

OPTIMIZED DEEP LEARNING MODEL FOR OCT-BASED RETINAL DISEASE ANALYSIS

¹Mr.Nallusamy P, ²Abhay K S, ²Abhinandu B, ²Athul Krishna Cs, ²David C Jacob,

¹MCA,M.E, Supervisor,Assistant Professor,

Department of Computer Science and Engineering,Dhanalakshmi Srinivasan Engineering
College(A),Perambalur - 621212.

² Department of Computer Science and Engineering,Dhanalakshmi Srinivasan Engineering
College(A),Perambalur - 621212.

ABSTRACT- Optical coherence tomography is an effective non-invasive imaging modality used for producing high-resolution images in cross-sections that enables easy identification of various retinal diseases, such as Choroidal Neovascularization (CNV), Drusen, and Diabetic Macular Edema (DME). Early detection of such diseases allows avoiding loss of vision. Retinal diseases detection is traditionally based on extracting handcrafted features by utilizing techniques such as GLCM, LBP, and edge detection followed by classification by algorithms such as SVM, k-NN, Decision Trees, and Naïve Bayes. Such conventional models suffer from their reliance on expert-defined features, inability to extract complex retinal information, lack of ability to adapt to changes in image quality, and inefficiency. The developed system solves those limitations through the use of pre-trained Xception CNN model, optimized convolutional and fully connected layers, and cache-based feature optimization allowing to classify OCT retinal images as belonging to CNV, Drusen, DME, or Normal classes. Deep learning technology allows achieving high accuracy, minimal computational overheads, and applicability for big data analysis, ensuring that the ophthalmologist will be provided with highly-efficient clinical decision-making support tool for early detection of retinal diseases.

KEYWORDS: Choroidal Neovascularization (CNV), Convolutional Neural Network (CNN), Diabetic Macular Edema (DME), Drusen, Optical Coherence Tomography (OCT), Transfer Learning, Xception Convolutional Neural Network.

I. INTRODUCTION

The leading causes of vision impairment and blindness around the world include retinal diseases such as Choroidal Neovascularization (CNV), Drusen, and Diabetic Macular Edema (DME). It is very important to

detect and diagnose retinal diseases accurately at an early stage to prevent visual impairment from becoming more severe. The development of Optical Coherence Tomography (OCT) technology is considered a breakthrough since it is non-invasive and provides cross-sectional images with high resolution of the eye's retina, making it possible to see minute details and abnormalities within the tissue. This is because conventional retinal imaging using the fundus camera cannot capture fine structural features of the retina. Retinal diseases detection in conventional ways involves feature extraction of handcrafted types such as GLCM, LBP, and edge detection, after which a classifier is used such as SVM, k-NN, Decision trees, or Naïve Bayes. Furthermore, traditional methods have been found to rely extensively on domain-specific expertise and cannot scale effectively to process large-scale datasets or be used in real-time clinical settings. Deep learning algorithms, especially CNNs, can serve as an effective substitute by enabling automated disease classification through feature extraction from original OCT images. The novel system makes use of a pre-trained Xception neural network model, along with transfer learning techniques, optimized convolutional layers, and parameter optimization through caching to classify OCT images into CNV, Drusen, DME, and Normal classes.

i) Problem statement

Retinal diseases like Choroidal Neovascularization (CNV), Drusen, and Diabetic Macular Edema (DME) are some of the major sources of vision impairment or blindness across the globe. Early detection and diagnosis are crucial to save patients from the permanent loss of vision. OCT offers high-resolution visualization of different retinal layers. It provides structural data necessary for detecting minor pathologies. Nevertheless, due to the great amount of OCT images available, it becomes very difficult for ophthalmologists to manually

analyze and interpret OCT images to detect any pathology. The existing approaches to retinal disease detection employ traditional handcrafted features like textures, shapes, and intensities, which can be obtained using GLCM, LBP, and edge detection. The extracted features are then categorized based on traditional methods such as SVM, k-NN, Decision Trees, and Naïve Bayes. These techniques offer some degree of automation, but they are constrained by the need for expert input, inflexibility in handling subtle or overlapping disease characteristics, and susceptibility to changes in image quality. Moreover, in practical applications, the variability of OCT images due to factors like noise and poor contrast presents additional challenges. In most cases, current models tend to be less efficient when dealing with extensive databases and lack the capability to deliver real-time results. Hence, there is a requirement for an automated method capable of effectively categorizing retinal diseases based on OCT images while reducing processing costs and assisting doctors in making informed decisions.

