CLASSIFICATION OF MULTIPLE EYE DISEASES USING RETINAL FUNDUS IMAGES

C. Sharmila Suttur[1], Aishwarya M[2]
1 Department of Electronics and communication Engineering, Assistant professor, Ramaiah Institute of technology, Bangalore, India
2 Department of Electronics and communication Engineering, Student, Ramaiah Institute of technology, Bangalore, India

Corresponding Author:
C Sharmila Suttur

ABSTRACT

Retinal fundus images have an important role in detection, tracking and treatment of different eye abnormalities. Early diagnosis and treatment of such eye abnormalities will help in preventing vision loss. Some of the commonly seen eye abnormalities include diabetic retinopathy (DR), optic disc cupping (ODC), media haze (MH), cataract and age-related macular degeneration (ARMD). This paper proposes an automated CNN based deep learning model for detection and classification of eye abnormalities. RFMiD is a publicly available dataset containing 3200 fundus images with 45 different eye abnormalities. A multi-layer deep neural network has been developed to train and test images of different eye abnormalities. This paper focuses on classification of the retinal eye diseases, DR, ODC, ARMD. This model outperforms other current models and demonstrates its effectiveness in identifying and categorizing retinal eye disorders.

Keywords:
Multiple Retinal Eye Diseases Convolutional Neural network Deep Learning

1. INTRODUCTION

The term “retinal eye diseases” refers to a broad spectrum of disorders effecting the retina which is the light sensitive tissue that lines the eye. With the increase in population, there is a pressing need for automated and efficient eye abnormalities diagnosis and treatment. According WHO, at least 2.2 billion people have eye abnormalities [1]. Most of the fundus eye diseases lead to vison loss or vision impairment and is the leading cause of blindness worldwide. Treatment of these diseases at severe stages is difficult. Patients suffering from these diseases are unaware because symptoms do not rise at the early stages. This is the main reason why the detection of disease at an early stage for proper treatment is very important. Most common eye abnormalities include DR, ODC, ARMD, media haze, amblyopia and various other than can cause blindness.

A dangerous side effect of diabetes that damages the blood vessels in the retina especially is called diabetic retinopathy. It is the main reason behind blindness in adults of working age. DR may not show any symptoms in the early stages, but if treatment is not received, the condition can worsen over time and cause blindness or visual loss [2].

The abnormal excavation or hollowing out of the optic disc, the region on the retina where the optic nerve leaves the eye, is referred to as optic disc cupping. It is frequently linked to glaucoma, a collection of conditions that affect the eyes and are characterized by progressive vision loss and optic nerve damage. Like DR, if ODC is not diagnosed and treated at early stages, the condition will get severe and will lead to vision loss or impairment [3]. A chronic and progressive eye disorder that degeneration (ARMD) is the primary cause of visual loss in people over 50. Hence, prevention or management of vision loss, non-invasive techniques for early detection and identification of eye abnormalities and prompt treatment is very crucial [4].

High-resolution pictures of the posterior region of the eye, specifically the retina, optic disc, macula, and surrounding vasculature, are called retinal fundus images. This non-invasive imaging method helps with the diagnosis, follow-up, and treatment of a variety of eye illnesses by offering vital insights into the anatomical and pathological states of the retina. Following pupil dilatation, fundus pictures are captured with specialized cameras, such as fundus cameras or retinal cameras. For optometrists and ophthalmologists, they are the main diagnostic tool that helps identify anomalies such ARMD, ODC, DR, and retinal detachments. Additionally, fundus images make it easier to monitor a disease's progression over time, allowing medical experts to monitor changes and evaluate the efficacy of treatment options. In general, retinal fundus imaging is essential for the early identification and treatment of ocular pathology, which ultimately improves patient outcomes and maintains visual health.

ANNs consist of layers of interconnected nodes, or neurons, that process complex input data, loo k for patterns, and produce predictions or classifications as an output.

After receiving inputs, each neuron transforms them using activation functions and weights, then sends the output to layers below. ANN learns by training itself from labelled data, which involves adjusting internal parameters like weights and biases to reduce the difference between actual and expected outputs.

CNNs are a family of DL models designed specifically to handle organized, grid-like data, such as images. Computer vision problems are revolutionized by CNNs with convolutional, pooling, and fully connected layers that automatically learn hierarchical representations of visual data. The paper's primary contribution is a well-developed, reliable system for diagnosing various eye disorders by classifying fundus images using the suggested CNN model. After converting an open-source multi-labeled dataset into a multiclass dataset, retrieved fundus images were processed and augmented to train the deep neural network and enhanced to handle real-world scenarios. Unseen fundus photos make up the test set, which is used to evaluate how well the taught deep learning model performs [5].

