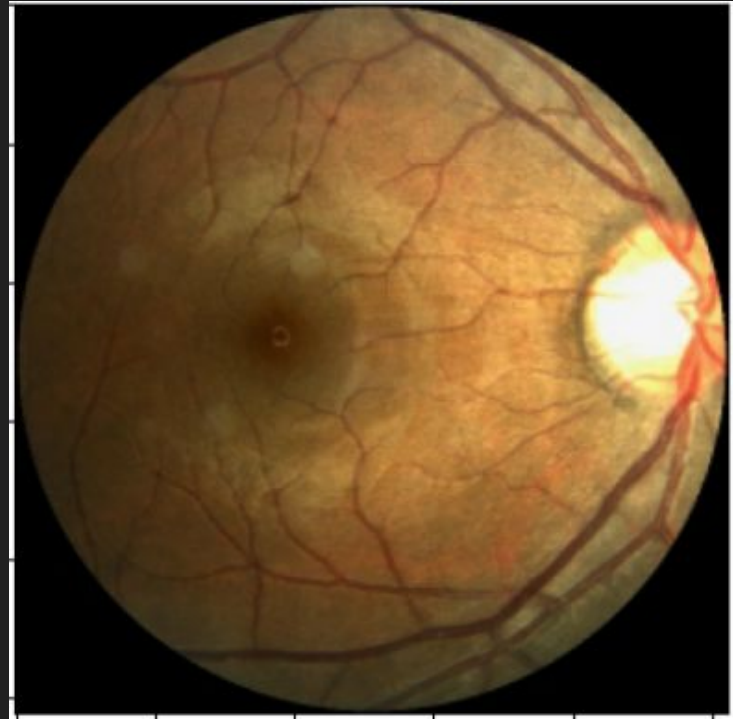


Eye Disease Classification

Members: Prajwal Sharma (21103020)