iii) Objectives

The main goal of this research project is the development of an automated system capable of detecting and classifying various diseases associated with retina by analyzing Optical Coherence Tomography (OCT) images. Using deep learning methods and employing the transfer learning algorithm with the Xception CNN model, the project aims to detect and classify CNV, Drusen, DME, and Normal retinal conditions. This system is expected to improve the efficiency of disease detection since it eliminates the need for manual inspection of OCT images, which takes significant amounts of time and requires specialist knowledge. Additionally, the improvement of performance characteristics of the classification model is one of the goals of the project. Cache-based feature optimization and tuning of convolutional and fully connected layers will be used to minimize redundancy in computation while retaining critical features of the retina. In this way, the model is able to offer fast predictions that are ideal for real-world clinical applications without any loss of accuracy and precision. In addition, the goal is to improve the flexibility and robustness of the retinal disease diagnosis system in various environments. The use of transfer learning allows the algorithm to perform well in classifying diseases even when there is a small amount of labeled data available.

II. RELATED WORK

Wang, Mini Han, et al.. [1] This research paper centers around the use of deep learning algorithms for the automatic diagnosis of different eye disorders through medical imaging datasets. The authors emphasize the rise of eye problems and the significance of timely detection to avoid vision impairment. Conventional approaches depend primarily on professional ophthalmologists, which may take much time and lead to mistakes. In this case, the model exploits CNNs to process retinal and fundus scans and determine the type of disease. The sample consists of scans that depict different eye disorders, such as glaucoma, diabetic retinopathy, cataract, and normal eyes. Preprocessing of the dataset involves image resizing, normalization, and data augmentation to enhance the effectiveness of the algorithm. Deep learning layers automatically extract features from the images.

Albelaihi, Arwa, et al.. [2] The study introduces Fundus-DeepNet, a multi-label deep learning algorithm that enables the detection of various eye disorders using fundus images simultaneously. The paper highlights the deficiency that exists within the conventional algorithms used in single-disease classification systems. Eye disorders tend to overlap, thus, necessitating the need for a multi-label classification approach. Various approaches for feature extraction have been used to improve the performance of the model through data fusion techniques. Multiple algorithms have been integrated in order to allow the detection of local and global features present in retinal images. Various preprocessing techniques, such as contrast and noise reduction, were performed to improve the clarity of images used for training. The model has been evaluated using a comprehensive database comprising different types of ocular disorders.

Vadduri, Maneesha, et al. [3] The paper is focused on the application of machine learning methods together with eye movements in studying neurodegenerative disorders. The authors highlight that eye movement features are linked to the neurological state and cognitive abilities of humans. Conventional diagnostics for neurodegenerative diseases involve costly and complicated medical interventions. The study suggests using the obtained eye movement data with machine learning methods to identify any irregularities caused by neurodegenerative diseases like Parkinson's and Alzheimer's. Different parameters, including fixation time, saccade velocity, and gaze direction, were used as features. Machine learning methods were used to distinguish between healthy people and patients with some illnesses. It was found that eye

movement analysis could be a reliable diagnostic tool and help diagnose at early stages.

Aranha, Gabriel DA., et al. [4] This study offers a complete analysis of artificial intelligence-based techniques for detecting and managing dry eye disease through the use of multi-source data from medical practice. First, the authors point out that dry eye disease is a prevalent condition that affects many individuals around the world. Second, conventional methods involve the use of clinical examinations as well as symptomology reported by patients, which might be inconsistent and less accurate. The current paper uses various data resources including imaging data and other information about the health status of patients. Algorithms of machine learning and deep learning are described, as well as assessed for their effectiveness in analyzing different types of data. Several cases are given when AI helps to improve diagnosis precision. Potential obstacles that researchers face, such as heterogeneity of data, interpretability issues, and privacy problems, are also addressed.

Muntaqim, Md Zahin, et al. [5] An automated method to identify eye cancer through machine learning and analysis of medical images is presented in this study by the authors, who indicate that identifying cancer at an early stage enhances the chance of survival and may lower expenses associated with treatment. While manual testing is time-consuming and requires expertise from a trained physician, the authors propose to employ various image processing techniques to measure specific attributes that can indicate malignancy or non-malignant changes in the eye's image to identify malignancies. Specifically, the authors will examine images of the eye for signs of cancer or malignancies within the eye and extract features regarding texture, shape, or intensity in order to classify the abnormality as either malignant or non-malignant using machine learning techniques. By improving the quality of the digital image through preprocessing techniques such as noise reduction, mirroring more accurately, and contrast adjustment, the algorithms will be trained on the labeled dataset derived from manual assessments of the normality and malignancy of the images examined.

