2024 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS)
Pune, India. Oct 17 - 19, 2024

# Eyes on Health: A Deep Learning Approach for Ocular or Eyes Disease Detection

Swapnil K. Shinde
*Research Scholar IIIT, Pune.*
*Vishwakarma Institute of Technology,*
Pune Maharashtra, India
swapnil.shinde@viit.ac.in

Amar Buchade
*Vishwakarma Institute of Technology,*
Pune Maharashtra, India
amar.buchade@viit.ac.in

Parikshit Mahalle
*Vishwakarma Institute of Technology,*
Pune Maharashtra, India
parikshit.mahalle@viit.ac.in

Mayuri Vengurlekar
*KJ College of Engineering and management research,*
Pune Maharashtra, India
mayurichaudhari126@gmail.com

Satish Yedge
*KJ College of Engineering and management research,*
Pune Maharashtra, India
satishyedge2000@gmail.com

Gajanan Arsalwad
*Trinity College of Engineering and management research,*
Pune Maharashtra, India.
gajanansggs@gmail.com

2024 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS) | 979-8-3503-5434-8/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICBDS61829.2024.10837388

***Abstract*— At present, eye conditions or eye diseases are the primary reason for blindness and vision loss around the globe. Identifying and forecasting eye illnesses with conventional techniques are difficult, lengthy, and susceptible to human mistakes. Any delay in identifying and foreseeing future issues will lead to the patient losing their eyesight or experiencing vision problems. In order to prevent this, we require a system that is capable of detecting and predicting eye diseases with effectiveness, efficiency, and automation. In this article, we developed a computerized system using a pre-existing EfficientNetB3 CNN family structure to detect eye diseases through deep learning technology. The dataset utilized in this research was obtained at no cost from the web and comprises 4,217 pictures. The model was trained with transfer learning and enhanced with an improved dataset through augmentation methods. Precision score, Recall score, and F1-score and accuracy are utilized for assessing the model's performance. Our findings indicate that the EfficientNetB3 model performs better than conventional CNN structures, achieving high precision in identifying various eye diseases. The accuracy of model 97% on the training dataset and 95% on the test dataset by incorporating image augmentation. We utilized characteristics from the EfficientNetB3 structure, tailored for identification and categorization in image datasets.**

***Keywords*— *Ocular diseases, Fundus images, Deep learning (DL), Machine Learning (ML), EfficientNetB3, Convolutional Neural Network (CNN).***

## I. INTRODUCTION

Millions of individual affecting the eye disease and posing huge burden on healthcare system represent major health concern worldwide. The most prevalent eye diseases are glaucoma, cataract, diabetic retinopathy and different types of retinal pathologies. Cataract: opacification of natural lens resulting in blurred vision and lowered color perception, it is mostly associated with aged people. it don't cause immediate threat to vision but make major impact on daily functioning Glaucoma: caused by continuous deterioration of optic nerve if not detected early and remain untreated results in complete loss of vision.

The early detection of eye disease is crucial for the person who is having family history of eye disease such like diabetes, or older aged peoples, or certain eye injuries or surgeries. These diseases can lead to vision impairment or even irreversible blindness if left untreated, the importance of early detection and timely intervention.

Commonly, the diagnosis of eye diseases has majorly depends on clinical examinations conducted by ophthalmologists, supplemented by fundus photography. The manual interpretation is time consuming, subjective and prone costly. Due to this there is huge demand for a system of automated prediction of eye disease based on fundus images is growing. We are making Deep Learning based system that predicts the eye disease based on fundus images. For experimental purpose we used Ocular disease dataset publicly available on kaggle.

*Overview of Deep Learning for medical image analysis:*

Deep learning (DL), has emerged as a recognized as technique for image analysis. Its ability to learn the complicated patterns and ease of use and program with a huge potential to determine accurate results from raw data. Many examples currently available in diagnosis of various diseases done by using deep learning, like. Skin cancer detection used CNN architecture for detection of skin cancer [1]. Many other diseases are also detected and predicted using deep learning. In this context, deep learning approach has been applied to automate the detection and classification of eye disease from fundus images. By using large dataset and appropriate network architecture can extract discriminative features from fundus images lead to correct diagnosis of eye disease

*Motivation for the Proposed Approach:*

Needs of an accurate, efficient and scalable solution of eye disease prediction. While existing approaches faces many challenges. Our system tried to address many of them for detection and classification with better accurate and more reliable solution by using pre-trained EfficientNetB3 deep learning architecture.