2. LITERATURE SURVEY

Several research has been conducted on diagnosing eye diseases using deep learning techniques.

In [1], The performance of five different transfer learning models has been analyzed and compared using a multi-image fundus dataset in this paper. Models such as VGG16, MobileNetV2, DenseNet121, ResNet50, EfficientNetB0, ConvNeXtXLarge, and CNNs are exploited in this research. Three hundred and two Retinal Fundus Multi-disease images make up the dataset used in this experiment. At first, the data format was unprocessed and included manual annotations.

In [2], 38,727 excellent fundus images were used to create an ensemble of convolutional neural networks, which were then subjected to a transfer learning procedure. Subsequently, the group underwent testing using 13,000 subpar fundus photos obtained using inexpensive apparatus. Therefore, by: (i) validating the proposed transfer learning strategy by identifying eye-related conditions and diseases in low-quality images; (ii) training the predictive models only with high-quality images acquired by expensive equipment; and (iii) achieving results comparable to the state-of-the-art even with low-quality images, the proposed approach advances the state-of-the-art. In this sense, the suggested method offers a fresh take on deep transfer learning, making it more appropriate and doable for public health systems in developing and emerging nations. Using shoddy photos, the suggested approach was able to reach accuracies of 87.4%, 90.8%, 87.5%, 79.1% to classify cataract, diabetic retinopathy, excavation, and blood vessels, respectively.

In [3], A multi-class classification, EyeDeep-Net is a diagnostic tool for ocular conditions that include media haze, optic disc cupping, and diabetic retinopathy. The RFMiD dataset, which comprises 3200 fundus images with 45 distinct anomalies, is the dataset that was employed in this instance. Twenty thousand of these photos were used in this study. Among the anomalies found were illnesses for which more than 100 photos were obtained for the study. The dataset was normalized by doing data augmentation. An image enhancement preprocessing approach was used. The different 2-dimensional convolutional layers, max-pooling layers, and batch normalization layers that make up the suggested EyeDeep-Net architecture were later adjusted with specific hyper-parameters. The results indicate 82.13% and 76.04% validation and testing accuracy, respectively.

In [4], A multiclass classification model based on deep learning was put out to detect and categorize eye conditions such age-related macular degeneration and cataracts. A pretrained ResNet-50 architecture is used by the model. There are 1096 retinal fundus images in the ODIR dataset that is being used in this instance. Techniques for preparing images are used, such as data augmentation, data shuffling, and image scaling. The loss function in the model is categorical

Vol. 21, No. 1, (2024)
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cross-entropy, and the Adam optimizer with a learning rate of 0.0001 is employed. The model's classification accuracy was 97%.

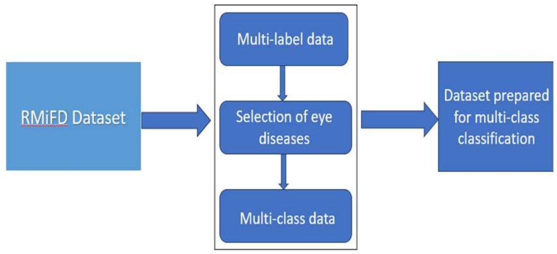
In [5], A review was proposed, with the primary goal of offering a thorough analysis of the many DL techniques lately used for fundus image-based detection of retinal diseases. Additionally, this study aims to provide future directions for researchers that are interested in AI-based diagnosis of retinal diseases. This article provides a thorough analysis of the various deep learning techniques used recently to diagnose five common eye conditions: DR, ODC, cataract, ARMD, and retinal deformity. The structure of this article follows the pipeline for implementing deep learning: first, frequently used datasets, evaluation metrics, image pre-processing methods, and deep learning backbone models are illustrated; next, a thorough analysis of various approaches for each of the five retinal diseases is provided.

3. PROPOSED METHODOLOGY

The proposed model is divided into 3 steps. The first step (fig 1) comprises of selection of eye diseases and dataset acquisition. The selection of eye diseases was done based on the number of images present. Diseases with a higher number was selected. The original dataset being multi-labeled was converted into multi-class for the multi-class classification. Among the 45 different abnormalities present in the dataset, DR, ODC and ARMD were selected.

The second step (fig 2) comprises of data augmentation and preprocessing before the data is given as the input to the CNN model. The dataset comprises of 395 images of DR, 282 images of ODC and 100 images of ARMD. As the number of DR images is more compared to the other two abnormalities, data augmentation is performed. The methods chosen for augmentation include geometric transformations i.e. Rotation range of 40, zoom range of 0.2, width and height shift range of 0.2, shear range of 0.2 and horizontal flip. After augmentation each class contains same number of images and hence the dataset is normalized. Table 1 shows the final number of images of all the four classes.