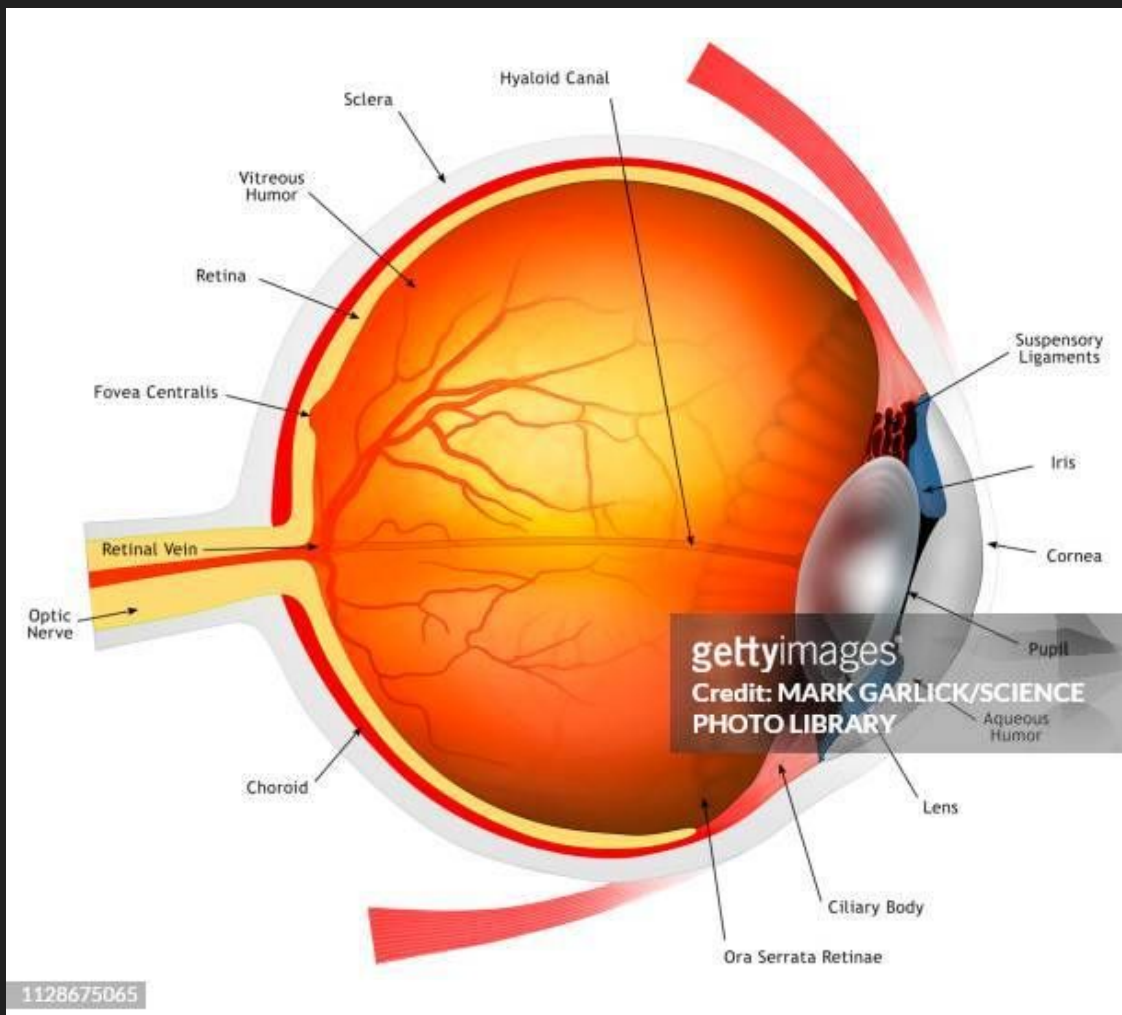
Mentors: Dr. Sudesh Rani

Dr. Poonam Saini



Content:

- ❑ Objectives
- ❑ Dataset
- ❑ Preprocessing
 - ❑ Keras Layers
 - ❑ OpenCV
- ❑ Models
- ❑ Results & Graphs
- ❑ Inferences Drawn
- ❑ Future Outlooks
- ❑ Conclusion



Objectives

- ❏ Educational Research: Reviewing existing literature on fundus image classification and eye defect detection.
- ❏ Data Preparation: Preprocessing and curating fundus image datasets for model training.
- ❏ Fundus Image Classification: Implementing deep learning models for automatic classification of fundus images.
- ❏ Comparing Model Performance: Analyzing and comparing the effectiveness of different classification models.
- ❏ Eye Defect Detection (Localization): Developing algorithms to detect and localize eye defects within fundus images.
- ❏ Web Application (Deployment): Creating a user-friendly interface to deploy the developed models for real-world usage.

Dataset

The dataset consists of

- ❑ Normal (1074)
- ❑ Diabetic Retinopathy (1098)
- ❑ Cataract (1038)
- ❑ Glaucoma (1007)

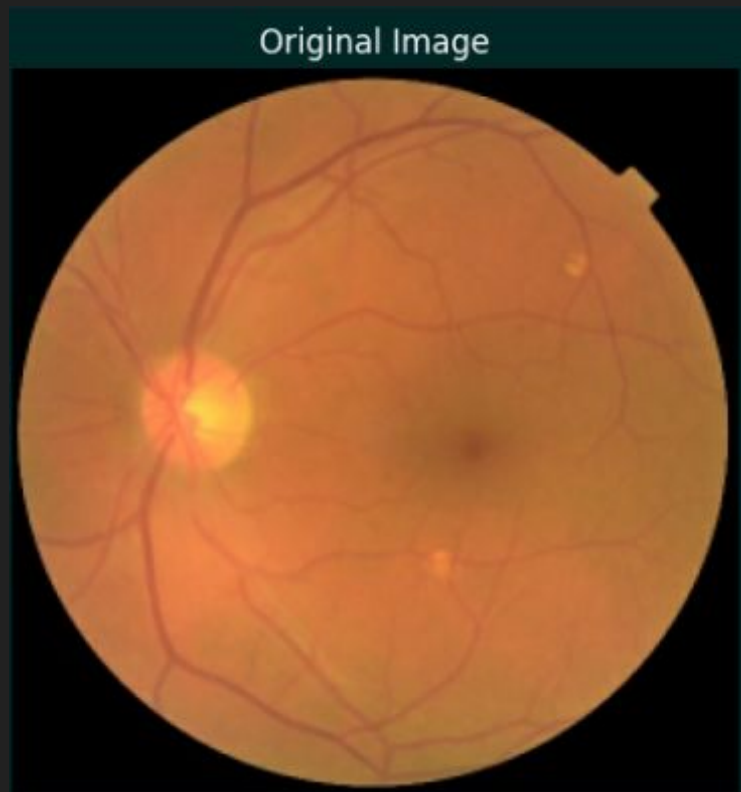
These Fundus (RGB) images are collected from various sources like IDRiD, Ocular recognition, HRF etc.