Further sections of the paper describe Related Work, Methodology Used, Results, Conclusion, Future Scope and References.

## II. RELATED WORK

In [2], Of the several eye diseases, only cataracts are identified using ML and DL models.

The dataset used was hosted on Kaggle using only photos of normal and cataract patients.

In this study, CNN and SVM were used to detect eye diseases. CNNs outperformed SVMs in terms of accuracy, showing accuracy 87.5% on training dataset and 85.42% on test dataset.

[3] Only cataract disease diagnosed from several disease, dataset used for research is free downloaded from online sources. Used data of cataract and normal images from dataset for making prediction. For disease detection used Convolutional Neural Network (CNN) based VGG-16 pre-trained architecture. VGG-16 achieved accuracy of 96.10 %. This model is fine tuned by keeping learning rate at 0.01 and accuracy has been measured at different epoch 5, 10, 15 and 20. They also measured loss of the model at each epoch. The least loss of 0.1651 is received at epoch 20.

In [4], A tailored Convolutional Neural Network (CNN) is employed for disease classification. The Flower-Pollination Optimization Algorithm (FPOA) method for feature extraction requires pre-processed images. FPOA enhances network efficiency and accuracy by fine-tuning the hyper parameter prior to running the CNN model. The CNN model's identified category is established through multi-class SVM (MSVM) classification. We acquired the ODIR dataset consisting of 5,000 images from Kaggle for the research project.In [5], Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machine (SVM) are employed for detecting cataract, glaucoma, and retinal diseases. Used a dataset available to the public on Kaggle. Gradient boosting achieves the accuracy of 90%, followed by logistic regression at 89% and random forest at 86%.

In [6], The four main types of eye diseases identified are typical vision, glaucoma, diabetic retinopathy, and cataracts. In this case, the Adam optimizer is used to optimize the proposed architecture, along with a specially designed CNN model.

In [7], Used AlexNet modified version of Convolutional Neural Network (CNN) for detection of glaucoma and diabetic retinopathy.

The dataset utilized in this investigation was obtained from publicly accessible online sources. CNN For categorization purposes, transfer learning is used to keep AlexNet. They developed NetTransfer, and I was able to get 94.30% accuracy for two classes. When the same model was used independently on two datasets, NetTransfer-II achieved 91.8% accuracy. The accuracy of the same model, known as NetTransfer-III, was 89.7% when it was applied to three different class datasets. NetTransfer-IV has a validation accuracy of 93.1%.

In [8], created eye disease classification model based on Inception-ResnetV2 with fine tuning mechanism. Inception-ResnetV2 is specifically known for its future extraction capabilities. Model pre-trained and fine tuned on labeled eye disease images dataset.

The model without fine-tuning achieved accuracy of 81%. It drastically improved accuracy after fine tuning to 94.74%.

In [9], The proposed work used dataset of 3200 images, labeled with the help of senior retina expert doctors. Named as RFMID (Retinal Fundus Multi-Disease Image Dataset). The framework designed to diagnose 8-12 disease from this dataset. Applied various machine learning algorithm. In which Random Forest achieved accuracy of 100% up to 10 disease, but while 12 disease accuracy goes down to 96.57% without augmenting the image dataset. Support Vector Machine(SVM) for 10 disease accuracy is 97.72% and for 12 disease accuracy is 96.59%, in same case applied KNN model achieved accuracy for 10 disease is 83.3% and for 12 disease 81.99%. Decision tree achieves accuracy for 10 disease is 97.21% and for 12 disease 78.34%.

In [10], This study detected texture characteristics in grayscale images through the Gray Level Co-occurrence Matrix (GLCM) and utilized pre-processed thermal information. Different combinations of features are used to extract and classify statistical information from RGB and HSI images with different classifiers. The SVM model is utilized for conducting cross validation in five separate folds. The broader applicability of the recommended model was specifically improved by incorporating a five-fold cross-validation. When employing fivefold cross validation, the SVM achieved accuracy 86.22%, specificity 79.17%, and sensitivity 94.07%.

## III. MATERIAL AND METHODS

This section discusses the dataset and operations on dataset to apply methodologies for detection of eye disease using EfficientNetB3.

Data collection, pre-processing, train-test split, model training, model validation and determine the accuracy of the model.