Vol. 21, No. 1, (2024)
ISSN: 1005-0930



Disease	Original images	Augmented images	Total
Diabetic Retinopathy	395	5	400
ODC	282	118	400
ARMD	100	300	400
Normal	400	-	400

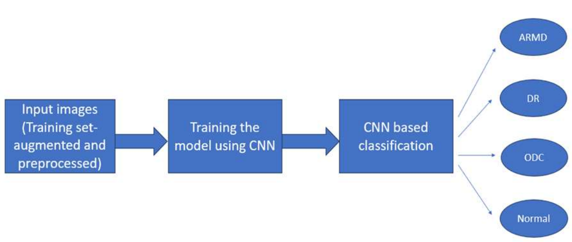
Figure 1. Dataset acquisition

Table 1. Dataset after augmentation

The following preprocessing is done on the images (Fig 2):

- **RGB to Gray**: It removes the complications associated with computational requirements and aids in the simplification of algorithms. It enhances easy visualization.
- **Image Sharpening**: A method of image editing called sharpening is used to enhance the contrast and sharpness of digital image outlines. Sharpening highlights the change from dark to light regions and raises the contrast between edge pixels.
- **Thresholding:** By dividing an image into distinct regions based on pixel intensity or value, thresholding helps distinguish objects or features of interest from the background.
- **Edge detection:** An image processing method called edge detection is used to identify the borders of objects in pictures.

The third step comprises of training the CNN model with the input images belonging to different classes and gives the probabilistic outcomes to classify the images in different categories (Fig 3.)



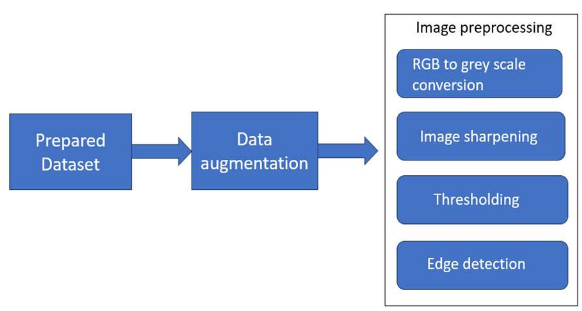


Figure 2. Data augmentation and preprocessing Figure 3. Classification on the retinal eye diseases using

a CNN model.

3.1 The methodology is as follows (Fig 4.)

Step 1 - Data Collection: A diverse dataset of retinal images is gathered, including images from diabetic patients with varying stages of retinopathy and images from healthy individuals for comparison. The dataset used in this paper is RMiFD, which contains 3200 images. These fundus images have 45 different abnormalities. Among these 45 abnormalities, three were selected which include Diabetic retinopathy, Optic disc cupping and Age-related macular degeneration. After the dataset is augmented, it contains 1600 fundus images.

Step 2 - Preprocessing: Preprocess the retinal images to enhance their quality and prepare them for analysis. RGB to grey scale conversion, image sharpening, thresholding and edge detection are the preprocessing techniques applied to the fundus images in this model.

Step 3 - Data Splitting: Divide the dataset into training, validation, and testing sets.

Step 4 - Feature Extraction: Utilize image processing techniques and DL methods to extract relevant features from retinal images, such as blood vessel patterns, hemorrhages, and microaneurysms.

Step 5 – DL Model Selection: Choose an appropriate deep learning architecture for image classification. CNNs are commonly used due to their effectiveness in image analysis.

Step 6 - Model Training: Train the selected DL model on the training dataset. This involves adjusting model parameters to learn the patterns and characteristics associated with retinal diseases.

Step 7 – Hyperparameter tuning: Optimize hyperparameters, including learning rate, batch size, and architecture-specific parameters.

Step 8 – Validation and evaluation: Validate the model's performance on the validation dataset and make necessary adjustments. Employ evaluation metrics like accuracy, precision, recall, F1-score, and ROC-AUC to assess model performance.

Step 9 – Testing: Check the model’s performance on test dataset which is unseen by the model.