Split Ratio:- Train:Test:Val = 8:1 : 1

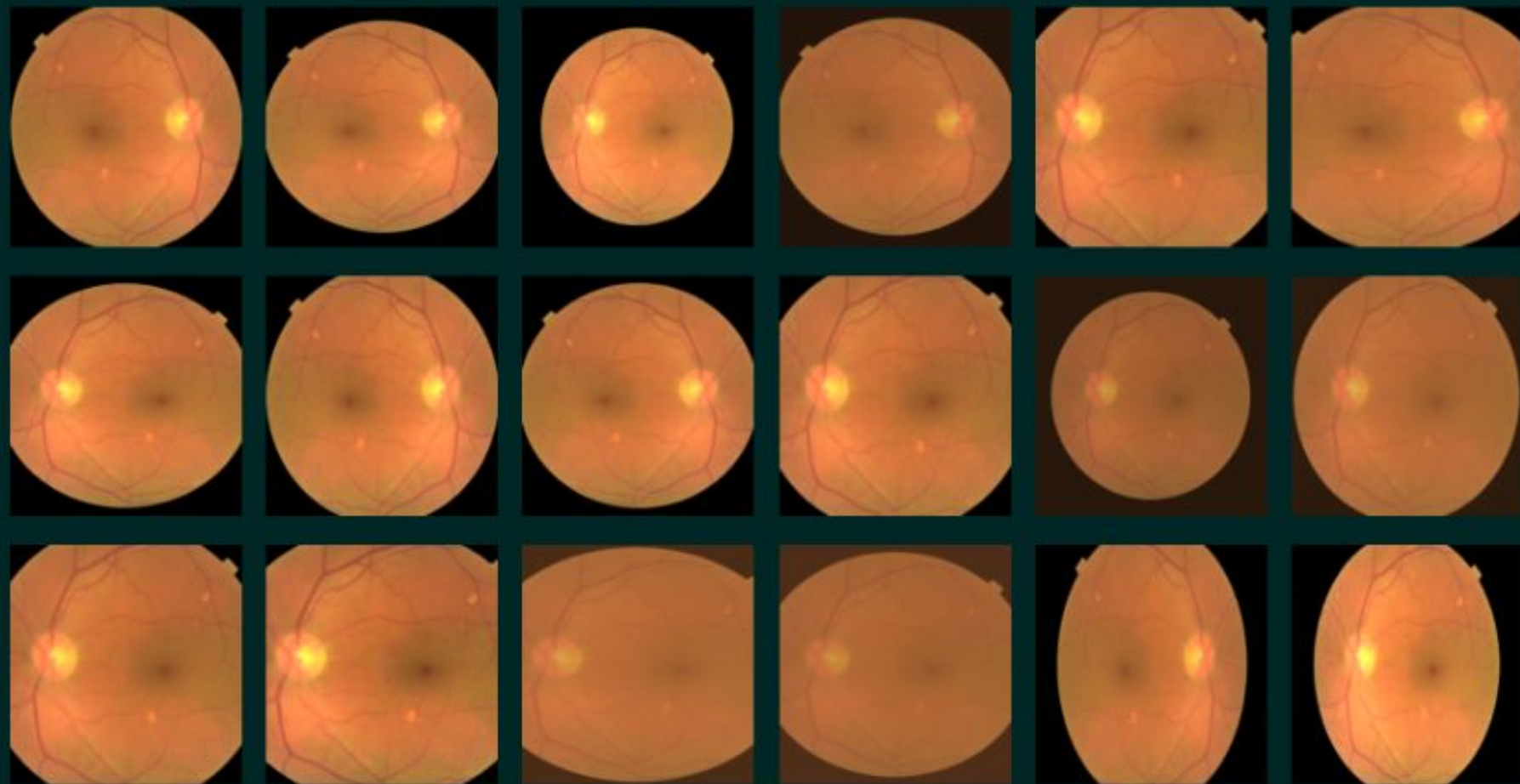


Preprocessing

- ❑ Using `tf.keras.layers`
 - ❑ Resizing
 - ❑ Rescaling
 - ❑ Random Zoom
 - ❑ width wise
 - ❑ Height wise
 - ❑ Random Flip
 - ❑ Horizontal flip
 - ❑ Random Contrast
 - ❑ $(-50, 50)$