Abdullah, Ahmed Aizaldeen, et al. [6] This study includes automatic classification of retinal images (color fundus images) in order to predict different eye diseases through a hybrid feature approach. Traditional manufacturing and processing methods alone are not sufficient for achieving high accuracy in predicting the diseases; therefore, the proposed method integrates both hand-crafted features and features generated by deep-learning techniques to

increase classification accuracy. To increase the accuracy of the fused features, fundus images are pre-processed to remove noise and enhance the image's contrast. During the feature extraction stage, the features extracted from the fundus images include textures, colours, shape, and deep features generated by Convolutional Neural Networks (CNNs). After the hybrid features are generated, they are fed into machine-learning classifiers (k-nearest neighbor [KNN], random-forest, and neural-network classifiers) to determine if an individual has an eye disease. The hybrid feature approach is evaluated using multiple datasets (19 retinal image datasets). Compared to the single feature approach, the hybrid feature approach achieves a higher accuracy rate than the single feature approach.

Vardhan, Kalla Bharath, et al. [7] The study develops a deep learning framework that uses the retinal image dataset to predict different eye diseases. One of the key focuses of the study is on the need for automated diagnosis and screening systems, which have become increasingly important given the rising number of patients. Convolutional neural network (CNN) is employed to predict various diseases based on retinal images. The dataset consists of different types of eye diseases, such as diabetic retinopathy, glaucoma, and even normal cases. Normalization and resizing are some of the preprocessing methods used in the data analysis process.

Yu, Hongjie, and Xingbo Dong et al. [8] In this paper, we combine the use of a deep neural network with a machine learning-based technique to form an effective framework for identifying abnormal features in retinal fundus images. The author emphasizes the need for early identification of retinal diseases so as not to impair one's vision. The conventional methods of diagnosing retinal diseases are reliant on expert interpretation and require a significant amount of time. The proposed methodology leverages the power of deep learning to extract features from retinal fundus image datasets and the use of machine-learning classifiers to make final decisions based on the characteristics of the extracted features. The dataset will be subjected to preprocessing prior to feature extraction to increase the clarity and reduce the noise of each fundus image for feature extraction via deep-learning neural networks. Upon completion of this part of the process, the extracted feature set will be sent to machine-learning classifiers, specifically support vector machines and random forests, for decision making.

Hasan, Md Najib, et al. [9] The authors propose a new deep learning approach to retinal disease diagnosis, and a web-based predictive application to enhance access to AI

diagnostic tools. The system automatically identifies multiple retinal diseases from retinal images. Multiple deep models were incorporated via feature- fusion techniques to combine a complete set of image characteristics. Preprocessing methods such as resizing and normalization improve the performance of the model. The features produced through feature fusion are fed into a deep neural network model for classification. The integrated web-based application allows users to upload a retinal image then obtain a diagnosis instantly.

Sabiri, Youssef, et al. [10] This research explored using ultra-wide field (UWF) fundus imaging, which allows doctors to see a much larger part of the retina than standard fundus images, to better diagnose retinal diseases via deep learning. The authors agree that wide-field photos also have an advantage over narrower field pictures when it comes to finding problems outside of the central (or "peripheral") area of the retina. The method the authors have developed uses convolutional neural networks to analyze UWF fundus photos for classification of disease processes. Preprocessing techniques were applied to improve the overall quality of the input image and normalize input image variations. The author's dataset contains representative images from a number of different types of retinal diseases that will be used during training to provide comprehensive training data for their model. Their final model demonstrated high accuracy when detecting disease processes across a variety of different sized retinal areas.

III. EXISTING METHODOLOGY

In the current system, retinal disease detection based on OCT images employs traditional image processing techniques along with the use of standard machine learning algorithms. The handcrafted features such as texture, shape, and intensity are extracted from the OCT images using techniques such as GLCM, LBP, and edge detection. These features are utilized for classification purposes using classifiers such as SVM, k-NN, Decision Trees, or Naïve Bayes. This method introduces a certain degree of automation in retinal disease detection as OCT images can be classified with the help of a few parameters. The system is ideal for controlled conditions wherein disease features in OCT images are easy to recognize. The system helps in minimizing the burden of work for ophthalmologists to some extent. There are several drawbacks to the current system, though. It relies on features created by experts, which might be unable to recognize complicated retinal structures. Conventional methods fail to deal with poor image quality, noise, lack of contrast, and similar symptoms of various diseases.