Vol. 21, No. 1, (2024)
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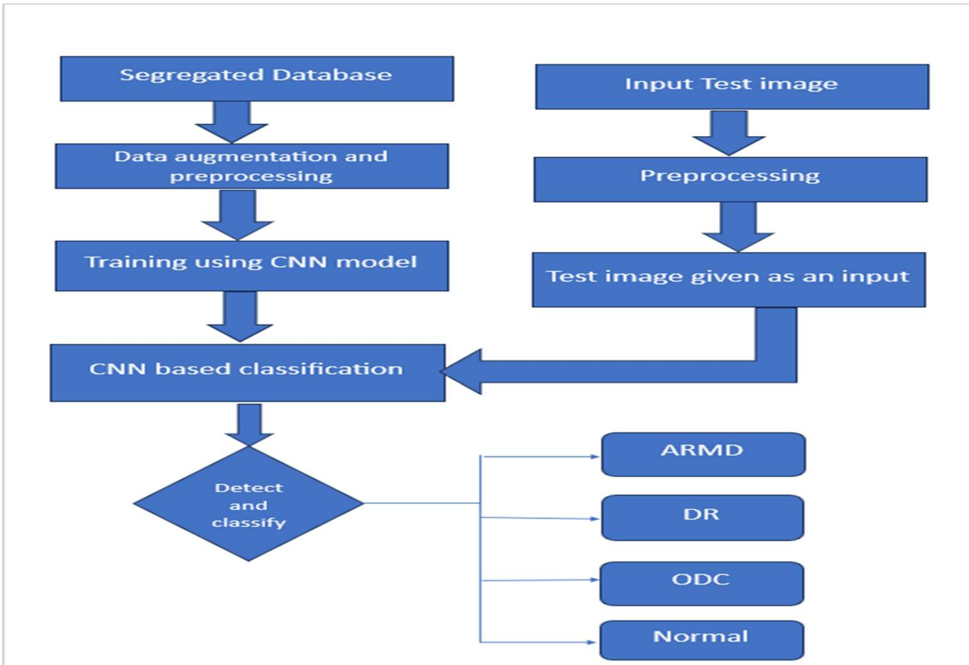


Figure 4. Flowchart

3.2 Model Training (Table 2)

Epoch	Layers	Accuracy	loss	Val_acc	Val_loss
50	3	0.2281	17.7735	0.2527	17.2032
80	3	0.2540	17.17764	0.2527	17.2073
80	4	0.2444	1.38649	0.2466	1.38643
99	5	0.9558	0.3648	0.9872	0.04931
100	5	0.8983	0.44707	0.9070	0.27299

Table 2. Model Training Values

- To decide upon the number of optimum layers and epochs for the CNN model, initially three layers were taken into consideration with 50 epochs. For three layers, with 50 epochs, the training accuracy obtained is 22%.
- For three layers with 80 epochs, the training accuracy obtained is 25.40%.
- Since the accuracy is very low for three layers, two more layers were taken into consideration.
- For four layers with 80 epochs, the training accuracy obtained is 24.44%.
- For five layers with 80 epochs, the training accuracy obtained is 92.38%
- The model now is trained for 100 epochs, and the accuracy is observed.

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

- Since the accuracy is dropping at the 100th epoch from 95.58% to 89.83%, 99 epochs with 5 layers is considered as the optimum number of epochs for training.
- A CNN sequential model is trained for detection and classification of DR, ODC and ARMD to whether it is one of those diseases or normal with a accuracy of 95.58%.

4. RESULTS AND DISCUSSION

4.1 CNN Model Implemented

In this paper, a CNN model is proposed to detect and classify retinal eye diseases. Fundus images are used as an input and these images are augmented. Original number of images was 1,177, and the dataset was increased to 1600 images after augmentation.
The augmented images were preprocessed by applying RGB to grey scale conversion, image sharpening, thresholding and edge detection (Fig 5.).