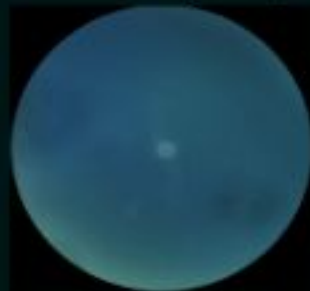


Augmented Image for the previous Image

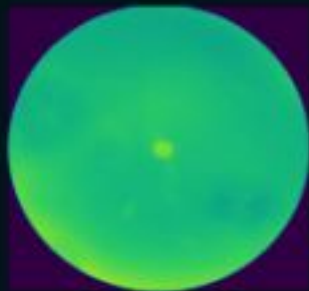


Histogram Equalisation

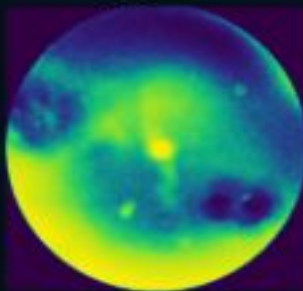
RGB(Original)



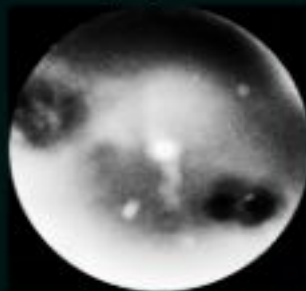
GRAY



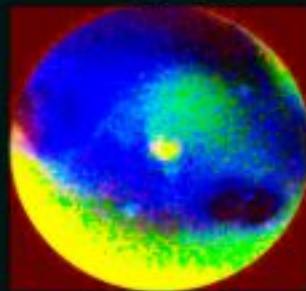
Equ_GRAY



Equ_RGB



Channel_Equ_RGB

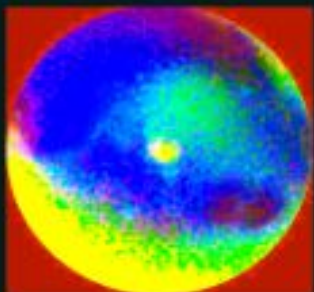


CLAHE

rgb(Original)