### *A. Dataset Description*

Dataset for this study can be obtained online from internet, which is open access. Consist of 4217 pictures total from 4 classes—Diabetic Retinopathy, Glaucoma, Cataract, and Normal—make up dataset.The distribution of images in the dataset presented in Figure 1.

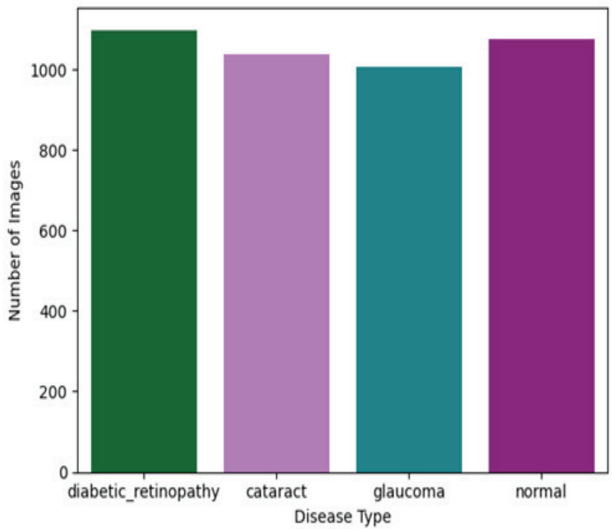


Fig. 1. Distribution of Dataset

Dataset contains 1098 images of diabetic retinopathy disease, 1038 images of cataract disease, 1007 images of glaucoma disease and 1074 images of normal or without anomalies.

The Fig. 2 and Fig. 3 depict the images of eye disease and healthy eyes. The disease type is labeled on image.

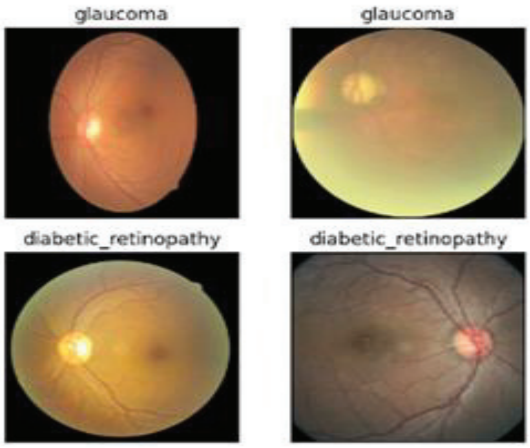


Fig. 2. Eye Disease

Fig. 2. Depict the image of glaucoma and Diabetic retinopathy disease.

Fig. 3 Depict the images of cataract and normal or healthy eye image.

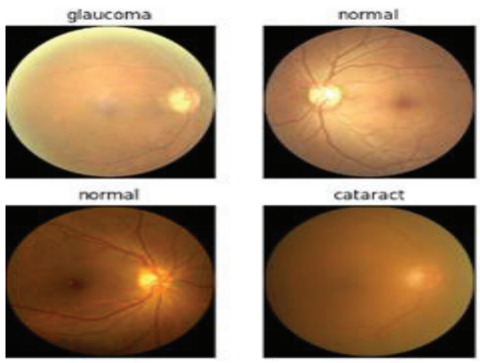


Fig. 3. Eye Disease

## B. *Methodology Description*

Firstly imported the dataset, it contains 4 directories for 4 classes of disease. Created data frame that contains images and class of images 0-glaucoma, 1- cataract, 2-normal, 3- diabetic retinopathy.

Fig.4. depicts the conversion.

[5]:

| | image | disease_type |
|---|---|---|
| 0 | /kaggle/input/eye-diseases-classification/data... | 0 |
| 1 | /kaggle/input/eye-diseases-classification/data... | 0 |
| 2 | /kaggle/input/eye-diseases-classification/data... | 0 |
| 3 | /kaggle/input/eye-diseases-classification/data... | 0 |
| 4 | /kaggle/input/eye-diseases-classification/data... | 0 |
| ... | ... | ... |
| 4212 | /kaggle/input/eye-diseases-classification/data... | 3 |
| 4213 | /kaggle/input/eye-diseases-classification/data... | 3 |
| 4214 | /kaggle/input/eye-diseases-classification/data... | 3 |
| 4215 | /kaggle/input/eye-diseases-classification/data... | 3 |
| 4216 | /kaggle/input/eye-diseases-classification/data... | 3 |

4217 rows × 2 columns

Fig. 4. Dataframe with disease class

With the help of train_test_split from sklearn.model_selection, divide the dataset into train and test. Following the split, 80 and 20 percent for training and evaluating the performance of the model.To obtain each disease's useful contribution to the train and test datasets, data is randomly selected. The test dataset has 843 photos, whereas the training dataset has 3374 images. Because we are using the EfficientNetB3 model, which requires input picture size of 300 X 300, we are scaling the photos to 300 X 300 while dividing it in test and train dataset.