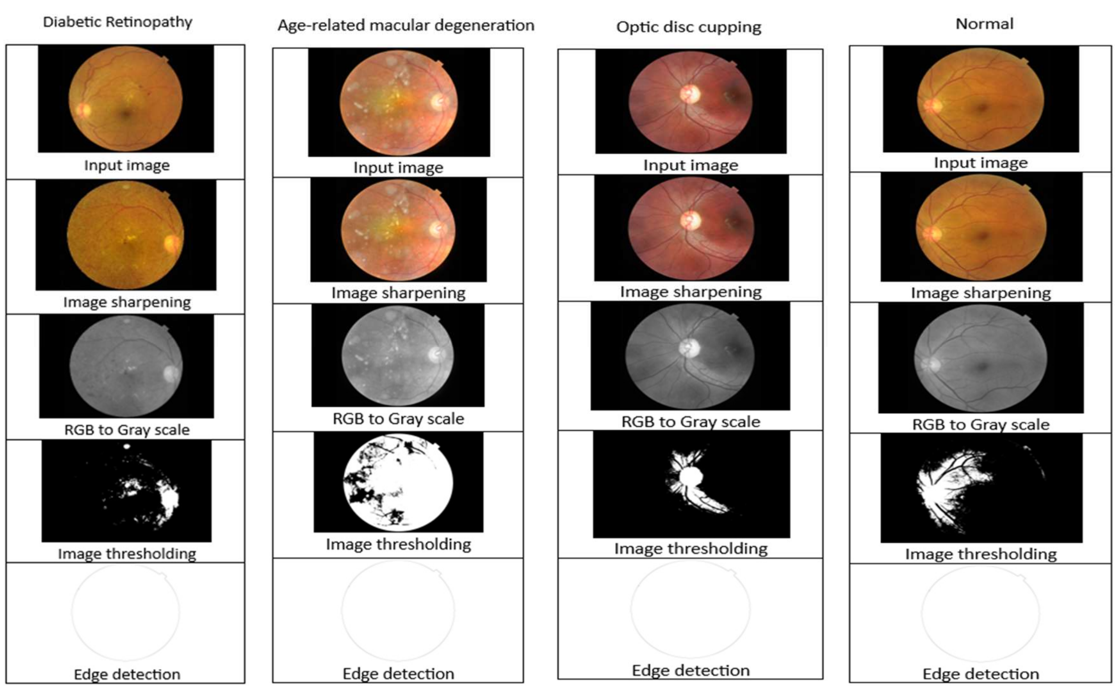


Figure 5. Preprocessing applied to the images

The proposed DL model for detection and classification of eye diseases using fundus images is represented using a block diagram, as shown in the figure below. The sequential CNN architecture proposed in this paper is shown below (Fig 6.)
The proposed model is built up with multiple convolutional layers having various filter sizes, batch normalization, max-pooling layers and fully connected layers. Adam optimizer was used which convergences the deep learning model faster.

The proposed architecture has one input layer, five convolution layers, five max pooling layers, two fully connected layer and a dropout layer.

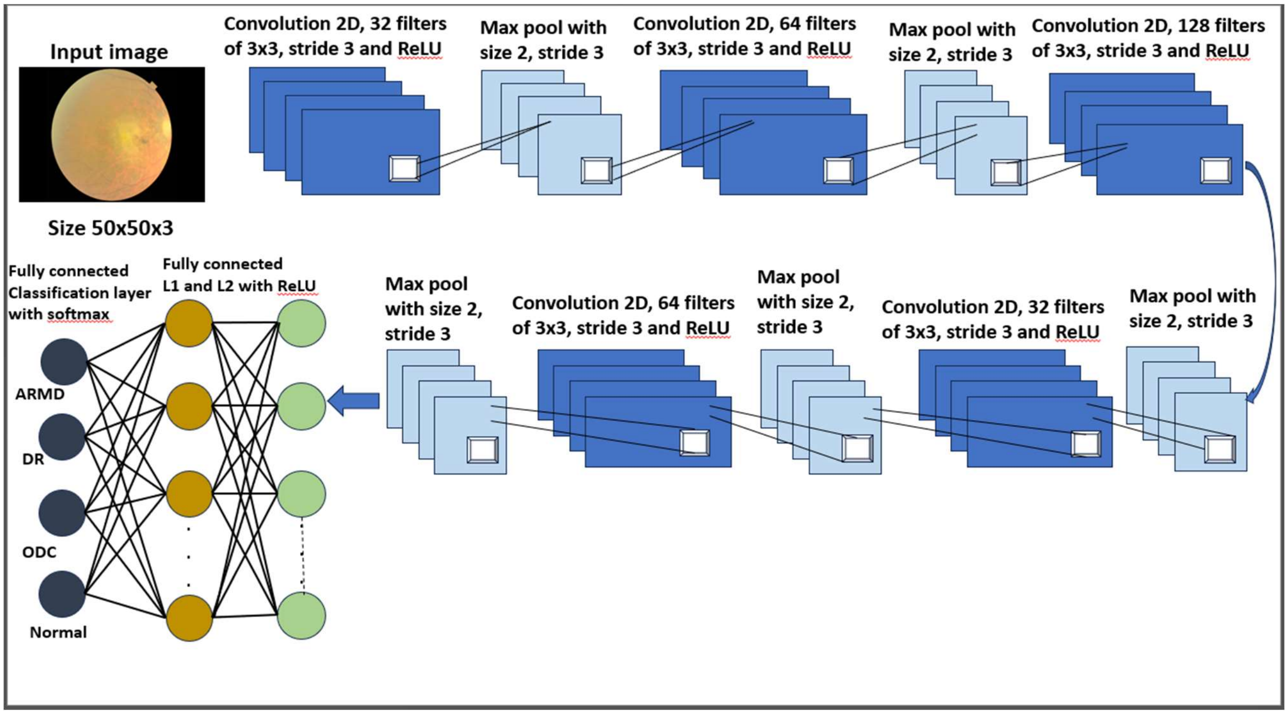


Figure 6. Proposed CNN model – block diagram

Training of the DL model is done with by tuning different hyperparameters and specifications as given in Table 3