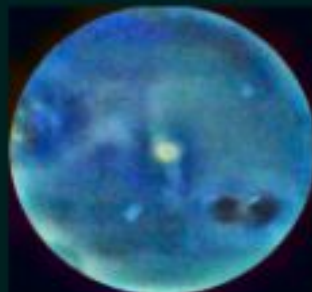
clip_limit = 100
grid_size = 1



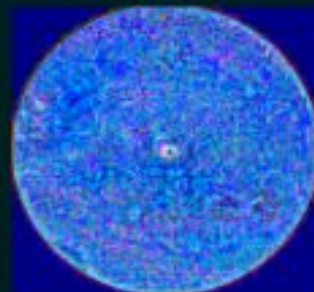
clip_limit = 1
grid_size = 100



clip_limit = 10
grid_size = 10



clip_limit = 50
grid_size = 50



Models

❑ Model From Scratch

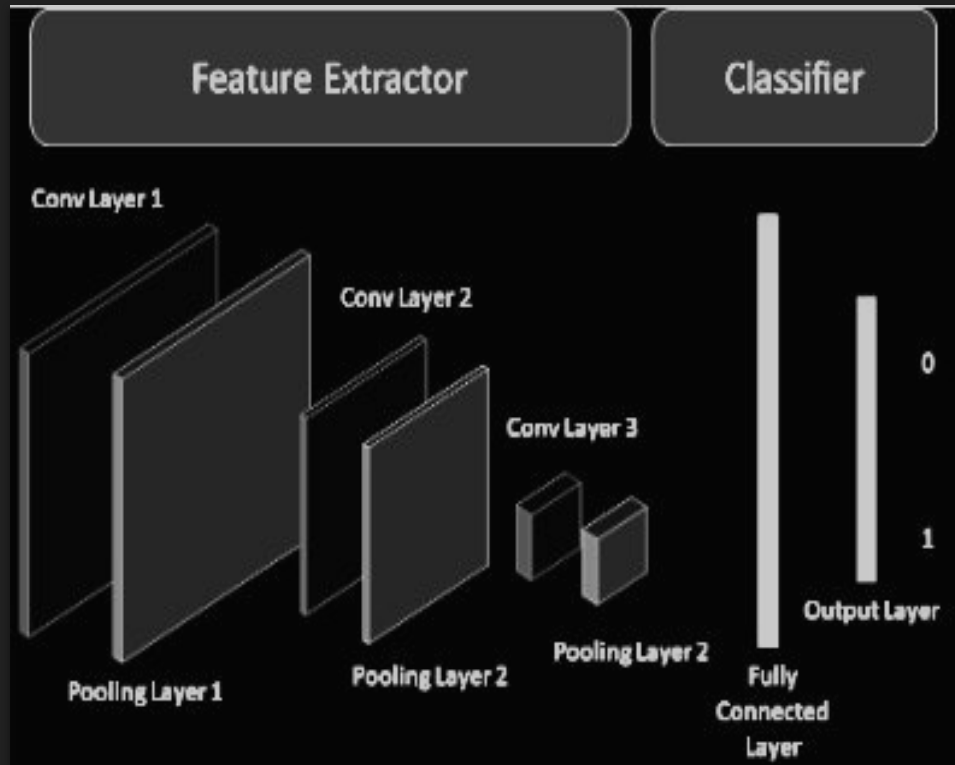
- ❑ Lenet_2
- ❑ ResNet_34

❑ Pretrained models

- ❑ EfficientNet-V2B0
- ❑ Inception-V3
- ❑ DenseNet-121
- ❑ VGG-16
- ❑ ResNet-50



Above pretrained models were pretrained on imagenet dataset



Model's Parameter

❑ Feature Extraction Parameter

- ❑ Image Size = (128,128)

❑ Classifier Parameter

- ❑ Units (128,16,4)

❑ General Parameters:

