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Classification of Diabetic Retinopathy using Residual Learning with a Custom Balanced Softmax Loss

Project Presentation & Defense

Computer Science

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Contents

Background

Diabetic Retinopathy:
•Millions affected globally
•Major cause of blindness in working-age adults

Current Challenge
•Limited, low-quality DR images with **class imbalance**
•**Manual diagnosis** by doctors after image capture

Goal
•**Improve classification accuracy** by addressing class imbalance.
•**Automate image** screening for early detection of diabetic retinopathy

Impact
•Early detection can prevent blindness

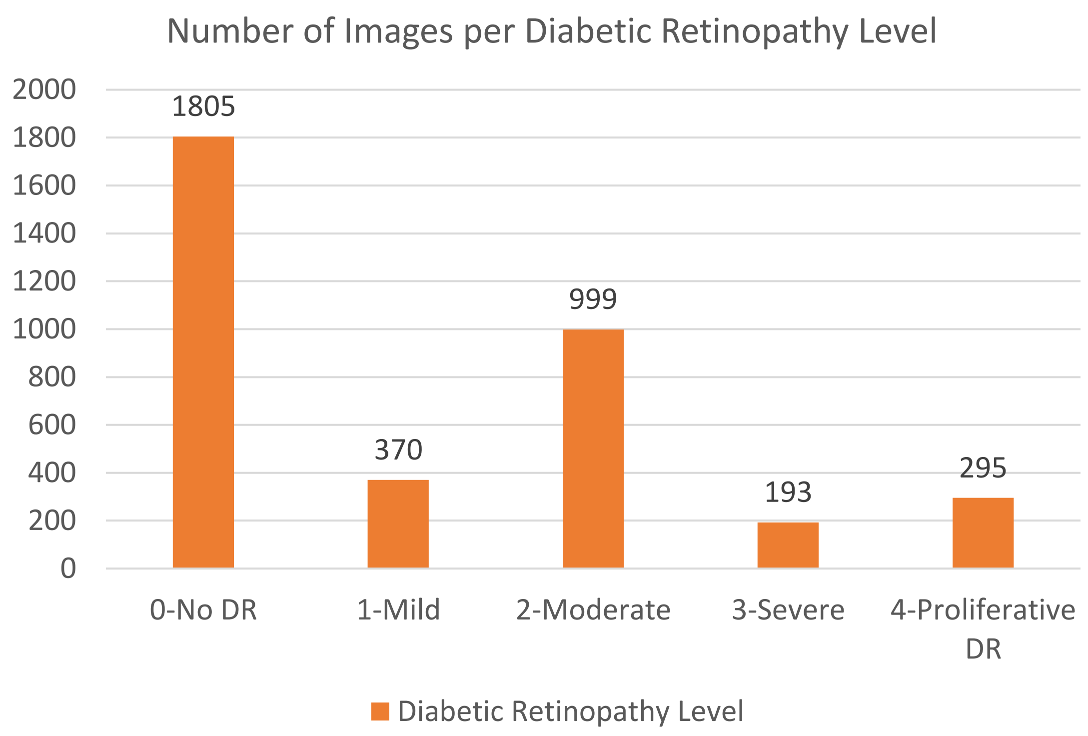
Indian DR patients

Dataset – Kaggle APTOS 2019 (3662)