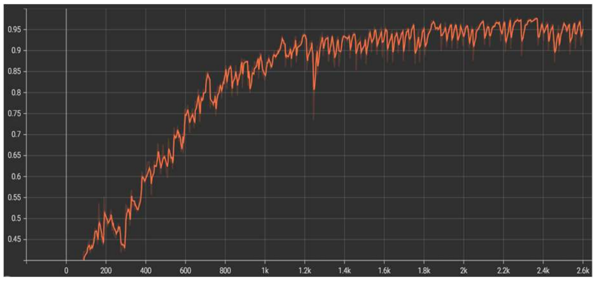
Name	Parameters
Input	Retinal fundus images from RFMiD dataset
Batch size	32
Learning rate	Fixed learning rate of 0.001
Loss function	Categorical cross-entropy
Activation function	ReLU, Softmax
Epochs	99
Optimization function	Adam

Table 3. Parameters of the model

The model provides a training accuracy of 96.24% and validation accuracy of 98.81%. Figure 10 and 11 show the graphs of testing and validation accuracy respectively.

4.1.1 Accuracy Graphs

Vol. 21, No. 1, (2024)
ISSN: 1005-0930



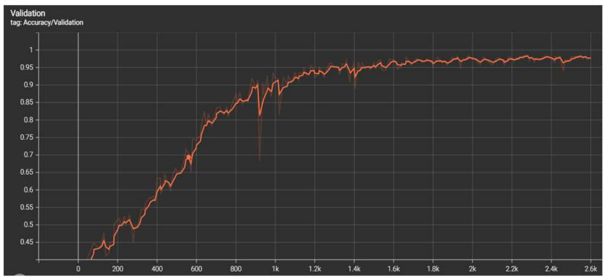


Figure 7.- Training accuracy vs step graph Figure 8. Validation accuracy vs step graph

A variety of statistical measures and classification indicators, including as precision, accuracy, F1-score, and recall, are used to evaluate performance. Figure displays the values of these parameters that were derived using this model.

	precision	recall	f1-score
ARMD	0.91	0.92	0.91
DR	0.66	0.53	0.59
Normal	0.62	0.68	0.64
ODC	0.34	0.43	0.38
accuracy			0.84
macro avg	0.84	0.84	0.84
weighted avg	0.84	0.84	0.84