- ❑ Optimizer = Adam
- ❑ Epochs = 100
- ❑ Batch Size = 16

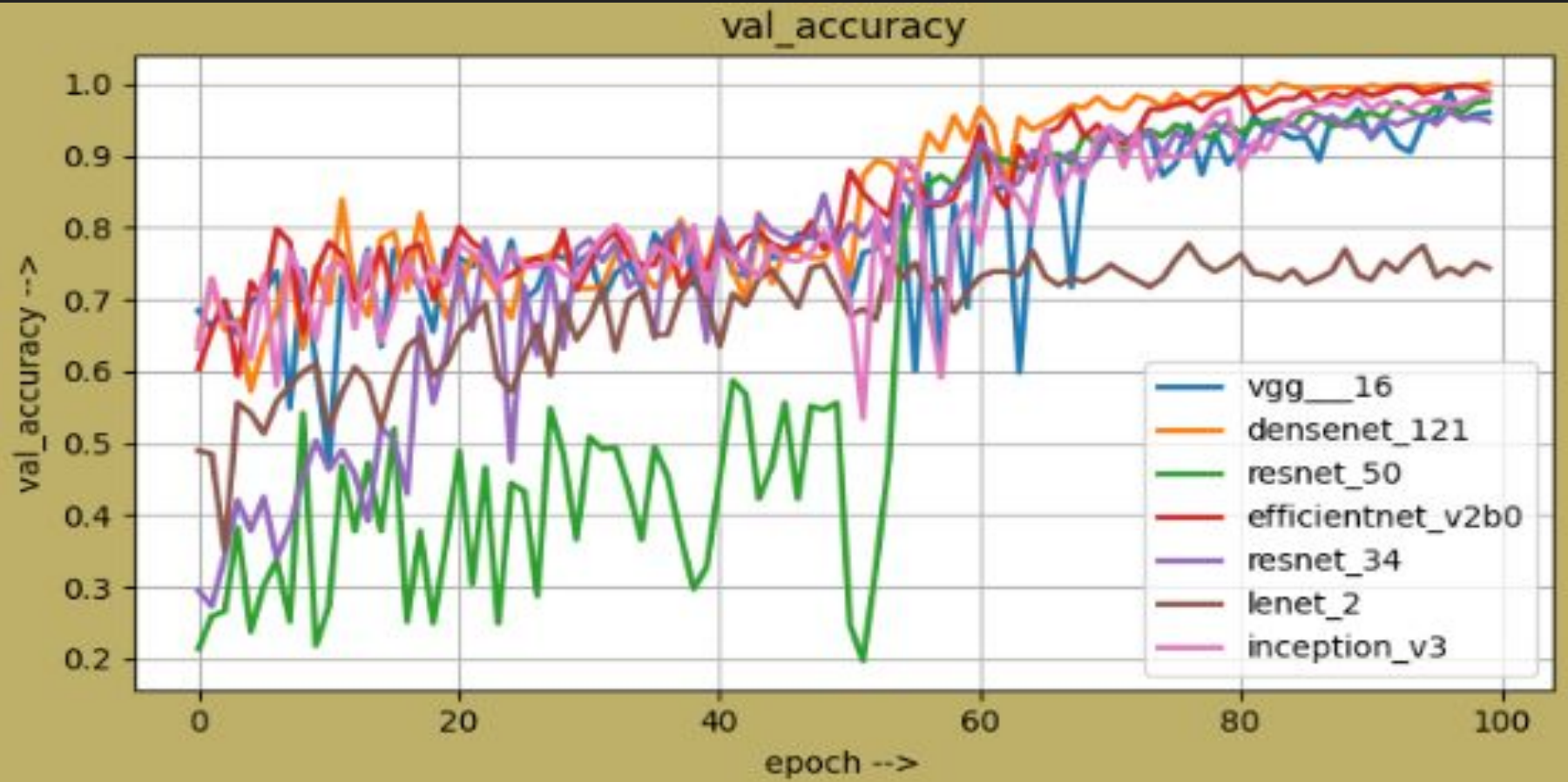
❑ Callbacks

- ❑ Checkpoint (for best Weights)
- ❑ ReduceLROnPlateau (0.7,5)

Model: "Full_Model"

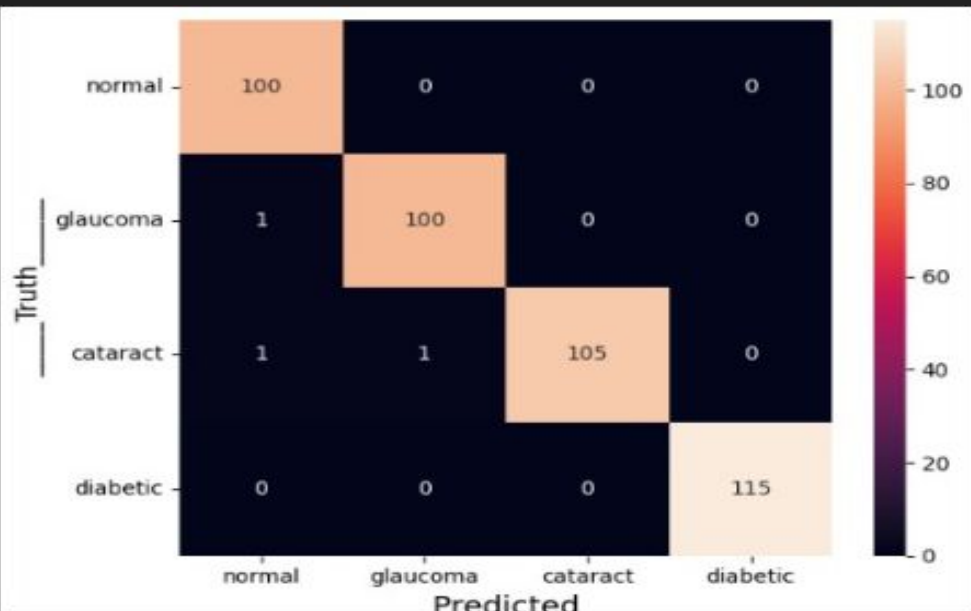
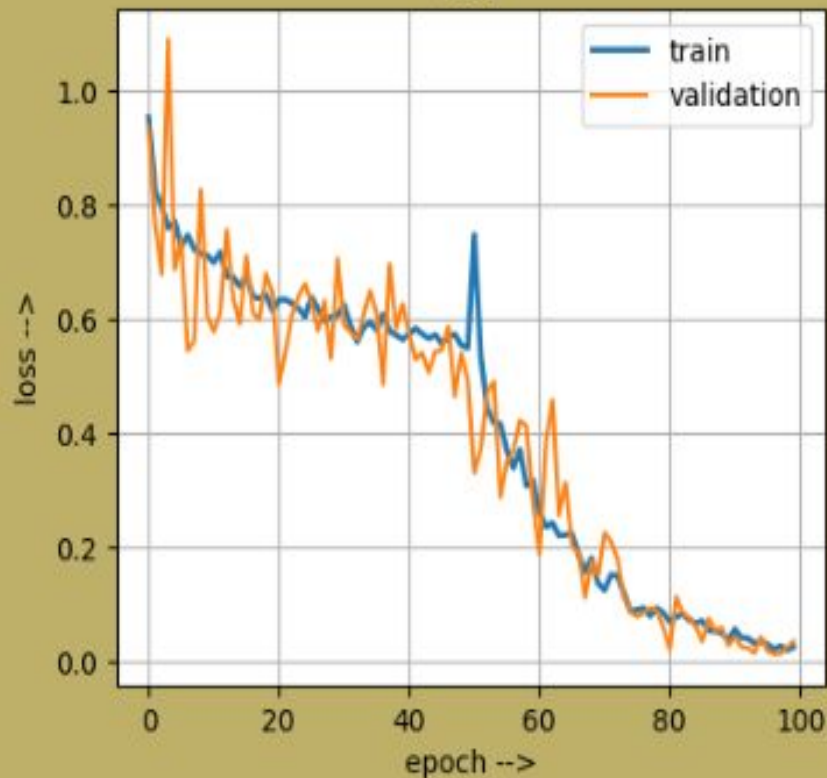
Layer (type)
Input (InputLayer)
Rescale (Rescaling)
Resize (Resizing)
Augment_Layers (Sequential)
base_Model (Sequential)
GlobalAveragePool (GlobalAveragePooling2D)
Dense1 (Dense)
Norm1 (BatchNormalization)
Dropout1 (Dropout)
Dense2 (Dense)
Norm2 (BatchNormalization)
Dropout2 (Dropout)
Output (Dense)