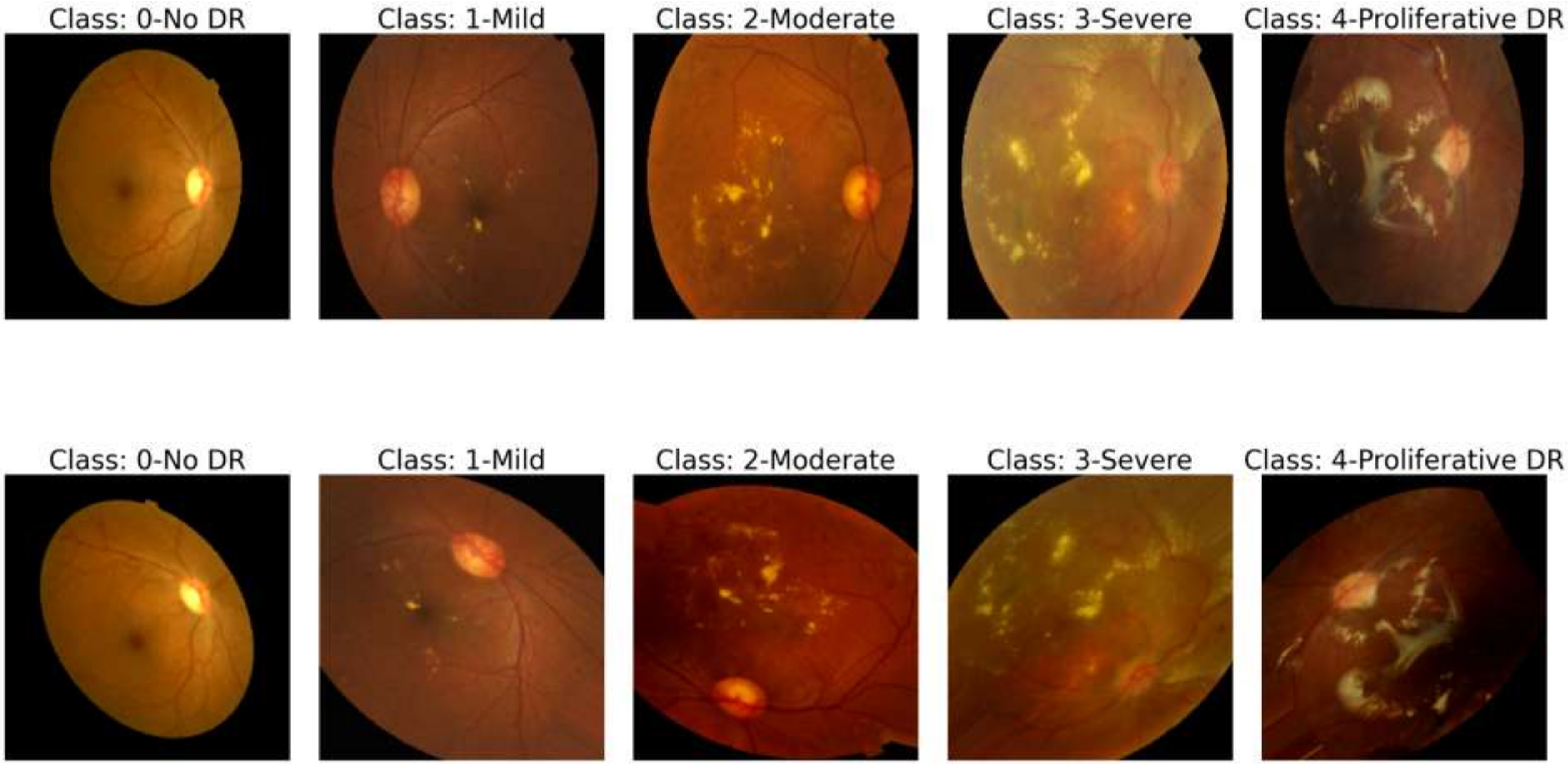
Classes

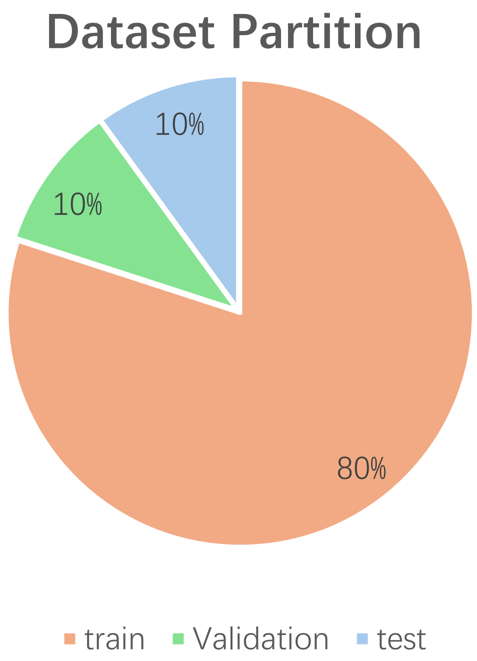
•Images are labeled with 5 severity levels of diabetic retinopathy:

- No DR
- Mild DR
- Moderate DR
- Severe DR
- Proliferative DR



Data Preprocessing





Model

ResNet: Residual connections for deeper learning.

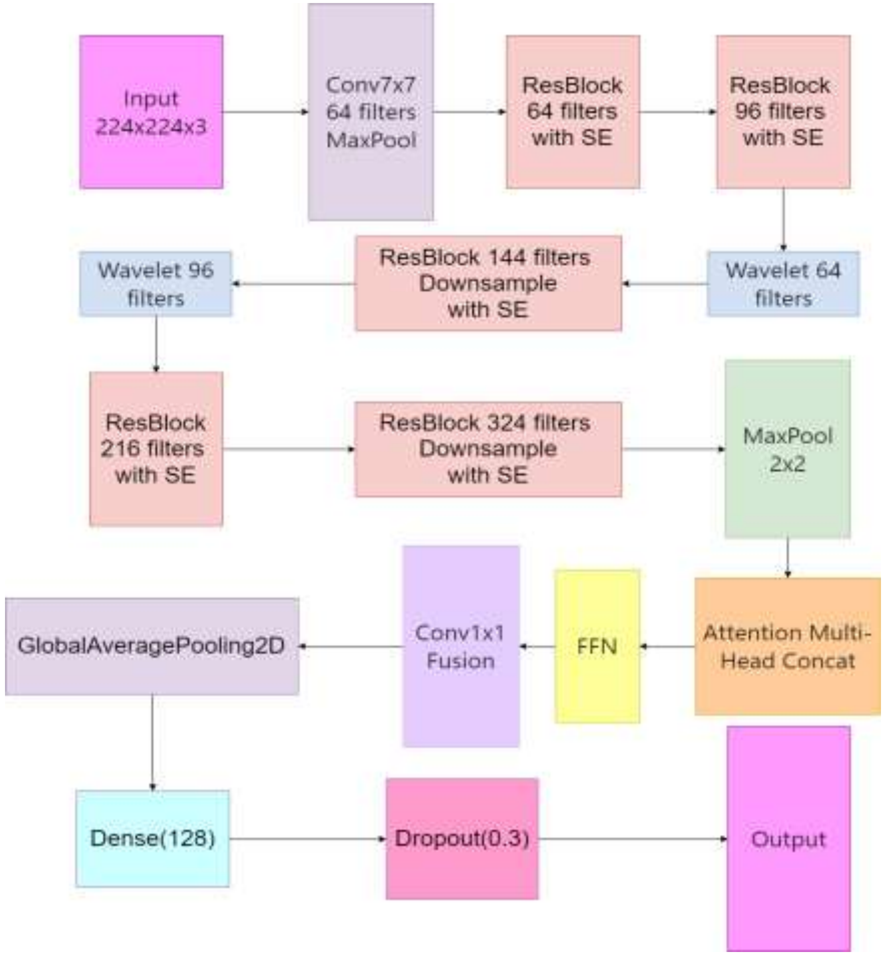
Squeeze-and-Excitation : Enhances important features by recalibrating channels.