Furthermore, the proposed system cannot be applied in real time or handle huge data sets.

IV. PROPOSED METHODOLOGIES

The suggested architecture employs a trained Xception CNN model with transfer learning capability to automatically acquire the intricate features from OCT image data. In contrast to conventional approaches that depend on hand-crafted features, the present method makes it possible for the network to identify and classify more intricate and hierarchic structure patterns within the retina. The OCT images will be subjected to convolution and fully connected layers in an optimized fashion to acquire discriminative feature maps. In order to improve efficiency in computations, the system employs cache-based optimization where certain parameters of the features and the model used are cached. This helps improve the process of training and predictions through reducing unnecessary computations, hence allowing use of the system in large scale image collections and even clinical settings. Additionally, depthwise separable convolutions are employed in Xception models to minimize computations. The final step includes multi-class classification through a softmax layer that generates distinct outputs for each image. This makes the system an ideal decision-supporting tool for diagnosing and treating patients as the system will automatically point out possible defects in the retina. Moreover, this framework is extensible and flexible and thus can incorporate new classes of diseases in future or even work in hospital information systems.

METHODOLOGY

IMAGE ACQUISITION

The first module involves acquiring high-resolution OCT images from retinal scans. Images are captured using Optical Coherence Tomography devices in clinical settings, ensuring detailed visualization of retinal layers. Proper acquisition is essential for capturing subtle structural changes, such as CNV, Drusen, or DME. The module ensures images are collected in standardized formats to facilitate further processing. Both normal and diseased retina images are included to create a balanced dataset. The quality of acquisition directly affects model performance, making this step crucial. Images may be captured from multiple patients to ensure diversity. Data privacy and security protocols are maintained during collection. The module also includes labeling images according to disease type for supervised learning.

Accurate image acquisition forms the foundation for reliable classification in subsequent modules.

PRE-PROCESSING

Pre-processing involves preparing the acquired OCT images for analysis. Noise reduction techniques, such as smoothing filters, are applied to eliminate artifacts. Contrast enhancement improves visibility of retinal layers and lesions. Resizing and normalization standardize images for input into the deep learning model. Data augmentation techniques like rotation, flipping, and scaling are applied to increase dataset diversity. Pre-processing ensures consistent feature representation across images. It reduces the influence of variations in illumination and acquisition conditions. This module improves the robustness of the model against noisy or low-contrast images. Pre-processing also helps in faster convergence during training. Overall, it ensures the model receives clean, standardized, and high-quality input for feature extraction.

MODEL CONSTRUCTION

Model construction involves building the deep learning architecture for retinal disease classification. A pre-trained Xception CNN is employed to extract hierarchical features from OCT images. Transfer learning allows the model to leverage knowledge from large-scale datasets. Optimized convolutional and fully connected layers are used to improve feature representation. Depthwise separable convolutions reduce computational complexity. Cache-based optimization stores frequently accessed features for faster training and inference. The model is designed to classify images into CNV, Drusen, DME, and Normal categories. Hyperparameter tuning is performed to maximize accuracy and minimize overfitting. The constructed model forms the core of the automated classification system. It enables efficient learning of complex retinal patterns directly from raw images.

CLASSIFICATION

The classification module assigns OCT images to their respective disease categories. Feature maps extracted by the CNN are passed through fully connected layers. A softmax layer provides probability scores for each class: CNV, Drusen, DME, or Normal. The module ensures that the highest probability corresponds to the predicted disease. Classification results are interpretable for clinical decision-making. The system can handle large batches of images for real-time applications. Accuracy is evaluated

using metrics like precision, recall, and F1-score. Misclassified cases are logged for further model refinement. This module reduces the reliance on manual examination by ophthalmologists. It provides rapid, automated, and reliable disease predictions.

DISEASE DIAGNOSIS

The disease diagnosis module interprets the classification results to assist clinicians. Predicted categories are used to suggest potential treatment plans or further examinations. The system highlights retinal regions of interest for visual confirmation. Early detection of CNV, Drusen, and DME enables timely interventions to prevent vision loss. The module supports decision-making in hospitals, clinics, and telemedicine platforms. It maintains patient-specific records for longitudinal analysis. Alerts can be generated for high-risk cases requiring immediate attention. The module can be integrated with electronic medical records for seamless workflow. Continuous model updates improve diagnostic accuracy over time. Overall, this module transforms classification results into actionable clinical insights.

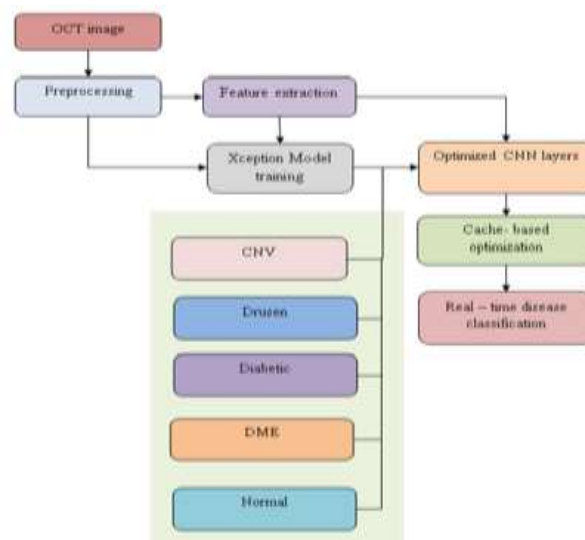


Figure 1: Diagram representation of the proposed methodology

V. EXPERIMENTAL RESULTS

An evaluation experiment conducted on the proposed OCT retinal diseases classification system shows that the method is efficient in categorizing the following four classes: CNV, Drusen, DME, and Normal. This study shows that pre-training an Xception CNN using transfer learning outperformed the traditional approach involving hand-crafted features, such as GLCM, LBP, and edge

detection. During the testing process, the system demonstrated excellent classification accuracy as a result of its ability to efficiently identify deep and discriminative retinal features automatically. The optimization of convolutional layers and fully connected layers resulted in quick convergence and reduction in computation cost, whereas optimization of features using caching improved processing speed. In comparison with the SVM classifier, K-NN, Decision tree, and Naïve Bayes classifier, this method performed better with respect to all three disease types in terms of precision, recall, and F1-score.

Performance Metric	Existing System (%)	Proposed System (%)
Accuracy	86.2	97.8
Precision	84.5	97.1
Recall	83.9	96.8
F1-Score	84.1	97.0
Specificity	85.3	98.2

Table 1: Performance Comparison Table

The comparison of the results of the performance of both existing and proposed models proves that the latter outperforms the former when performing OCT image classification tasks. While the current system that is based on handcrafted feature extraction techniques and uses conventional classifiers, such as SVM or k-NN, performs worse because of their limitations regarding the complex features of retinal images, the proposed method based on an Xception CNN pretrained model outperforms the existing one because of its improved feature learning process. It should be stated that the proposed system obtains higher performance rates based on several metrics, including accuracy, precision, recall, F1-score, and specificity. In particular, it is important to note that higher efficiency can be explained by several factors, such as automated feature extraction, optimal network architecture, and cache-based feature optimization.