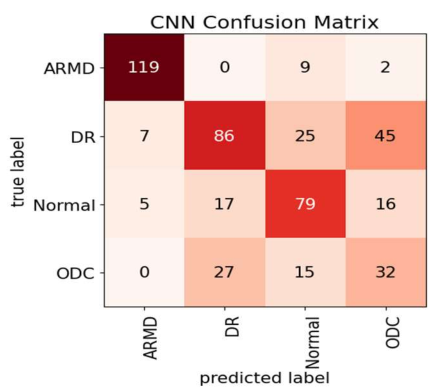


Figure 9. Classification Report Figure 10. Confusion Matrix for CNN Model

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

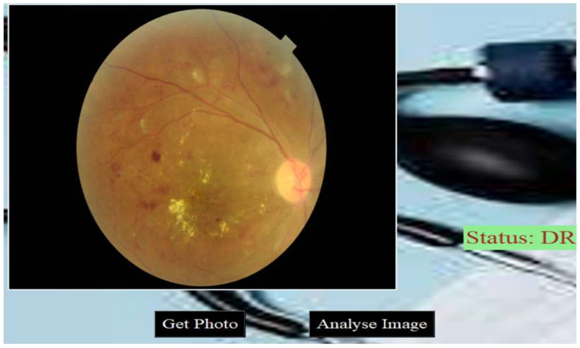


Figure 11. Detection of Diabetic Retinopathy

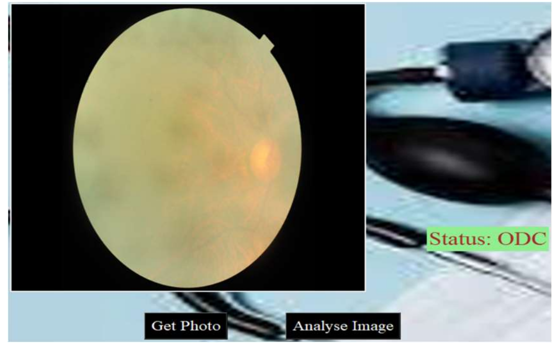


Figure 12. Detection of Optic disc cupping

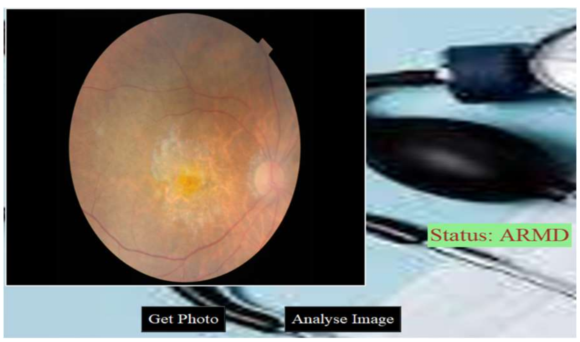


Figure 13. Detection of Age-related macular degeneration

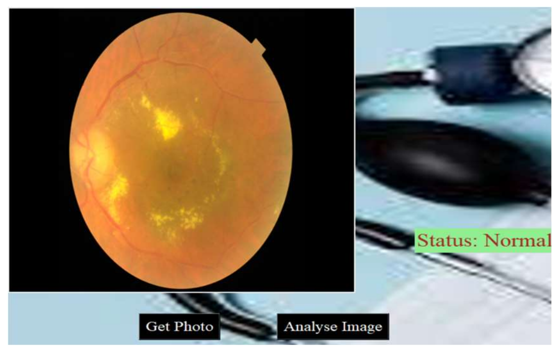


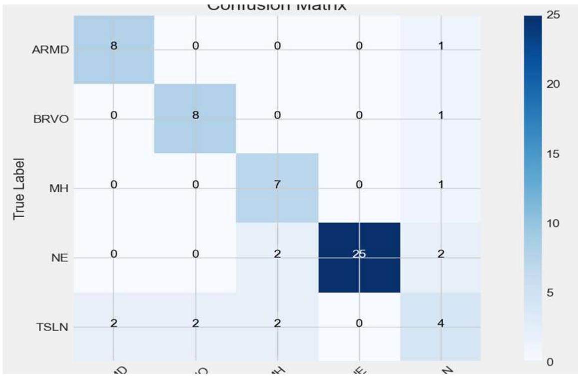
Figure 14. Normal image

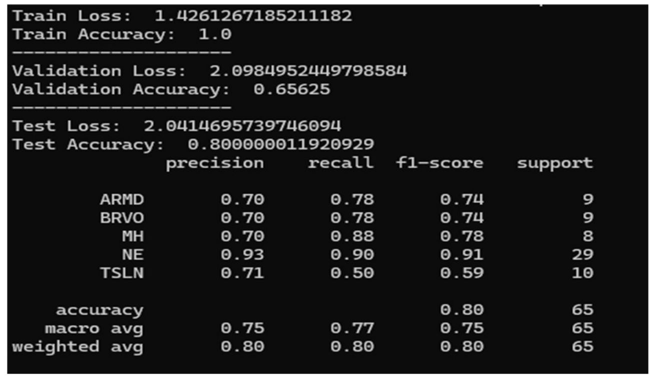
4.2 EfficientNetB3 Model:

An EfficientNetB3 and MobileNetV2 model is proposed to detect and classify multiple eye diseases such as ARMD, and branch retinal vein occlusion (BRVO), Fundus Tessellation (TLSN), Media Haze (MH) and Normal Eye (NE). The results of these models are compared with the CNN sequential model.

Figure 15. Training and Validation Plots on pre-processed images: EfficientNetB3

In this result (Fig 15), train_loss and val_loss epochs is plotted, and training accuracy vs validation accuracy vs epoch is plotted for EfficientNetB3.





Train Loss: 1.4261267185211182
Train Accuracy: 1.0

Validation Loss: 2.0984952449798584
Validation Accuracy: 0.65625

Test Loss: 2.0414695739746094
Test Accuracy: 0.800000011920929

	precision	recall	f1-score	support
ARMD	0.70	0.78	0.74	9
BRVO	0.70	0.78	0.74	9
MH	0.70	0.88	0.78	8
NE	0.93	0.90	0.91	29
TSLN	0.71	0.50	0.59	10
accuracy			0.80	65
macro avg	0.75	0.77	0.75	65
weighted avg	0.80	0.80	0.80	65

Figure 16. Confusion Matrix on pre-processed images Figure 17. Classification report

The correctness of the model is evaluated in this result using the confusion matrix (Fig 16). This model has correctly identified diabetic retinopathy as more data points are separated in the matrix's diagonal line.

