role in DL for eye disease detection, as it helps prepare the data in a format that can be efficiently fed into neural networks. Here are the typical pre-processing steps for DL in the context of eye disease detection: Resize the images to a standard size to ensure consistent input dimensions for the CNN model, normalize pixel values to the range [0, 1], Augment the dataset using rotation, flipping, and scaling techniques to increase its size and diversity and split the dataset into training, validation, and test sets. A typical split ratio is 60-20-20, where 60% of the data is used for training, 20% for validation, and 20% for testing. Extract features from the retinal images using the CNN model. These features serve as input for classifiers. Then, Flatten or use global average pooling to convert the output feature maps into a vector for each image.

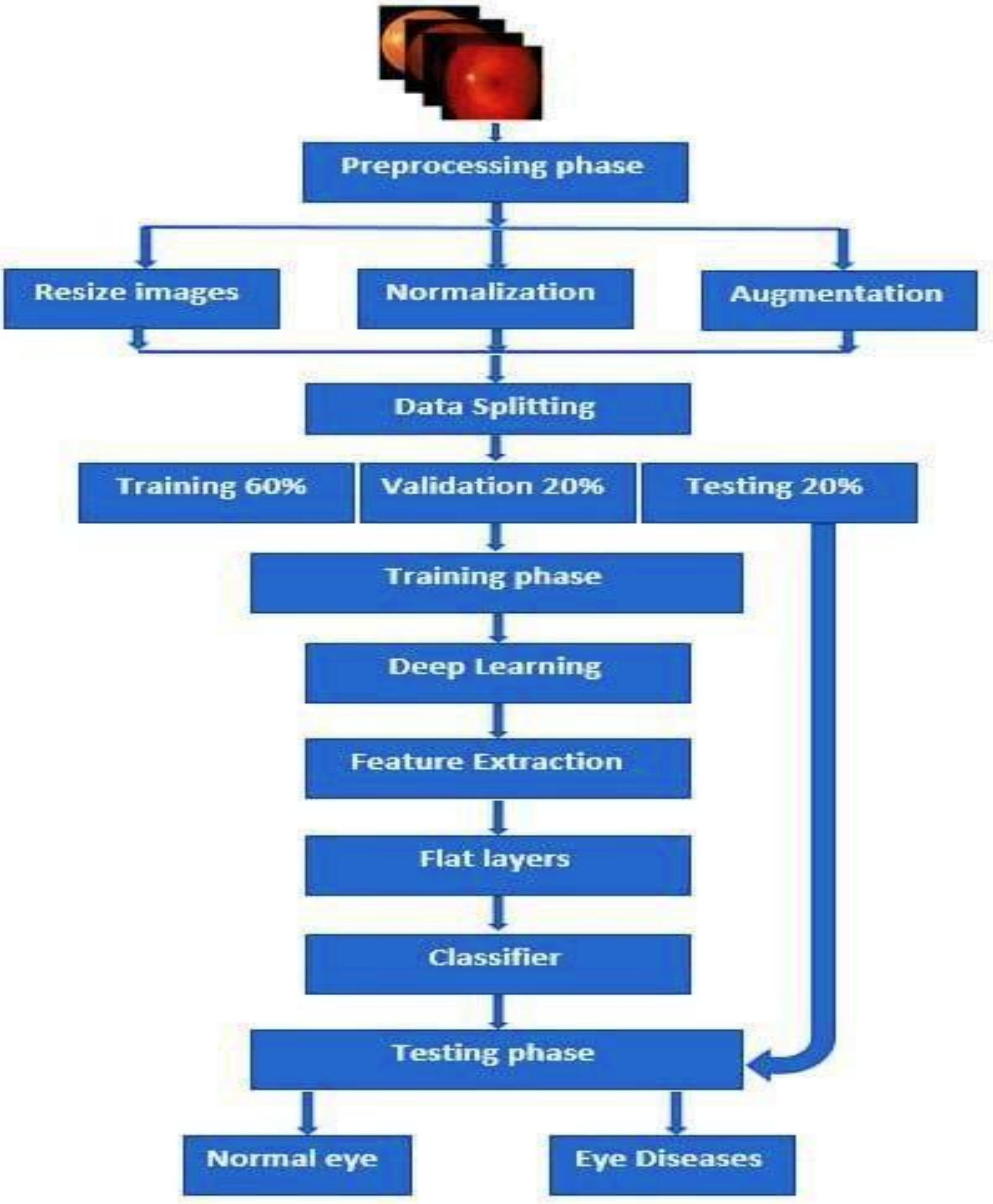

Figure 4: Eye disease classification process

II. Literature REVIEW

This section deals with previous work on eye disease detection and classification and the methods used through Deep Learning (DL) to detect them early to avoid blindness. The different eye disease datasets listed in Tables 1 to 2 are described below.