Comparisons



Model Results

efficientnet_v2b0 Performance
loss



	precision	recall	f1-score	support
0	0.98	1.00	0.99	100
1	0.99	0.99	0.99	101
2	1.00	0.98	0.99	107
3	1.00	1.00	1.00	115
accuracy			0.99	423
macro avg	0.99	0.99	0.99	423
weighted avg	0.99	0.99	0.99	423

GradCam Images Using Trained Models

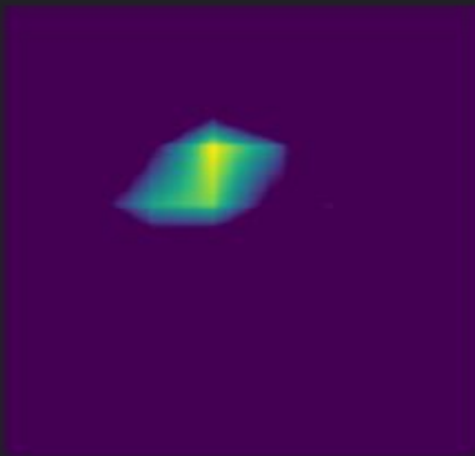
GradCAM (Gradient-weighted Class Activation Mapping) is a technique in computer vision that visualizes the regions of an image that are important for predicting a particular class.

GradCAM provides valuable insights into the decision-making process of deep learning models, aiding in model interpretation and understanding