The in detailed model is shown in Fig. 5. Description of EfficientNetB3 is given below.

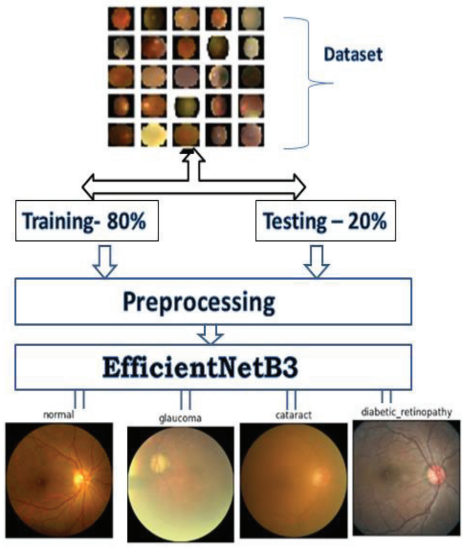


Fig. 5. Proposed Model

EfficientNetB3: Compared to earlier CNN family architectures, this family of convolutional neural networks (CNNs) is designed to provide great performance with fewer computational resources. It makes use of a novel scaling technique that uses a compound coefficient to scale all dimensions, including depth, width, and resolution, consistently.

Table 1 describes the EfficientNetB3 architecture in detail. It is the EfficientNetB0-B7 architectural family, designed specifically for deep learning models based on images. It facilitates achieving excellent results.

*Model Hyper-parameters:*

In order to optimize the model's performance, particular hyperparameter values were selected and put into practice.

Adam is the most often used optimization technique in deep learning model training. Performs the optimization depending on momentum. During training, it automatically adjusts the learning rate.

Loss Function: For multi disease classification categorical cross entropy as loss function is used in this study.

This loss function helps to differentiate between the actual results and the predicted results. The training of the model lasted 25 epochs in total. [1]

Batch Size: model trained on batch size 32.

Learning Rate: During training, it regulates the size and step. Greater running rates require greater strides, while lower running rates require smaller strides. When training this model, we chose a learning rate of 0.001.

*Model Implementation*

Resize: Prior proceeding to apply EfficientNetB3 on dataset, all the images from the train and test dataset are resized to 300 X 300. It is required input image size for EfficientNetB3.

Data Augmentation: ImageDataGenerator is used to do data augmentation on the train and test datasets. With real-time data augmentation, it is a powerful tool from Keras that generates batches of tensor image data. It alters the photos in a number of ways, including rotating, shearing, flipping, and zooming. It enhances the model's ability to be more broadly used.

Working: To train our model, we employ the pre-trained EfficientNetB3 architecture. To recognize the learned information, weights are allocated based on the weights obtained from the pre-trained "ImageNet" dataset. Effects of pre-trained models: Pre-trained models assist increase model accuracy and need less time to train on real datasets.

A few custom layers were added to the EfficientNetB3.

A layer in Keras called GlobalAveragePooling2D uses global average pooling to lower the dimensionality of feature maps before sending them to the output layers or fully connected layers. In order to keep the model from overfitting, dropout is utilized. Dense layer was added as a completely connected layer using "Relu" as the activation function.

## IV. RESULTS AND DISCUSIION

The metrics used to measure the performance of the model are F1 Score, Precision Score, and Recall Score. Assessing performance by utilizing both the test and train datasets. After enhancing the images in the dataset, the model achieves 97.2% accuracy on the training dataset and 95% on the test dataset. It reaches 86% accuracy for the train dataset and 83% for the test dataset without any enhancement. It can be inferred that enhancing the images will help improve the performance of the model.

The outcomes are shown in figure 6.