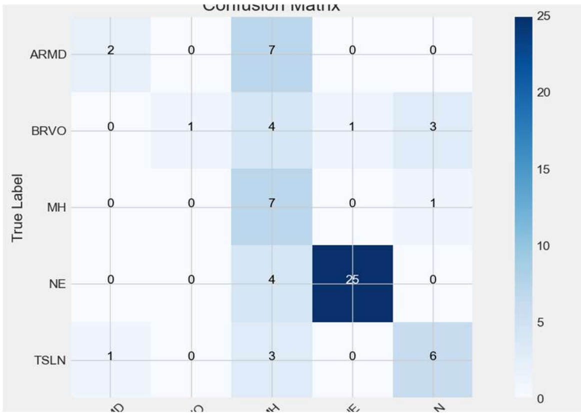
4.3 MobileNetV2 model:

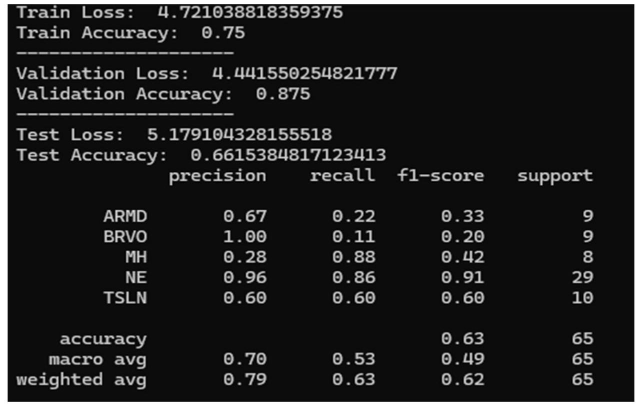
These are the plots of train_loss vs val_loss and train_acc vs val_acc where loss decreases with each epoch and is best at 40th epoch and accuracy increase with epochs and has the best at 38th

epoch.

Fig 18. Train_loss Vs Val_loss and Train_acc Vs Val_acc Plot for pre-processed image

Vol. 21, No. 1, (2024)
ISSN: 1005-0930





```
Train Loss:  4.721038818359375
Train Accuracy:  0.75
--------------------
Validation Loss:  4.441550254821777
Validation Accuracy:  0.875
--------------------
Test Loss:  5.179104328155518
Test Accuracy:  0.6615384817123413
              precision    recall  f1-score   support

        ARMD       0.67      0.22      0.33         9
        BRVO       1.00      0.11      0.20         9
          MH       0.28      0.88      0.42         8
          NE       0.96      0.86      0.91        29
        TSLN       0.60      0.60      0.60        10

    accuracy                           0.63        65
   macro avg       0.70      0.53      0.49        65
weighted avg       0.79      0.63      0.62        65
```

Fig 19. Confusion Matrix   Fig 20. Classification report

This is the classification report (Fig 20) which gives the precision, recall, f1-score, support for different diseases using mobilenet architecture.

Table 3. Comparison between CNN model, EfficientNet-B3 and MobileNet-V2

Parameters	CNN sequential(Proposed)	EfficientNet-B3	MobileNet-V2
Training Accuracy	95.58	100	75
Training Loss	0.3648	2.69	4.72
Validation Accuracy	98.72	87.5	87.5
Validation Loss	0.04931	3.06	4.44
Test Accuracy	81.68	80	66.1
Test Loss	3.3581	3.17	5.17

Table 3. summarizes the Performance parameters of our proposed CNN model, with Pretrained models, EfficientNetB3 and MobileNet V2. Our model has achieved better validation and test accuracy, with only 5 layers. Hence demonstrates better Performance, with less computation time, and simple architectural model.

Table 4. Comparison table of Proposed CNN Model with another CNN Model

Parameters	CNN sequential (Proposed)	Eye Deep Net
Testing Accuracy	81.68	82.13
Validation Accuracy	98.72	76.04

5. CONCLUSION AND FUTURE SCOPE

The detection and classification of eye abnormalities is important in clinical treatments. With increase in population there is a pressing need for an automated system that detects and classifies eye diseases with higher efficiency. The eye diseases when not detected at an early stage will lead to vision loss. These diseases do not show symptoms at an early stage. Therefore, there is a need to detect these diseases at early stages to prevent vision loss. The proposed model detects and classifies three major eye abnormalities which includes ARMD, DR, and ODC. The model provides training and testing accuracy of 95.24% and 81.68% respectively. Future scope may include the use of sophisticated classification techniques with a large dataset. For quick and dependable solutions, a similar strategy might be used to other medical imaging issues. Augmentation methods with higher efficiency can be used to increase the number of images. One of the most powerful techniques used is Generative Adversarial Networks (GAN). They consist of a Generator, which creates false data, and a Discriminator, which differentiates between real and false data. Through adversarial training, the Generator learns to produce increasingly realistic data, making it valuable for augmenting small or imbalanced datasets. This technique is especially beneficial in fields where data collection is expensive or time-consuming, such as medical imaging. U-Net can also be used for classification. Its unique structure consists of a symmetric U-shaped design with a contracting path (encoder) and an expansive path (decoder). The encoder captures context and features through a series of convolutional and max-pooling layers, while the decoder reconstructs the spatial dimensions using up-sampling and convolutional layers.

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Vol. 21, No. 1, (2024)
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