Wavelet Transforms: Captures multi-resolution features for better detail.

Attention Mechanism: Focuses on relevant features for better context.

MaxPooling: Reduces spatial dimensions to retain essential features.

Feedforward Neural Network : Fully connected layers for decision making after feature extraction.



Model Structure

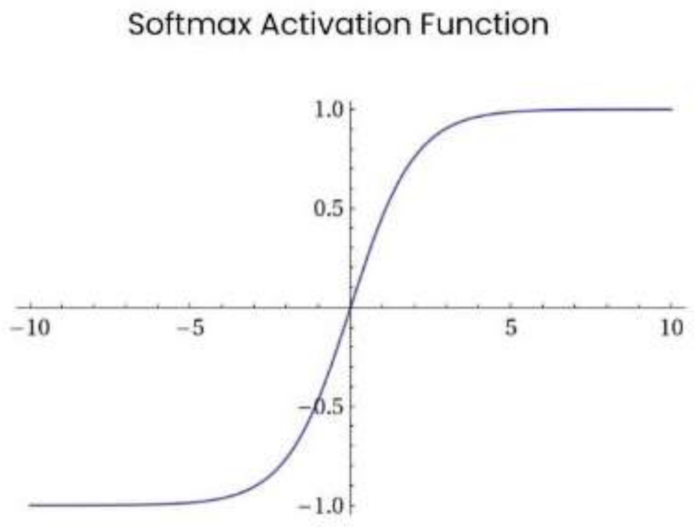
Loss Function

Problem:

Standard Softmax favors majority classes in imbalanced datasets.

Solution:

Balanced Softmax adjusts logits using class frequency (log counts), increasing focus on minority classes.