3.1 Diabetic Retinopathy Detection

Y. Wu and Z. Hu [12] used transfer learning and models such as VGG19, InceptionV3, and Resnet50. Disease was used. DR is caused by diabetes. Therefore, this article proposes a method for DR recognition using transfer learning. The experimental results show that this method's classification accuracy achieved 60%, better than the traditional direct. In [13], the authors present Distributed DL (DDL), Data Parallelism (DP), AND model parallelism (MP) to detect and classify DR. The gathered images are from the APTOS DR dataset available on Kaggle. The MP strategy yields a higher validation accuracy of 62.13% and converges faster than DP strategies, whose validation accuracy is 55.72%. In [14], VGG-16, Inception-V3, and RESNet-101 models were used to detect diabetic retinopathy. The number of images equals 130 out of 110 DR and 20 typical regulars obtained from Kaggle. The final results show that this method's classification accuracy reached 73.52% for VGG-16, 74% for Inception-V3, and 81.28% for RESNet-101. After that, a deep CNN algorithm was described for classifying eye diseases, including Diabetic macular edema (DME) and Normal. The number of images was 3500, obtained from Kaggle (OCT image). The final accuracy of DME was 82% by the 5-Convolutional layer, and the Precision and Recall of the CNN model per DME class were 87%% and 74%, respectively.

At the same time, the results of Normal achieved Precision and Recall at 77% and 89%, respectively [15].
A model proposed in [16] efficiently detects DR in real time. Early examination is critical to avoid problems with poor vision that lead to blindness in Kaggle. Seven hundred seventy- eight images were used for the training process, while 274 were used for validation. A total of 778 images were utilized for training purposes, whereas 274 images were employed for validation. A total of 778 images were used for training purposes, whereas 274 images were employed for validation. Based on the InceptionV3 model, the proposed CNN model achieved a validation accuracy of over 90%, with up to 5% improvement in testing accuracy. In [17], DR is currently considered one of the most challenging diseases caused by diabetes. This disease affects the retina and the blood vessels in the retina back, which causes poor vision and loss of sight and leads to blindness. The final results of accuracy were Sequential model 94%, VGG19 Architecture 73%, denseNet21 Architecture 81%, and SVM 87%. They focused on DL using transfer learning like ResNet-50 [18]. In this article, DR was used, and the images were obtained from the Kaggle website using two types of data: APTOS and EyePACS. The final result accuracy was 97.87%, and the Quadratic weighted kappa (QWK) score was 0.985. CNN used residual skip connection to segment exudates in retinal images [19]. Benchmark databases, E-aphtha, HEI-MED, and DiaretDB1, have 340 images. It is distributed as follows: 82 for E-aphtha, 169 for HEI-MED, and 89 for DiaReTDB1. The final results achieve sensitivity (0.97, 0.92, and 0.95) and accuracy (0.98, 0.99, 0.98) on E-ophtha, HEI-MED, and DiaReTDB1, respectively.

Table 2.1: Diabetic Retinopathy Datasets

SI. No	Study	Dataset	Diseases	Images count
1	[12]	Kaggle	Diabetic Retinopathy	
2	[13]	APTOS DR dataset	Diabetic Retinopathy	
3	[14]	Kaggle	Diabetic Retinopathy and Normal	130 images out of 110 of DR and 20 normal
4	[15]	Kaggle: OCT images	Diabetic macular edema (DME) and Normal	3500
5	[16]	Kaggle	Diabetic Retinopathy	778 images
6	[17]	Kaggle	Diabetic Retinopathy	
7	[18]	APTOS and EyePACS	Diabetic Retinopathy	
8	[19]	E-ophtha, HEI-MED and DiaReTDB1	Diabetic Retinopathy	82 for E-ophtha, 169 for HEI-MED 89 for DiaReTDB1
9	[20]	EyePACS and APTOS2019	referable diabetic retinopathy (RDR) and vision-threatening DR	
10	[21]	Kaggle	Diabetic eye disease	Total is 181240

Table 2.2: Glaucoma Datasets

SI. No	Study	Dataset	Diseases	Images count
1	[22]	RIM-ONE and RIGA	Glaucoma	750 and 455
2	[23]	ORIGA dataset	Glaucoma	650
3	[24]	Kaggle	Glaucoma	Total of 2662 images.
4	[25]	dataset of 5413 3321 samples is utilized and 1272 eyes are used for testing	Glaucoma	4593

III. EYE DISEASE CLASSIFICATION CHALLENGES AND LIMITATIONS

Despite the promising advancements in eye disease classification using machine learning (ML) and deep learning (DL) models, several challenges and limitations persist [15]. This section outlines the key constraints observed in recent studies.In [29], a major limitation was the small size of the training dataset, which adversely affected model performance and reduced classification accuracy. Similarly, [37] proposed a multiclass classification model for four types of eye diseases, but the absence of a preprocessing step to prepare the data for training likely hindered the model's classification accuracy and overall effectiveness.The work in [12] identified a complex model architecture and a high number of training epochs—approximately 300—as significant drawbacks. These factors led to increased training time and memory consumption. A similar issue was observed in [20], where the model required 200 epochs and a batch size of 64, making it computationally expensive. Additionally, this model lacked hyperparameter tuning, which limited its ability to be thoroughly evaluated and optimized.In [25], the use of low-quality images for training resulted in a less robust classification model.
The study proposed several mitigation strategies, such as increasing the size of the training dataset and implementing label smoothing to improve model generalization and reduce overconfidence. Batch normalization techniques were also recommended to address training stability.

IV. PERFORMANCE EVALUATION MEASURES

Many measurements are applied to evaluate machine learning models for classification and detection. Accuracy is a metric that assesses the classifiers using the test dataset. Using various evaluation methods helps to analyze the resulting data from different aspects and gives a better assessment and visual representation of results. In the following, the mathematical representation of different metrics involving Accuracy, Precision, Sensitivity, Specificity, and F1-score.

A summary of several eye disease classification methods based on diseases found, datasets and models utilized, accuracy, Precision, F1-score, and recall are presented in Tables 5.1 explained below. Deep learning techniques were employed in each research study to identify and classify different types of eye problems. While some researchers have utilized many datasets, others have only used one. Similarly, several works can identify several diseases, while others can only remember one

Table 5.1. Summary of Deep Learning Methods for Diabetic Retinopathy Classification.

SI. No	Study	Model	Result
1	[12]	Transfer Learning, VGG19, InceptionV3 and Resnet50	accuracy achieved 60%, better than the traditional direct.
2	[13]	Distributed deep learning (DDL) and Data parallelism (DP) and model parallelism (MP)	The MP provides faster convergence and higher validation accuracy of 62.13% compared to DP validation accuracy 55.72%.
3	[14]	VGG-16, Inception-V3 and RESNet101	The Accuracy 73.52% for VGG-16, 74% for Inception-V3 and 81.28% for RESNet-101
4	[15]	CNN	The accuracy of DME was 82% by the 5-Convolutional Layer, and Precision and Recall of CNN were 87%% and 74%, respectively.
5	[16]	CNN (InceptionV3)	validation accuracy of over 90%, with up to 5% improvement in testing accuracy.
6	[17]	CNN	Accuracy was Sequential model 94%, VGG19 73%, denseNet21 model 81% and SVM 87%.
7	[18]	DL using Transfer learning (ResNet-50)	accuracy of 97.87% and Quadratic weighted kappa (QWK) score of 0.985.
8	[19]	CNN	accuracy (0.98, 0.99, 0.98) and sensitivity (0.97, 0.92, and 0.95) on E-ophtha, HEI-MED, and DiaReTDB1, respectively.
9	[20]	EfficientNET	Accuracy of 0.984 for RDR and 0.990 for DR on EyePACS dataset. While for APTOS 2019 dataset AUC of 0.966 and 0.998 for referable and vision-threatening DR, respectively
10	[21]	VGG16, VGG19 and NASNetLarge	The VGG16 model achieved 99.07% training accuracy and the most negligible loss (0.02).

.IV. CONCLUSION AND FUTURE WORK

Automated screening techniques have significantly improved the efficiency of eye disease diagnosis by reducing the time required for image analysis. These systems not only save ophthalmologists time and resources but also enable earlier treatment initiation for patients. Manual interpretation of retinal images is often labor-intensive, time-consuming, and subject to human bias. Furthermore, there is a notable shortage of trained ophthalmologists—particularly in developing countries—who are qualified to accurately analyze these images.

This paper presents a comprehensive review of recent deep learning (DL) techniques used for diagnosing retinal diseases, with a focus on common conditions such as diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD), and cardiovascular-related ocular disorders. If left undetected, these diseases can lead to irreversible vision loss, posing substantial personal, familial, and economic challenges—especially in resource-limited regions.

The review highlights state-of-the-art DL-based methods for automated detection and classification of eye diseases. A brief overview of DL architectures is provided, alongside a discussion of publicly available retinal image datasets. Due to their superior performance in image classification tasks, Convolutional Neural Networks (CNNs) have been the predominant choice for most studies in this domain. CNNs have consistently demonstrated high accuracy in detecting various retinal diseases and even in multi-disease classification tasks.

The reviewed techniques share a common reliance on computational resources, with many models prioritizing performance while overlooking architectural simplicity. A common limitation across most DL models is the lack of a strong theoretical foundation, which is a recurring issue in DL applications for medical image analysis.

Future research should explore the integration of CNNs with ensemble learning methods to leverage both powerful feature extraction and robust classification capabilities. Hybrid models could achieve high levels of accuracy, precision, recall, and F1-score, particularly when optimized through effective preprocessing, feature selection, and filter application. Such models should be capable of handling high-resolution images with minimal storage requirements, reducing computational cost and complexity.

Utilizing pre-trained models can further streamline the deployment process, eliminating the need to train DL networks from scratch and enabling faster implementation in clinical settings. This paper also discussed the current challenges and limitations in the field, while proposing potential strategies for overcoming them. Ultimately, the insights and contributions presented in this review are essential for the practical deployment of AI-based eye disease classification systems. These technologies have the potential to support medical professionals in early disease detection and intervention, improving patient outcomes and healthcare delivery in both developed and developing regions.

References

[1] Malik, T.G. (2021). Artificial Intelligence in Ophthalmology. Pakistan Journal of Ophthalmology, 37(1).A. Lohrasebi, T. Koslowski, Modeling water purification by an aquaporin-inspired graphene-based nano-channel. J. Mol. Model. **25**, 280 (2019). https://doi.org/10.1007/s00894-019-4160-y

[2] Badah, N., Algefes, A., AlArjani, A. and Mokni, R. (2022). "Automatic Eye Disease Detection Using Machine Learning and Deep Learning Models. Pervasive Computing and Social Networking", pp.773-787. DOI: https://doi.org/10.1007/978-981-19-2840- 6_58

[3] Medical Tourism Mexico, Diabetic retinopathy information and locations in Mexico, US owned and operated since 2017, https://www.medicaltourismex.com/specialties/ophthalmologist/diabeticretinopathy

[4] World Health Organization. Elimination of Avoidable Visual Disability Due to Refractive Errors: Report of an Informal Planning Meeting. In Proceedings of the Informal Planning Meeting, Geneva, Switzerland, 3–5 July 2000; Technical Report; World Health Organization: Geneva, Switzerland, 2000.

[5] Abràmoff, M.D.; Garvin, M.K.; Sonka, M. Retinal imaging and image analysis. IEEE Rev. Biomed. Eng. 2010, 3, 169–208. [CrossRef].

[6] Singh, R.; Kaur, R.; Kaur, N. Survey on Detection of various Retinal Manifestations of Eye. Res. Cell Int. J. Eng. Sci. 2016, 20, 177–283.

[7] EssilorLuxottica, Understanding glaucoma, https://global.essilor.com/ UK/blog/what- affects-the eyes/understanding-glaucoma.

[8] Kankanala, L.M.; Jayashree, G.; Balakrishnan, R.; Bhargava, A. Automated cataract grading using slit-lamp images with machine learning. J. Ophthalmol. 2021, 2021. [CrossRef]

[9] Yang, W.; Yu, J.; Jia, Y.; Qin, Y.; Zhang, L.; Liu, J. Deep learning-based automatic cataract diagnosis on fundus images. IEEE Trans. Med. Imaging 2021, 40, 1888–1899.

[10] Ophthalmic Consultants of the Capital Region, About Cataracts, https://ophthalmicconsultants.com/cataracts/what- are-cataracts.

[11] Al-Dulaimi, H.W., Aldhahab, A. and Al Abboodi, H.M., 2023. Speaker Identification System Employing Multi- resolution Analysis in Conjunction with CNN. International Journal of Intelligent Engineering & Systems, 16(5).

[12] Y. Wu and Z. Hu, "Recognition of diabetic retinopathy based on transfer learning," 2019 IEEE 4th Int. Conf. Cloud Comput. Big Data Anal. ICCCBDA 2019, pp. 398– 401, 2019, DOI: 10.1109/ICCCBDA.2019.8725801.

[13] M. S. Patil and S. Chickerur, "Study of Data and Model parallelism in Distributed Deep learning for Diabetic retinopathy Classification," Procedia Comput. Sci., vol. 218, pp. 2253–2263, 2022, DOI: 10.1016/j.procs.2023.01.201

[14] B. O. F. Technology, U. The, and G. Of, "DEEP LEARNING-BASED SEVERITY PREDICTION FOR DIABETIC RETINOPATHY Project report submitted in partial fulfillment of the requirement for the degree of," no. May, 2021.

[15] T. Daghistani, "Using Artificial Intelligence for Analyzing Retinal Images (OCT) in People with Diabetes: Detecting Diabetic Macular Edema Using Deep Learning Approach," Trans. Mach. Learn. Artif. Intell., vol. 10, no. 1, pp. 41–49, 2022, DOI: 10.14738/tmlai.101.11805.

[16] N. Islam, U. Saeed, R. Naz, J. Tanveer, K. Kumar, and A. A. Shaikh, "DeepDR: An image guide diabetic retinopathy detection technique using attention-based deep learning scheme," 2019 2nd Int. Conf. New Trends Comput. Sci. ICTCS 2019 - Proc., pp. 1–6, 2019, DOI: 10.1109/ICTCS.2019.8923097.

[17] K. Swathi, E. S. N. Joshua, B. D. Reddy, and N. T. Rao, "Diabetic Retinopathy Detection Using Deep Learning," ASSIC 2022 - Proc. Int. Conf. Adv. Smart, Secur. Intell. Comput., pp. 1–5, 2022, DOI: 10.1109/ASSIC55218.2022.10088331.

[18] M. S. Patil, S. Chickerur, C. Abhimalya, A. Naik, N. Kumari, and S. Maurya, "Effective Deep Learning Data Augmentation Techniques for Diabetic Retinopathy Classification," Procedia Comput. Sci., vol. 218, pp. 1156– 1165, 2022, DOI: 10.1016/j.procs.2023.01.094.

[19] A. Manan, T. M. Khan, A. Saadat, M. Arsalan, and S. S. Naqvi, "A Residual Encoder-Decoder Network for Segmentation of Retinal Image-Based Exudates in Diabetic Retinopathy Screening," 2022, [Online]. Available: http://arxiv.org/abs/2201.05963.

[20] M. Chetoui and M. A. Akhloufi, "Explainable Diabetic Retinopathy using EfficientNET," Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, vol. 2020- July, pp. 1966–1969, 2020, DOI: 10.1109/EMBC44109.2020.9175664.

[21] P. Sharma and A. K. Sandhu, "Deep Transfer Learning Methods for the Prediction of Diabetic Eye Disease: An Experimental Analysis," pp. 1510–1514, 2023, DOI: 10.1109/icacite57410.2023.10183277.

[22] M. Alghamdi and M. Abdel-Mottaleb, "A Comparative Study of Deep Learning Models for Diagnosing Glaucoma from Fundus Images," IEEE Access, vol. 9, pp. 23894–23906, 2021, DOI: 10.1109/ACCESS.2021.3056641.

[23] G. Gutte, B. Khaire, V. Harne, R. Shamalik, and S. Chippalkatti, "Detection of Glaucoma Eye Disease Using Deep Learning," 2023 IEEE Int. Conf. Smart Inf. Syst. Technol., pp. 257–260, 2023, DOI: 10.1109/sist58284.2023.10223519.

[24] V. V. N. S. Kumar, G. Harinath Reddy, and M. N. GiriPrasad, "A novel glaucoma detection model using Unet++- based segmentation and ResNet with GRU-based optimized deep learning," Biomed—Signal Process. Control, vol. 86, no. PA, p. 105069, 2023, DOI: 10.1016/j.bspc.2023.105069.

[25] H. A. Hosni Mahmoud and E. Alabdulkreem, "Bidirectional Neural Network Model for Glaucoma Progression Prediction, " J. Pers. Med., vol. 13, no. 3, 2023, DOI: 10.3390/jpm13030390.