Original Image



Gradient Clipped Image

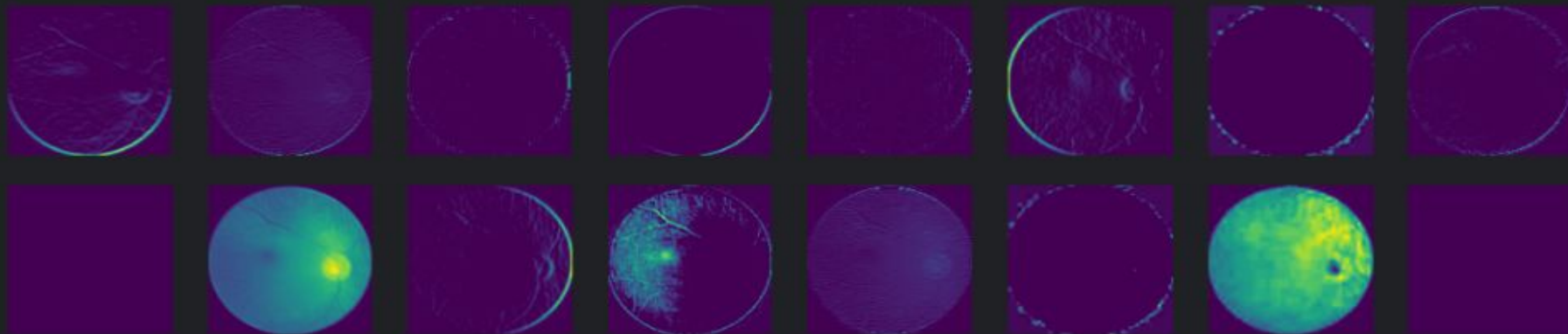


Grad Camed Image

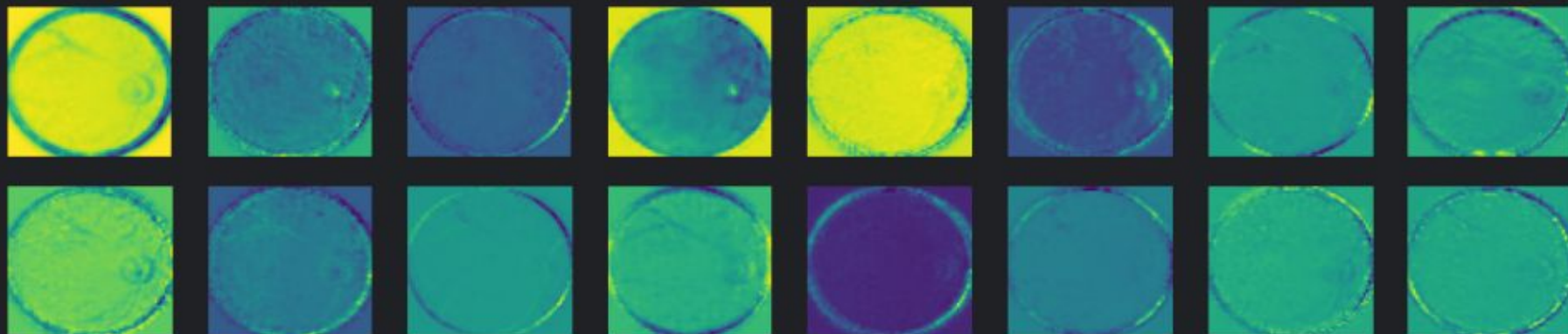


Hidden Layers Feature Maps

feature maps size (128,128)



feature maps size (64,64)



Future Outlook

- ❑ Diverse Dataset and Eye Disease Classification: Expanding dataset diversity for improved classification accuracy.
- ❑ Advanced Preprocessing Techniques: Implementing additional preprocessing methods to refine model performance.
- ❑ Exploring Python Libraries: Utilizing diverse Python libraries to enhance functionalities.
- ❑ Defective Part Localization: Extending classification to include defect localization for precise diagnosis.
- ❑ Web Server Deployment: Deploying final models on web servers for easy access by stakeholders.
- ❑ Research Paper References: Incorporating a wider range of research papers for informed methodology.
- ❑ Comparative Analysis: Comparing results with existing research for validation and improvement insights.

Conclusion

- ❑ Exceptional model performance: Achieved over 99% accuracy on all test, train, and validation data without overfitting.
- ❑ Effective strategy: Transfer learning combined with fine-tuning proved successful in training pretrained models.
- ❑ Vital role of augmentation and preprocessing: Contributed significantly to enhancing model performance



References

❑ Dataset :

- ❑ [1] Guna Venkat Doddi. (Nov,2022). Eye_diseases_classification. Version 1.Retrieved 10 Feb,2024.[Dataset]. from <https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification>.

❑ Research Papers

- ❑ [2] B.Şener ,E. Sumer , Classification of Eye Disease from Retinal Images Using Deep Learning,December 2023 [Research Paper] .Available: https://www.researchgate.net/publication/376140342_Classification_of_Eye_Disease_from_Retinal_Images_Using_Deep_Learning . [Accessed 20 Feb ,2024]
- ❑ [3] A. Shamsan,Dr. E. Senan Automatic Classification of Colour Fundus Images for Prediction Eye Disease Types Based on Hybrid Features ,11 May,2023 [Research Paper]. Available : <https://www.mdpi.com/2075-4418/13/10/1706>.[Accessed 21 Feb, 2024]
- ❑ [4] Dr.T. Nazir, Dr. A. Irtaza,Retinal Image Analysis for Diabetes-Based Eye Disease Detection Using Deep Learning,5 Sept 2020 [Research Paper]. Available : <https://www.mdpi.com/2076-3417/10/18/6185> .[Accessed 26 Feb, 2024]