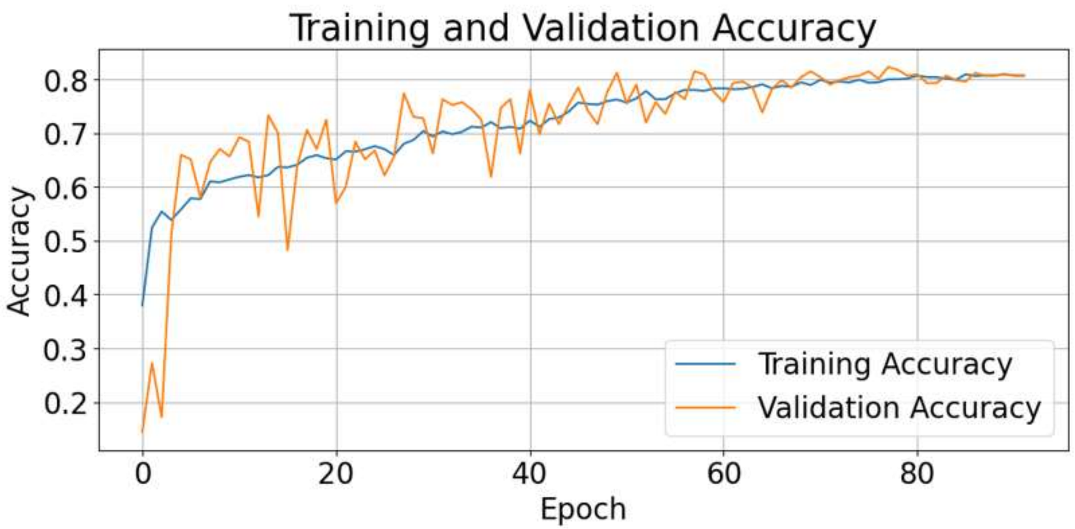


Softmax Activation Curve

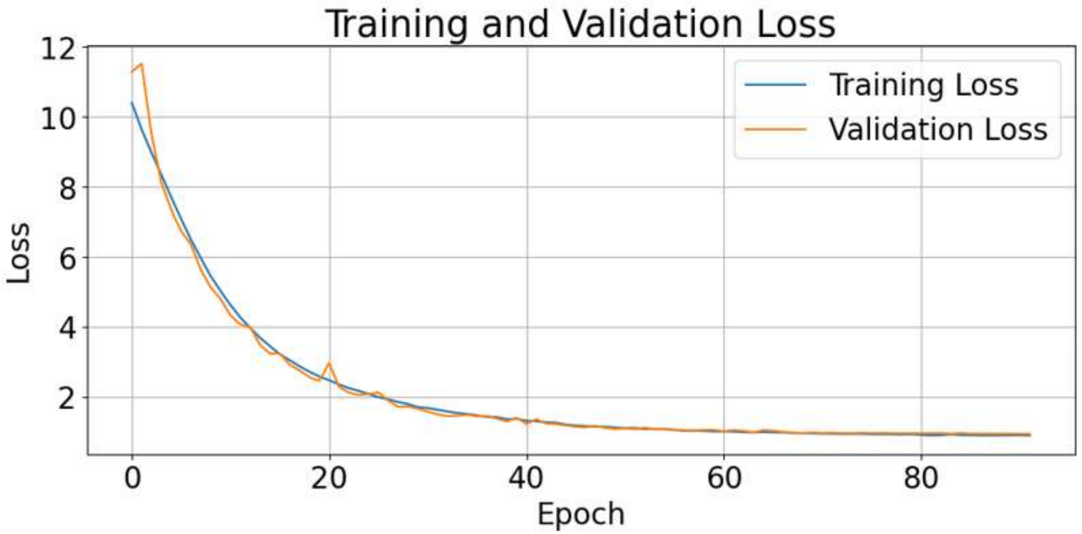
$$\text{Adjusted Logits} = \text{Logits} + \log(\text{Class Frequency})$$