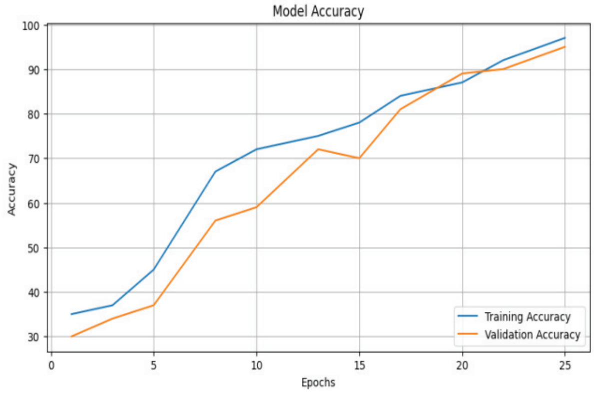


Fig. 6. Accuracy chart of model

The performance measurement metrics charts are shown below.

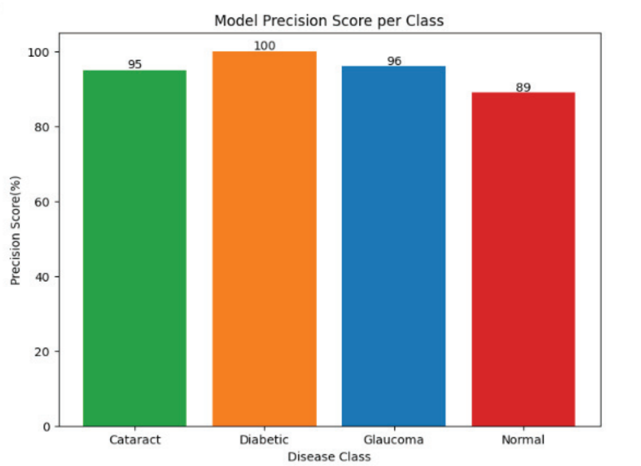


Fig. 7. Precision Score

The model results the precision score for each class, for cataract it is 95, Diabetic it is 100, Glaucoma is 96 and Normal vision it is 89 presented in Figure 7.

The Recall Score of the model for each class for Diabetic Retinopathy is 100, for cataract 99, for Glaucoma it is 86 and for Normal Vision is 95 presented in Figure 8.

TABLE I. ARCHITECTURE OF EFFICIENTNETB3

| Block No. | Layer Name | Resolution | Filter Size | Channels | No. of Layers |
|---|---|---|---|---|---|
| 1 | Conv | 300 X 300 | 3 X 3 | 40 | 1 |
| 2 | MBConv1 | 150 X 150 | 3 X 3 | 24 | 2 |
| 3 | MBConv6 | 150 X 150 | 5 X 5 | 32 | 3 |
| 4 | MBConv6 | 75 X 75 | 3 X 3 | 48 | 3 |
| 5 | MBConv6 | 38 X 38 | 3 X 3 | 96 | 5 |
| 6 | MBConv6 | 19 X 19 | 5 X 5 | 136 | 5 |
| 7 | MBConv6 | 10 X 10 | 5 X 5 | 232 | 6 |
| 8 | MBConv6 | 10 X 10 | 3 X 3 | 384 | 2 |
| 9 | Conv | 10 X 10 | 1 X 1 | 1536 | 1 |
| 10 | Global Pooling | 10 X 10 | | | 1 |
| 11 | Dense | 10 X 10 | | | 1 |

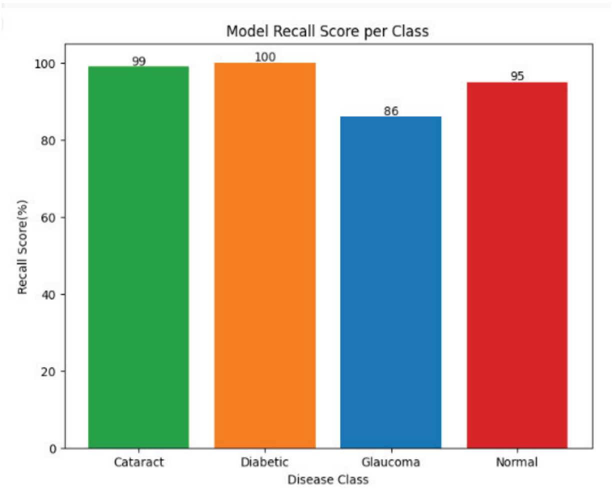


Fig. 8. Recall Score

F1 score of the model for each class, Cataract it is 97, for Diabetic Retinopathy – 100, for Glaucoma -90 and for Normal Vision 92 presented in Figure 9.