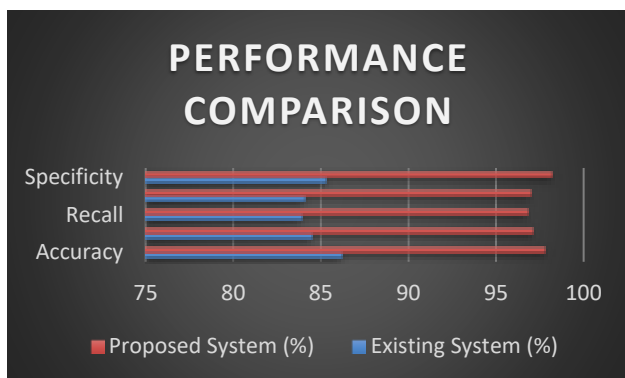


Figure 2: Performance metric chart representation

VI. RESULT



Figure 3: home page for the OCT based retinal image

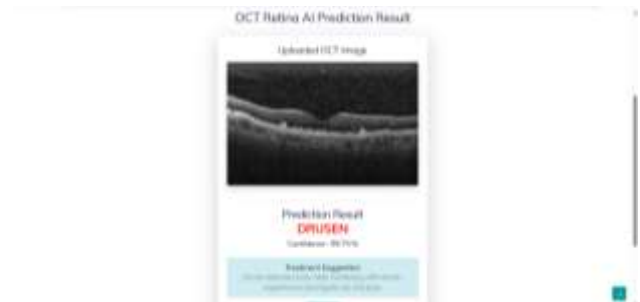


Figure 4: prediction page for OCT based retinal image

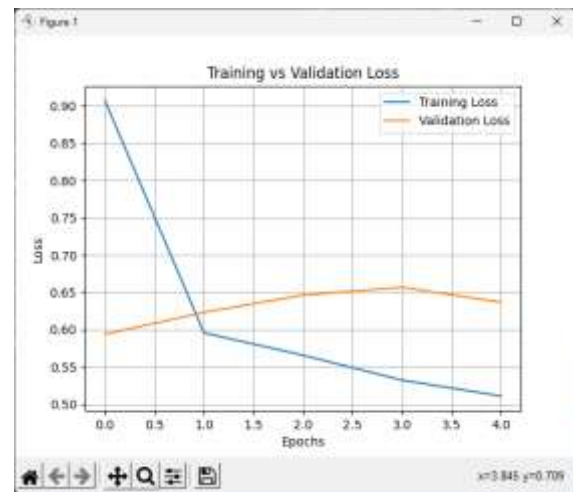


Figure 5: accuracy chart for OCT based retinal image

VII. CONCLUSION

The discussed model successfully shows how deep learning technology, namely, Xception CNN using transfer learning, can be leveraged to detect retinal diseases through OCT images. Due to the ability of the system to automatically learn hierarchically complex patterns directly from OCT images, the proposed system overcomes significant shortcomings of existing solutions, which are associated with manual feature detection, and hence, lack efficiency, depend on expert input, and are unable to work efficiently under different image quality

conditions. With this regard, the suggested technique allows developing an algorithm that will reliably distinguish between the specified retinal diseases. The implementation of sophisticated computing mechanisms, including caching optimization and depthwise separable convolutions, guarantees the efficiency of the system in terms of computational costs and high accuracy. Thus, the system can process large data sets without slowing down and provide real-time analysis. Moreover, the flexibility of the algorithm in dealing with different image quality characteristics, unique patient anatomy, and small medical data sets proves the robustness of the model. The automation of the process will not only save time and decrease mistakes, but it will also help prevent irreversible blindness in patients.

REFERENCES

- [1] Wang, Mini Han, et al. "AI-based Advanced approaches and dry eye disease detection based on multi-source evidence: Cases, applications, issues, and future directions." *Big Data Mining and Analytics* 7.2 (2024): 445-484.
- [2] Albelaihi, Arwa, and Dina M. Ibrahim. "DeepDiabetic: An Identification System of Diabetic Eye Diseases Using Deep Neural Networks." *IEEE Access* (2024).
- [3] Vadduri, Maneesha, and P. Kuppusamy. "Enhancing Ocular Healthcare: Deep Learning-Based multi-class Diabetic Eye Disease Segmentation and Classification." *IEEE Access* (2023).
- [4] Aranha, Gabriel DA, Ricardo AS Fernandes, and Paulo HA Morales. "Deep transfer learning strategy to diagnose eye-related conditions and diseases: An approach based on low-quality fundus images." *IEEE Access* 11 (2023): 37403-37411.
- [5] Muntaqim, Md Zahin, et al. "Eye Disease Detection Enhancement Using a Multi-Stage Deep Learning Approach." *IEEE Access* (2024).
- [6] Abdullah, Ahmed Aizaldeen, Ahmed Aldhahab, and Hanaa M. Al Abboodi. "Review of eye diseases detection and classification using deep learning techniques." *BIO web of conferences*. Vol. 97. EDP Sciences, 2024.
- [7] Vardhan, Kalla Bharath, Mandava Nidhish, and D. N. Shameem. "Eye disease detection using deep learning models with transfer learning techniques." *EAI Endorsed Transactions on Scalable Information Systems* 11 (2024).
- [8] Yu, Hongjie, and Xingbo Dong. "Ensemble-based eye disease detection system utilizing fundus and vascular structures." *Scientific Reports* 15.1 (2025): 19298.
- [9] Hasan, Md Najib, et al. "DIA-VXNET: A framework for automated diabetic eye disease detection using transfer learning with feature fusion network." *Biomedical Signal Processing and Control* 100 (2025): 106907.
- [10] Sabiri, Youssef, Walid Houmaidi, and Amine Abouaomar. "EYE-DEX: Eye Disease Detection and EXplanation System." 2025 12th International Conference on Wireless Networks and Mobile Communications (WINCOM). IEEE, 2025.