Core formula of Balanced Softmax loss function

Results



a) Train acc: 0.8071, Val acc: 0.8065



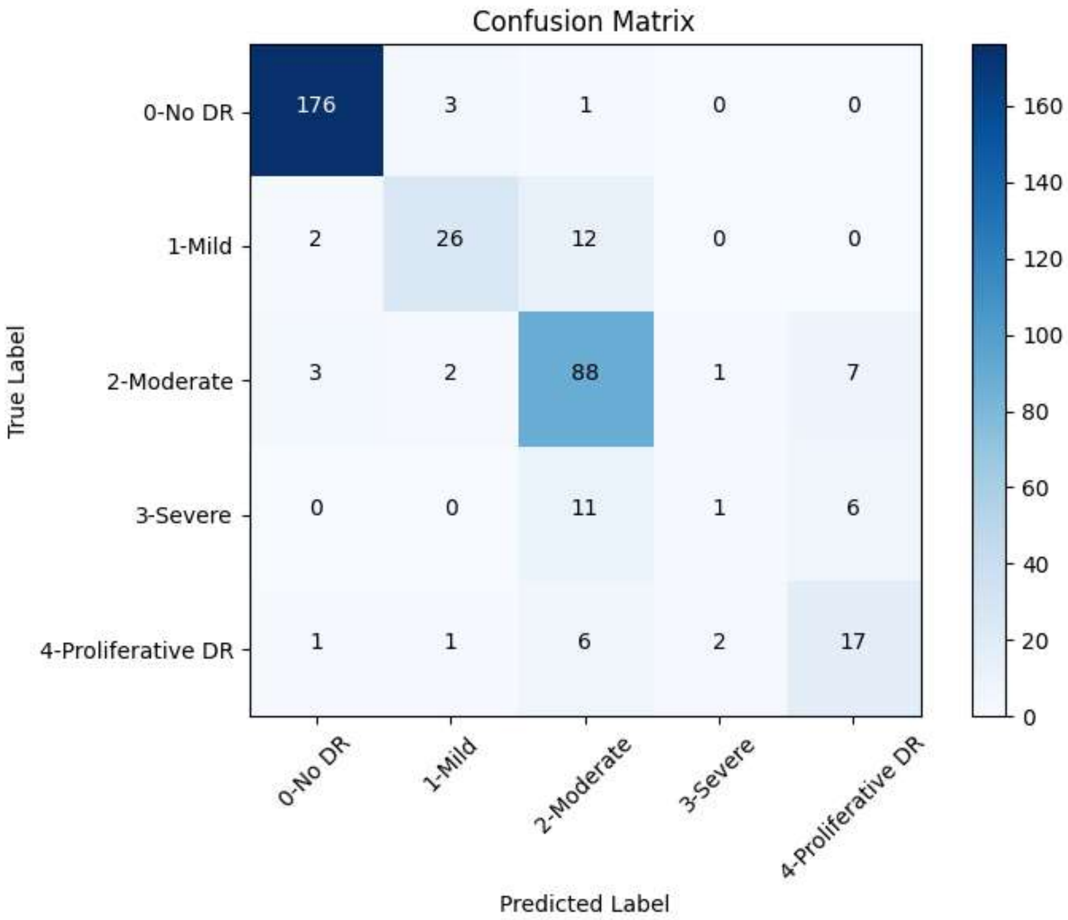
b) Train Loss: 0.8934, Val Loss: 0.9405

Model Convergence Achieved+

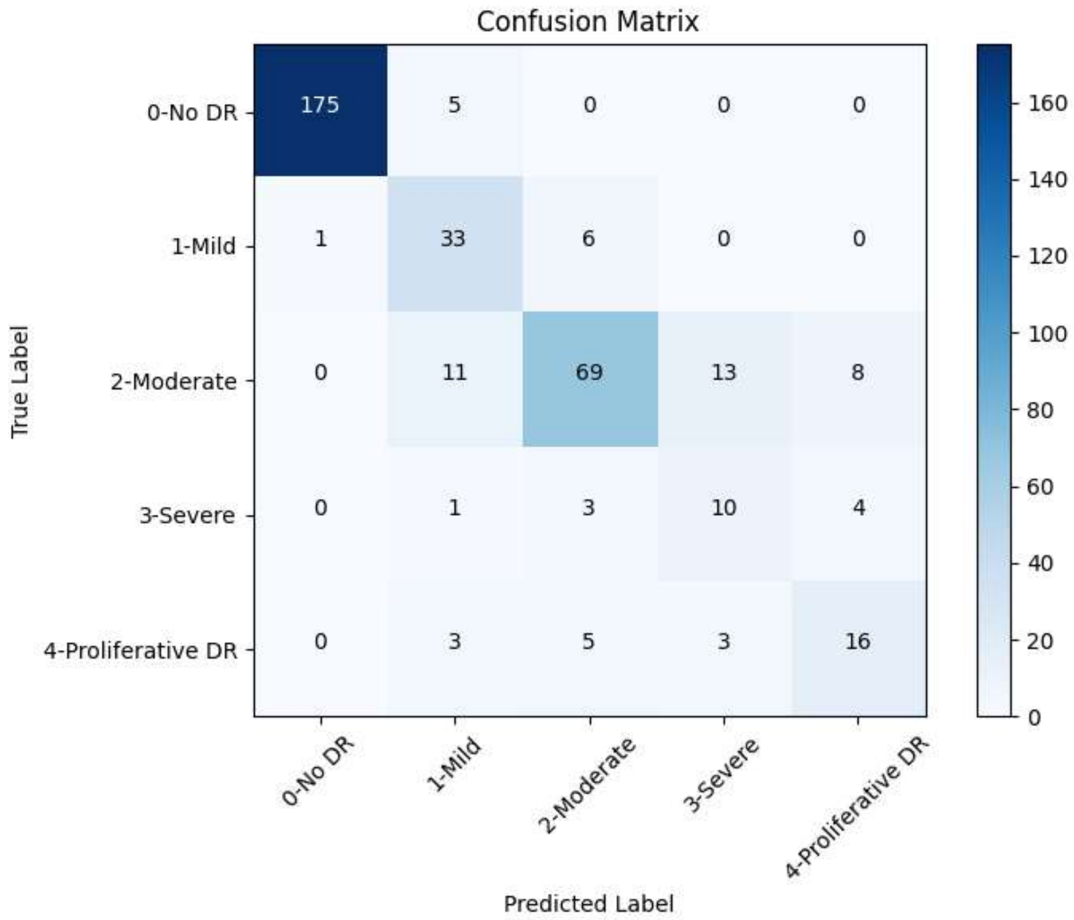
Balanced Performance

Good Generalization

Results

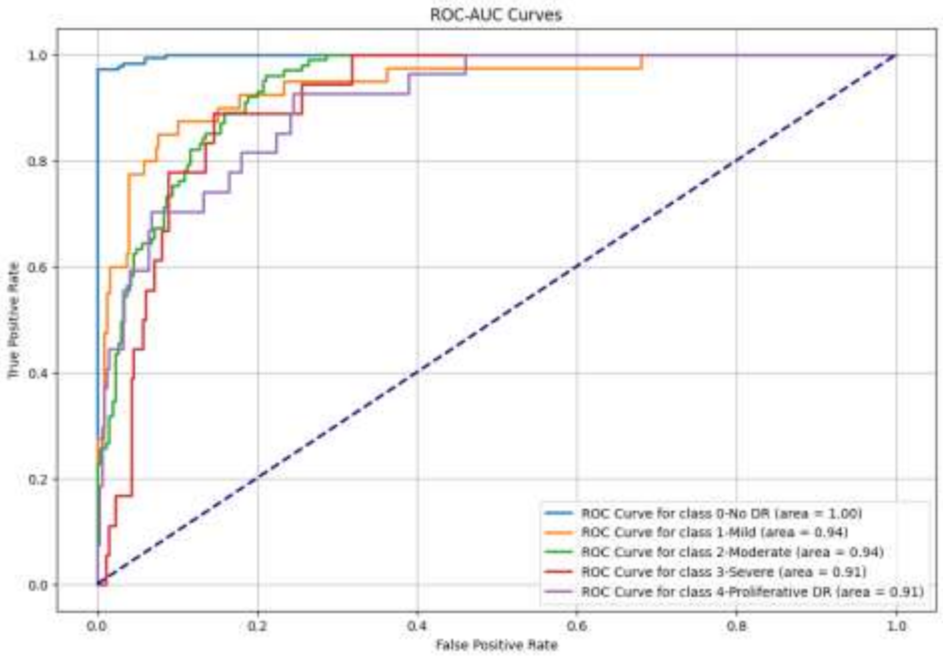


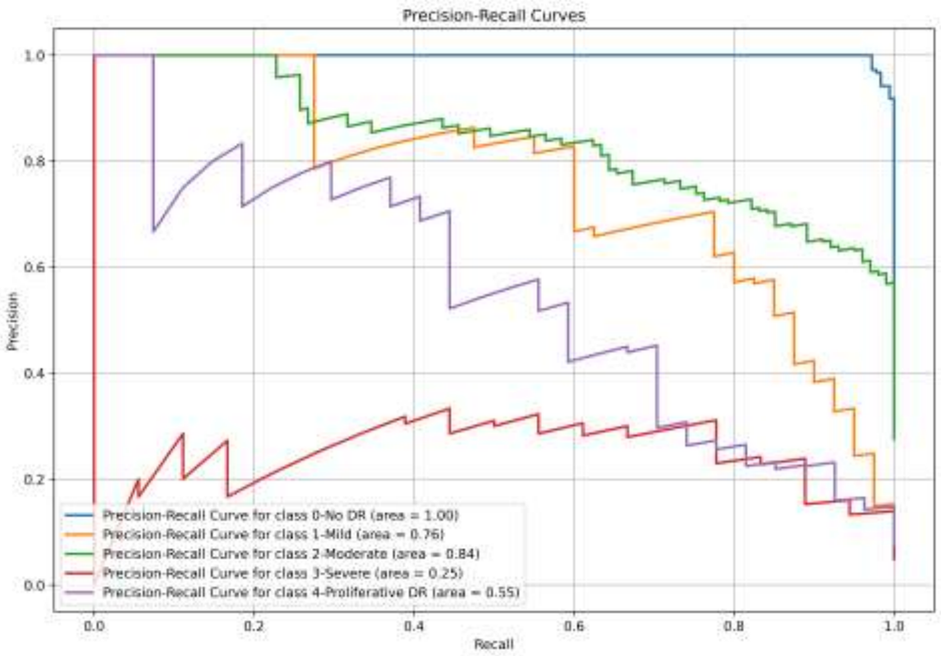
ResNet Model



My Model

Results





ROC-AUC:

- **Class 0 (No DR)** achieved AUC of **1.00**.
- Other classes show strong performance, with AUCs ranging from **0.91 to 0.94**.

Precision-Recall:

- **Class 0 (No DR)** has the best precision and recall.
- **Severe** and **Proliferative DR** show lower precision and recall with AUCs of **0.25** and **0.55**.

Results

Model	Acc (Micro)	Acc (Macro)	F1-S	Pre	Rec	Spec	Total params
EfficientNetV2B0	0.83	0.64	0.64	0.66	0.64	0.96	6083925
InceptionV3	0.83	0.71	0.70	0.69	0.71	0.96	22584437
MobileNetV2	0.80	0.60	0.62	0.69	0.60	0.94	2422597
ResNet50	0.85	0.68	0.69	0.71	0.68	0.96	23850629
VGG16	0.85	0.67	0.69	0.72	0.67	0.96	14780997
My model	0.83	0.73	0.70	0.68	0.73	0.96	8394029

Performance Comparison of Pretrained Models

Results

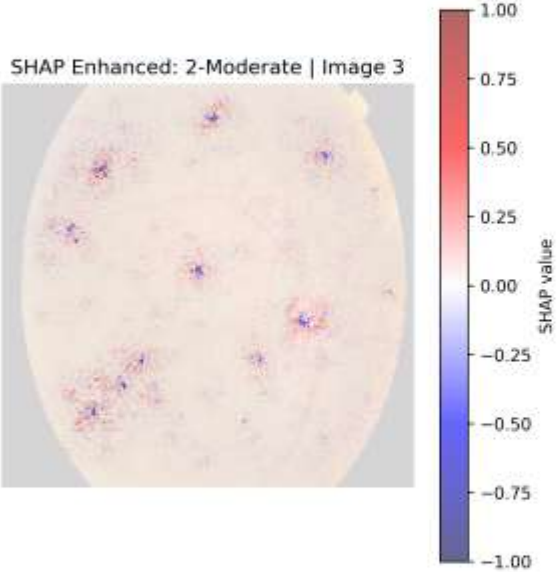
Model	Acc (Micro)	Acc (Macro)	F1-S	Pre	Rec	LOSS
ResNet50	0.85	0.68	0.69	0.71	0.68	Categorical Crossentropy
ResNet50	0.81	0.76	0.70	0.68	0.76	Balanced Softmax Loss
My model	0.84	0.64	0.64	0.67	0.64	Categorical Crossentropy
My model	0.83	0.73	0.70	0.68	0.73	Balanced Softmax Loss

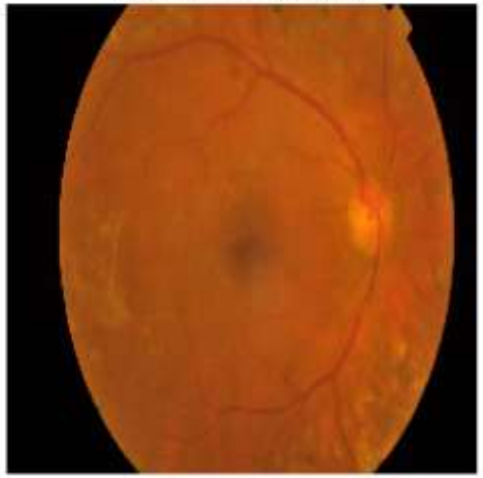
Performance Comparison of ResNet50 and Proposed Model with Different Loss Functions

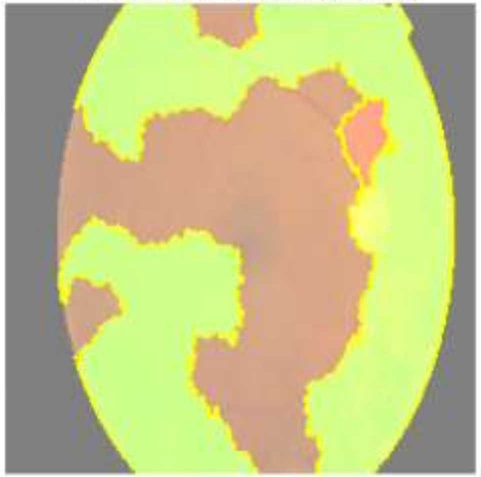
Model	Acc (Micro)	Acc (Macro)	F1-S	Pre	Rec	LOSS	Class
ResNet 50	0.87	0.79	0.80	0.83	0.79	Categorical Crossentropy	4
My model	0.87	0.84	0.81	0.80	0.84	Balanced Softmax Loss	4
ResNet 50	0.85	0.68	0.69	0.71	0.68	Categorical Crossentropy	5
My model	0.83	0.73	0.70	0.68	0.73	Balanced Softmax Loss	5

Performance Comparison for 4-Class vs 5-Class Classification with Different Loss Functions

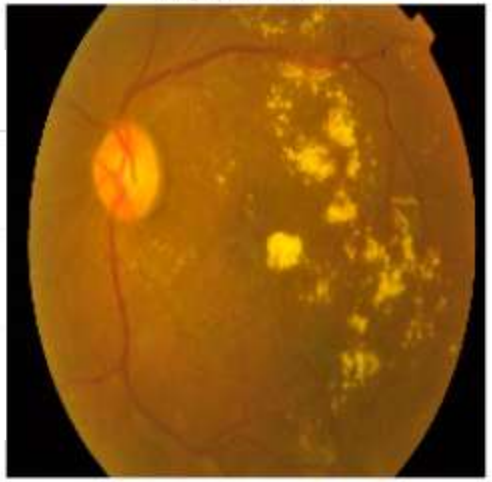
XAI - LIME, Grad-CAM, SHAP

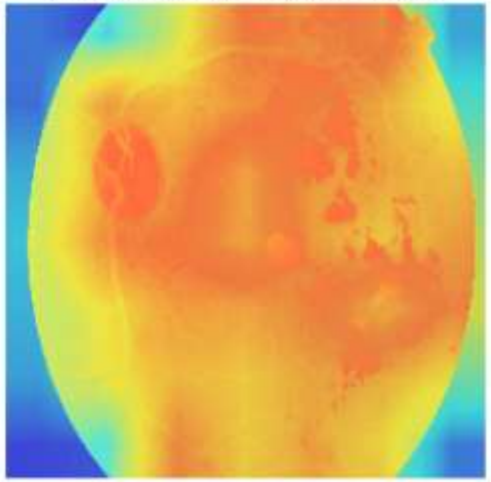




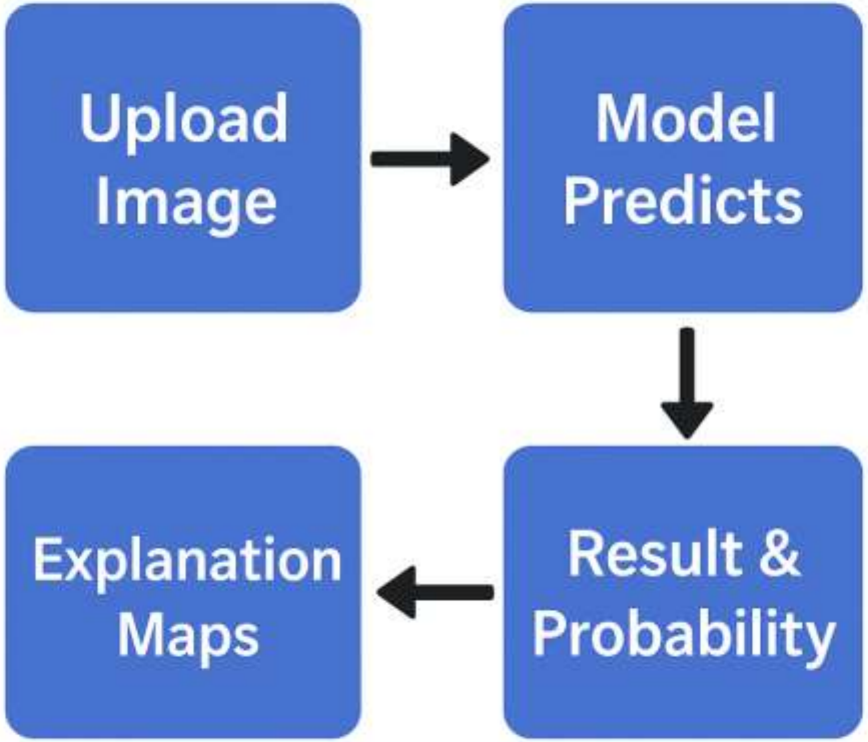


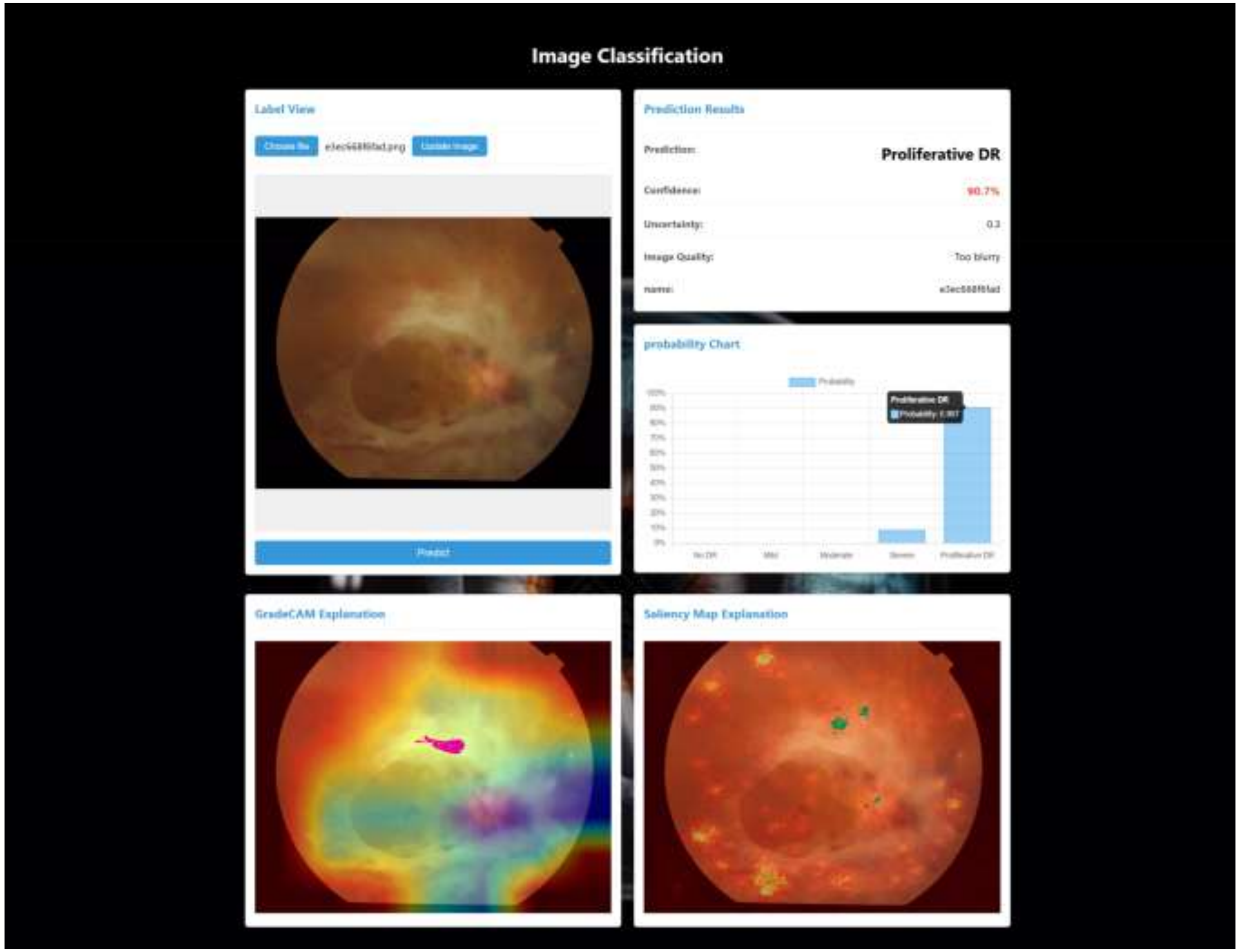
Method	Explanation Style
LIME	Highlights important regions using green and red overlays.
Grad-CAM	Generates colorful heatmaps to show where the model focuses.
SHAP	Uses red-blue shading to show pixel-level contribution scores.





GUI - enabled web deployment





GUI

Future Work

- **Pretrained model integration**
  To boost classification accuracy and improve handling of class imbalance.
- **Lightweight model exploration**
  To reduce training time and enable faster, more efficient deployment.
- **Cross-dataset generalization**
  To evaluate performance on other imbalanced medical image datasets.

Thank You!

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