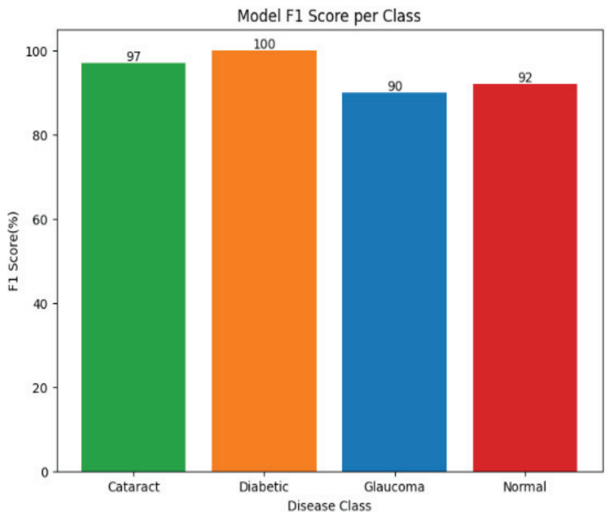


Fig. 9. F1 Score

## V. CONCLUSION

The eye disease makes major impact on daily routine functionality of the patient. If not detected and treated as earlier then it causes a major threat of complete loss of vision.

Our implemented system will remove the need of manually diagnosis of eye disease. The model works on dataset of fundus images while processing we make augmentation of images to achieve better accuracy.

The model is based on CNN family pre-trained architecture EfficientNetB3, specially designed for performing detection and classification on image dataset.

The model achieved 97% accuracy on trained dataset and 95 % accuracy on test dataset. The model performed better on augmented images, and having accuracy greater than all other models in current research. Models used many performances measuring metrics Precision, Recall and F1 Sore. Moreover, this research utilized transformative potential of deep learning in detection and classification of eye disease to advancing the healthcare solutions.

## REFERENCES

[1] P. Mahalle, S. Shinde, P. Raka, K. Lodha, S. Mane and M. Malbhage, "Skin Cancer Detection Using CNN," 2023 International Conference on Computer Science and Emerging Technologies (CSET), Bangalore, India, 2023.

[2] R. Pahuja, U. Sisodia, A. Tiwari, S. Sharma, and P. Nagrath, "A dynamic approach of eye disease classification using deep learning and machine learning model," in *Proceedings of Data Analytics and Management*, Singapore: Springer Nature Singapore, 2022.

[3] G. Singh, K. Guleria and S. Sharma, "A Pre-Trained VGG16 Model for Cataract Eye Disease Prediction," *2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)*, Bangalore, India, 2023.

[4] A. Saini, K. Guleria and S. Sharma, "An Efficient Deep Learning Model for Eye Disease Classification," *2023 International Research Conference on Smart Computing and Systems Engineering (SCSE)*, Kelaniya, Sri Lanka, 2023.

[5] G. Ramanathan, D. Chakrabarti, A. Patil, S. Rishipathak and S. Kharche, "Eye Disease Detection Using Machine Learning," *2021 2nd Global Conference for Advancement in Technology (GCAT),* Bangalore, India, 2021.

[6] R. Singh, N. Sharma and R. Gupta, "The Proposed Convolutional Neural Network Architecture for the Detection and Classification of Eye Diseases," *2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE),* Chennai, India, 2023.

[7] Arias-Serrano, I., Velásquez-López, P.A., Avila-Briones, L.N., Laurido-Mora, F.C., Villalba-Meneses, F., Tirado-Espin, A., Cruz-Varela, J. and Almeida-Galárraga, D., 2023. Artificial intelligence based glaucoma and diabetic retinopathy detection using MATLAB—Retrained AlexNet convolutional neural network.

[8] R. E. Varghese and I. A. Pandian, "Inception-Resnet V2 Based Eye Disease Classification Using Retinal Images," *2023 3rd International Conference on Mobile Networks and Wireless Communications (ICMNWC)*, Tumkur, India, 2023.

[9] P. T. Karule, S. B. Bhele, P. Palsodkar, P. T. Agarkar, H. R. Hajare and P. R. Patil, "Detection of Multi-Class Multi-Label Ophthalmological Diseases in Retinal Fundus Images Using Machine Learning," *2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET),* Nagpur, India, 2024.

[10] D. Selvathi and K. Suganya, "Support Vector Machine Based Method for Automatic Detection of Diabetic Eye Disease using Thermal Images," *2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT),* Chennai, India, 2019.

[11] Dataset from kaggle "https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification"