DIABETES DETECTION THROUGH RETINOPATHY

HACKATHON REPORT

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INTRODUCTION

This report outlines our project on *Diabetes Detection Through Retinopathy*, developed during the hackathon. Our goal was to utilise deep learning to detect diabetic retinopathy from retinal images, enabling early diagnosis and reducing the risk of blindness.

PROBLEM STATEMENT

Diabetic retinopathy is a major cause of vision impairment worldwide. The manual diagnosis process is time-consuming and requires expert ophthalmologists. Our aim was to automate and enhance the detection process using AI-driven image classification models.

TECHNOLOGY STACK

- **Programming Language:** Python, HTML, CSS
- **Frameworks & Libraries:** PyTorch, Django, Matplotlib, Numpy, scikit-learn
- **Model Architectures:** EfficientNet-B3, InceptionV3, ResNet
- **Dataset:** kushagratandon12/diabetic-retinopathy-balanced
- **Development Tools:** Google Colab, Visual Studio Code

DATASET DETAILS

• The dataset can be downloaded from
https://www.kaggle.com/datasets/kushagratandon12/diabetic-retinopathy-balanced/data
• The dataset consists of labeled retinal fundus images.
• Images are provided in JPEG format.
• There are 5 Types Of Diabetic Retinopathy Stages:

1. No_Dr
2. Mild
3. Moderate
4. Severe
5. Proliferative DR

IMPLEMENTATION STEPS

Step 1: Data Preprocessing

- Downloaded the dataset of retinal images.
- Applied resizing and normalization.

Step 2: Model Development

- Implemented and trained multiple deep learning models.
- Fine-tuned pre-trained architectures, including ResNet, EfficientNet, and Inception.

Step 3: Model Training & Evaluation

- Trained models using different hyperparameters.
- Evaluated models using accuracy, precision, recall, and F1-score.

Step 4: Front-end Development

- Developed a Django-based web application for real-time diabetic retinopathy detection.
- Integrated the trained model into Django views to process uploaded images.
- Hosted the web application for accessibility.

METHODOLOGY & MODEL TRAINING

To optimize performance, we employed the following training strategies for three different models before finalizing our most efficient model:

Model 1: Pre-trained EfficientNet-B3

- **Pretrained Model:** Used EfficientNet-B3 with ImageNet weights.
- **Hyperparameters:**
  - Learning Rate: 0.001 (Adam optimizer)
  - Batch Size: 32
  - Epochs: 10
- **Loss Function:** Cross-Entropy Loss
- **Evaluation:** Achieved the best training accuracy of 98.89% and validation accuracy of 77.94% after fine-tuning.
- **Notebook:** initialModel.ipynb

	precision	recall	f1-score	support
0	0.65	0.66	0.66	1000
1	0.68	0.67	0.67	971
2	0.67	0.67	0.67	1000
3	0.93	0.93	0.93	1000
4	0.97	0.96	0.97	1000
accuracy			0.78	4971
macro avg	0.78	0.78	0.78	4971
weighted avg	0.78	0.78	0.78	4971

Model 2: Final Fine-tuned EfficientNet-B3

- **Pretrained Model:** Used EfficientNet-B3 with pre-trained weights from previous training.Trained model on validation set to improve accuracy.
- **Hyperparameters:**
  - Learning Rate: 0.0001 (Adam optimizer)
  - Batch Size: 16
  - Epochs: 14
- **Loss Function:** Cross-Entropy Loss
- **Evaluation:** Achieved the best validation accuracy of 79.75% after fine-tuning.
- **Notebook:** modelFinetuned.ipynb
- **Model:** fineTunedEfficientnet_b3.pt

```
Epoch 9/20, Loss: 0.6910, LR: 1e-05
Validation Accuracy: 79.75%
Epoch 10/20, Loss: 0.6886, LR: 1.0000000000000002e-06
Validation Accuracy: 79.68%
Epoch 11/20, Loss: 0.6876, LR: 1.0000000000000002e-06
Validation Accuracy: 79.73%
Epoch 12/20, Loss: 0.6876, LR: 1.0000000000000002e-06
Validation Accuracy: 79.64%
Epoch 13/20, Loss: 0.6897, LR: 1.0000000000000002e-06
Validation Accuracy: 79.39%
Epoch 14/20, Loss: 0.6905, LR: 1.0000000000000002e-06
Validation Accuracy: 79.71%
```

Model 3: Fine-tuned EfficientNet-B3

- **Pretrained Model:** Used EfficientNet-B3 with ImageNet weights.
- **Hyperparameters:**
  - Learning Rate: 0.001 (Adam optimizer)
  - Batch Size: 32
  - Epochs: 10
- **Loss Function:** Cross-Entropy Loss
- **Evaluation:** Achieved the best validation accuracy of 78.26% after fine-tuning.
- **Notebook:** tuningHyperparams.ipynb
- **Model:** efficientModel.pt

Model 4: Pre-trained Inception-V3

- **Pretrained Model:** Used Inception-V3 with ImageNet weights.
- **Hyperparameters:**
  - Learning Rate: 0.0001 (Adam optimizer)
  - Batch Size: 32
  - Epochs: 13
- **Loss Function:** Cross-Entropy Loss
- **Evaluation:** Achieved the best validation accuracy of 83.21% after fine-tuning.Due to a bug in the code the training process stopped also computation

```
Epoch 9 | Train Loss: 0.2282 | Val Loss: 0.4867 | Val Accuracy: 82.25%
No improvement for 1 epochs...
Epoch 10 | Train Loss: 0.1980 | Val Loss: 0.4777 | Val Accuracy: 83.25%
No improvement for 2 epochs...
Epoch 11 | Train Loss: 0.1732 | Val Loss: 0.4546 | Val Accuracy: 83.63%
No improvement for 3 epochs...
Epoch 12 | Train Loss: 0.1647 | Val Loss: 0.5345 | Val Accuracy: 83.07%
No improvement for 4 epochs...
Epoch 13 | Train Loss: 0.1466 | Val Loss: 0.5183 | Val Accuracy: 83.21%
No improvement for 5 epochs...
 due to constrain we stop here
Training is completed! Team Masakali
```

limit on google colab disconnected the current state. We believe that the training process can lead to a validation score of above 85% accuracy.

- **Notebook:** inceptionFineTuned.ipynb
- **Model:** fineTunedInception.pt

MODEL COMPARISONS & PERFORMANCE

Model	Testing Accuracy	Precision	Recall	F1-Score
EfficientNet-B3	98.89%(slight overfitting)	78%(avg)	0.66,0.67,0.67, 0.93,0.96	78%(avg)
Fine-Tuned EFnet-B3	98.89%(slight overfitting)	Approximately same as above	Same as above	Same as above
Inception-V3	97%	84% on test set	Not tested	Not tested

We finalised the fine-tuned EFnet-B3 model as we already created an interface for testing the EFnet-B3 and only found out about inceptionv3 when it was already too late :((. The best we could do is train and provide the model file.

CHALLENGES FACED

1. Limited Computation Power in Colab

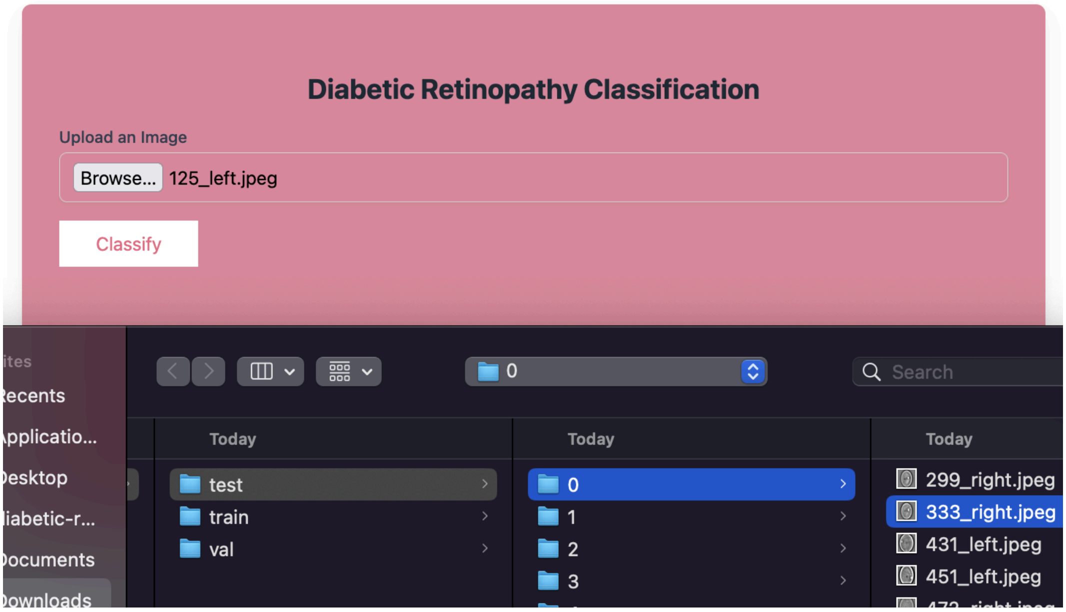
Due to hardware constraints, such as limited GPU memory and processing power, training times were prolonged, and batch sizes had to be reduced.

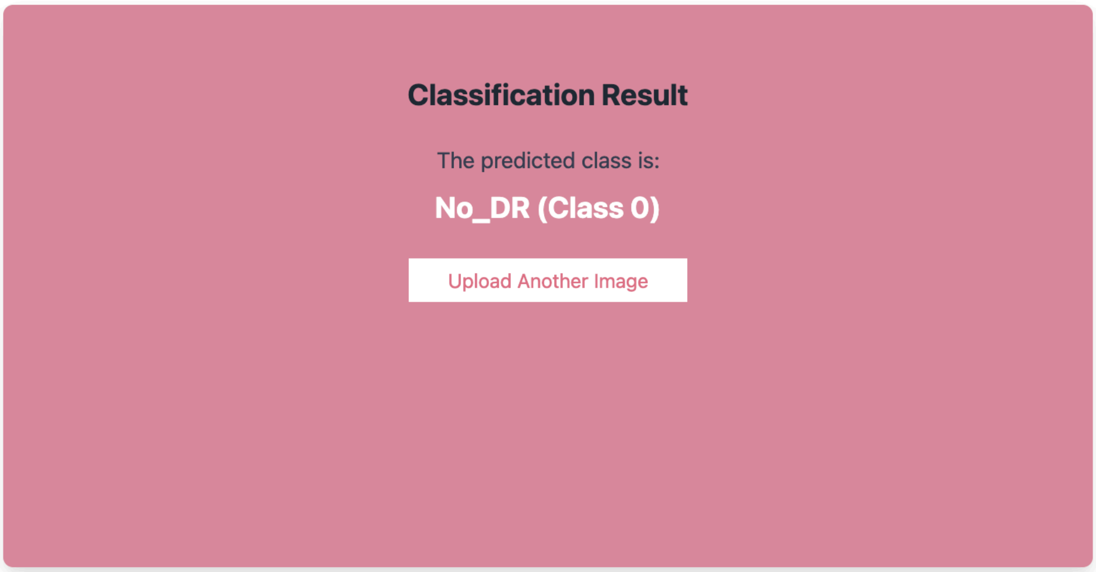
2. Overfitting While Training EfficientNet-B3 Model

EfficientNet-B3, being a powerful yet complex model, showed signs of overfitting during training. The model performed exceptionally well on the training dataset but struggled to generalize on validation data.

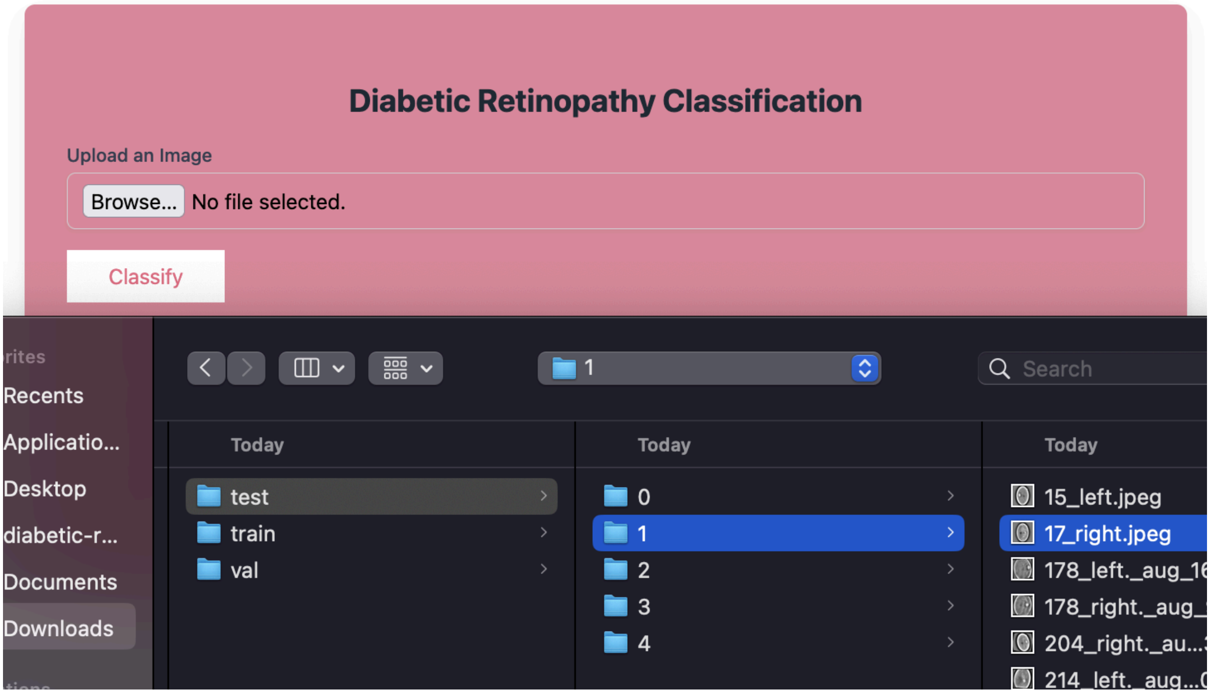
TESTING SNAPSHOTS

1. Class 0

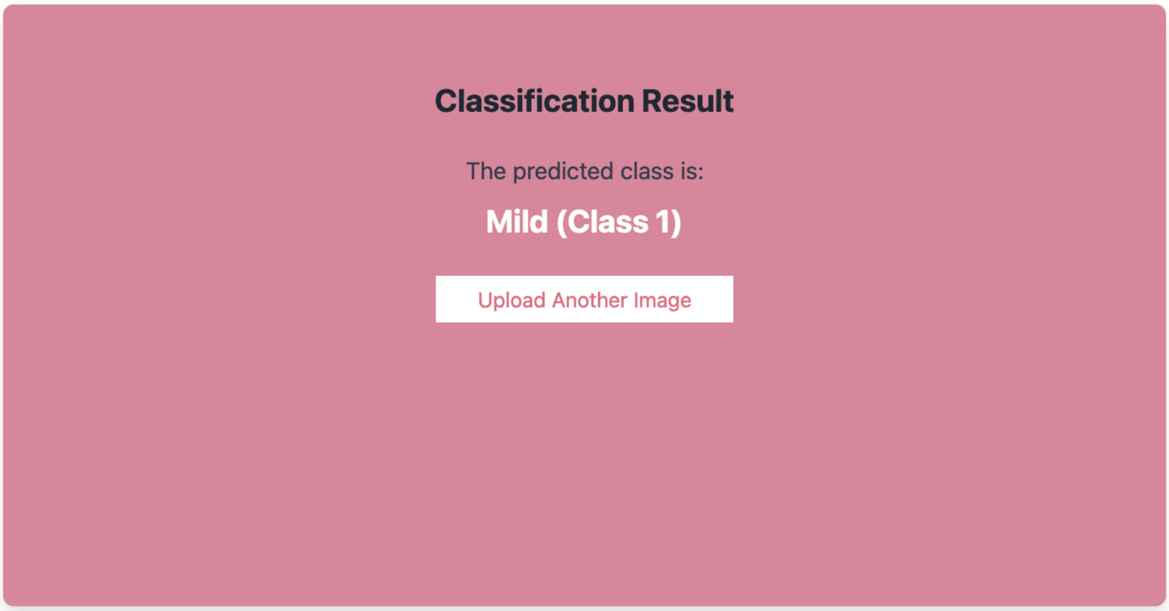




2. Class 1

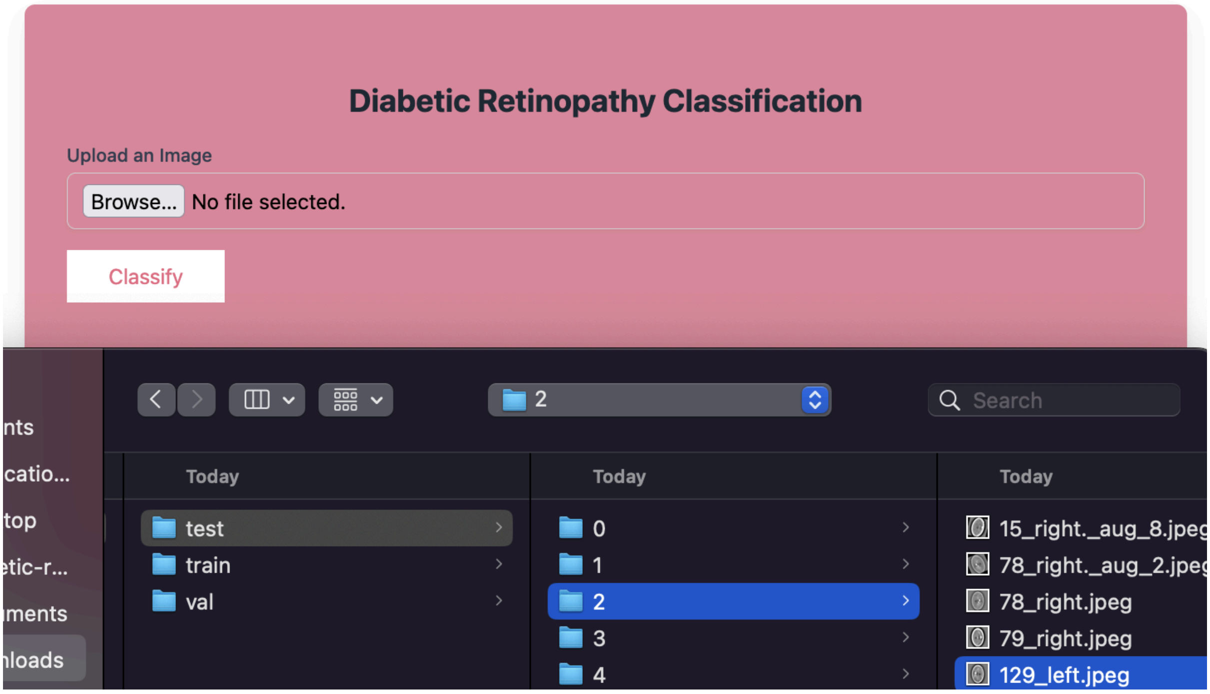


Diabetic Retinopathy Classification
Upload an Image
Browse... No file selected.
Classify
rites
Recents
Applicatio...
Desktop
diabetic-r...
Documents
Downloads
1
Search
Today
test
train
val
Today
0
1
2
3
4
Today
15_left.jpeg
17_right.jpeg

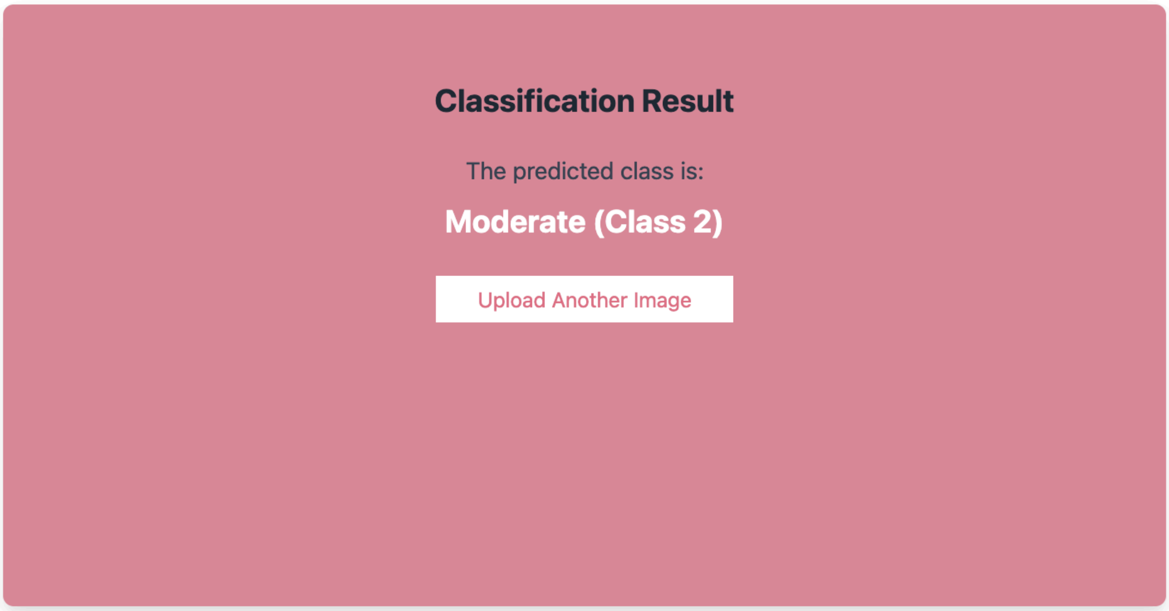


Classification Result
The predicted class is:
Mild (Class 1)
Upload Another Image

3. Class 2

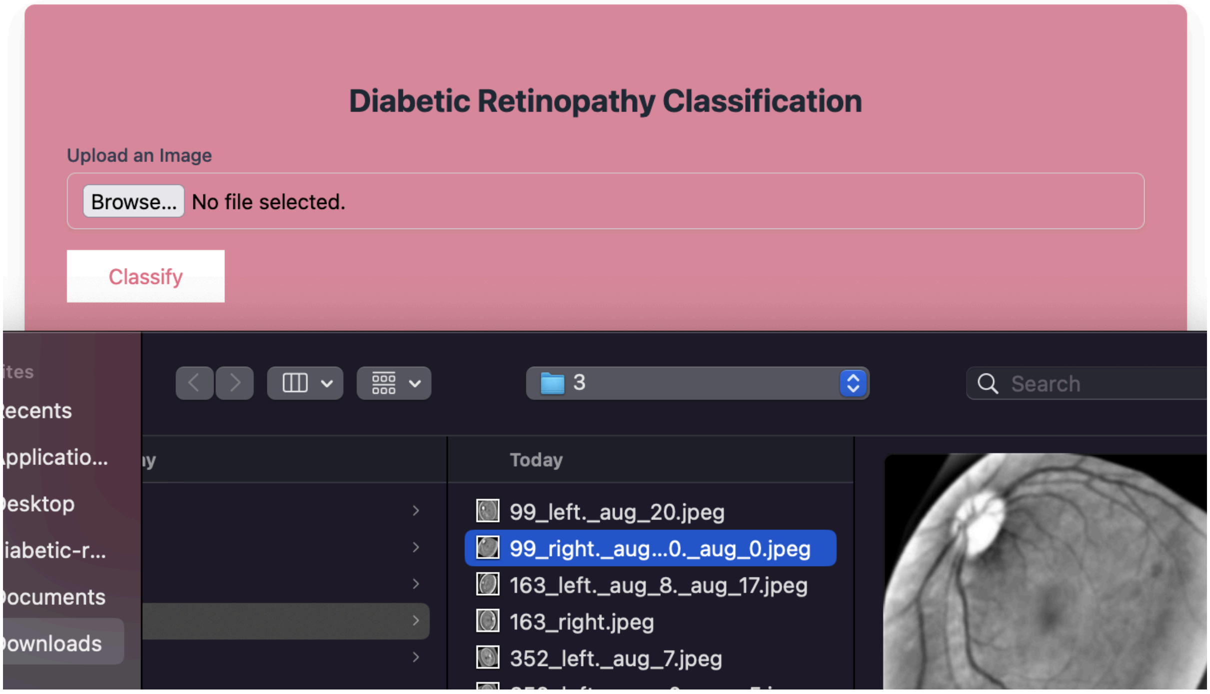


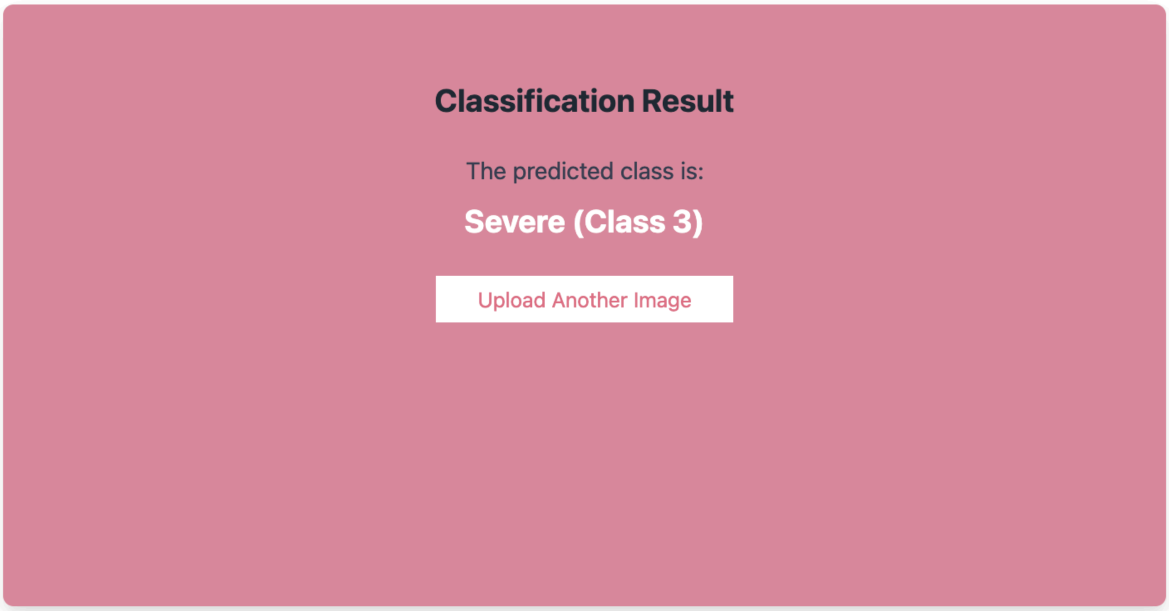
Diabetic Retinopathy Classification
Upload an Image
Browse... No file selected.
Classify
2
Search
nts
catio...
top
etic-r...
ments
nloads
Today
test
train
val
Today
0
1
2
3
4
Today
15_right._aug_8.jpeg
78_right._aug_2.jpeg
78_right.jpeg
79_right.jpeg
129_left.jpeg



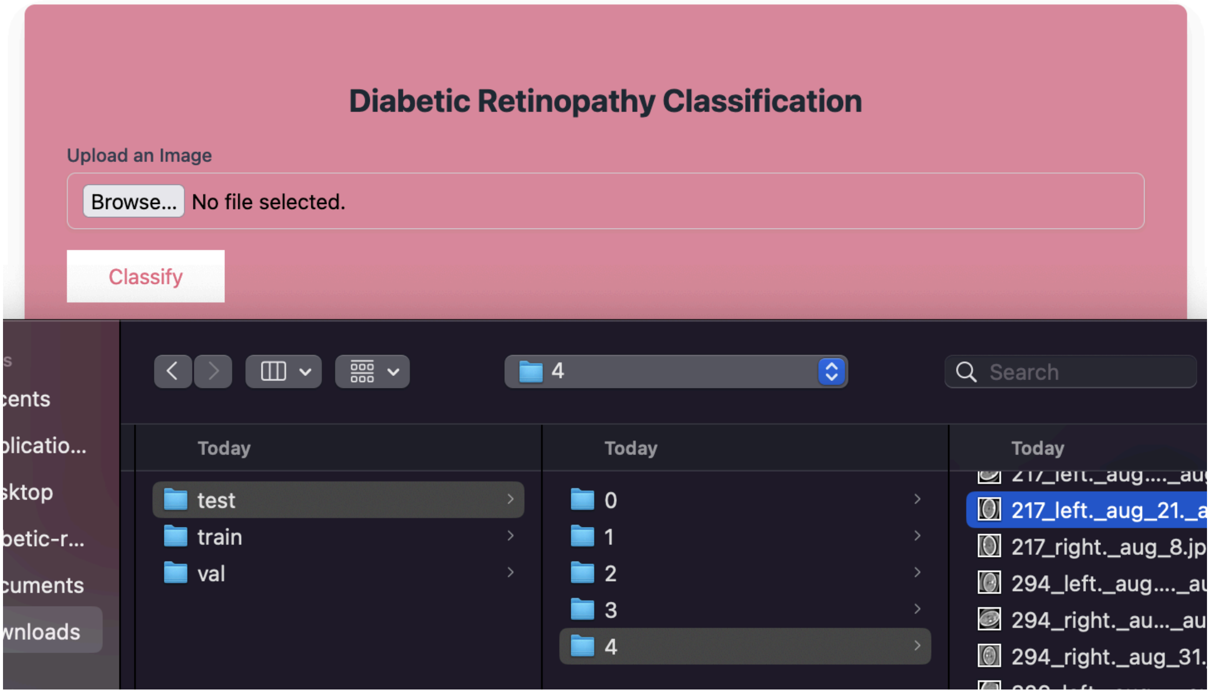
Classification Result
The predicted class is:
Moderate (Class 2)
Upload Another Image

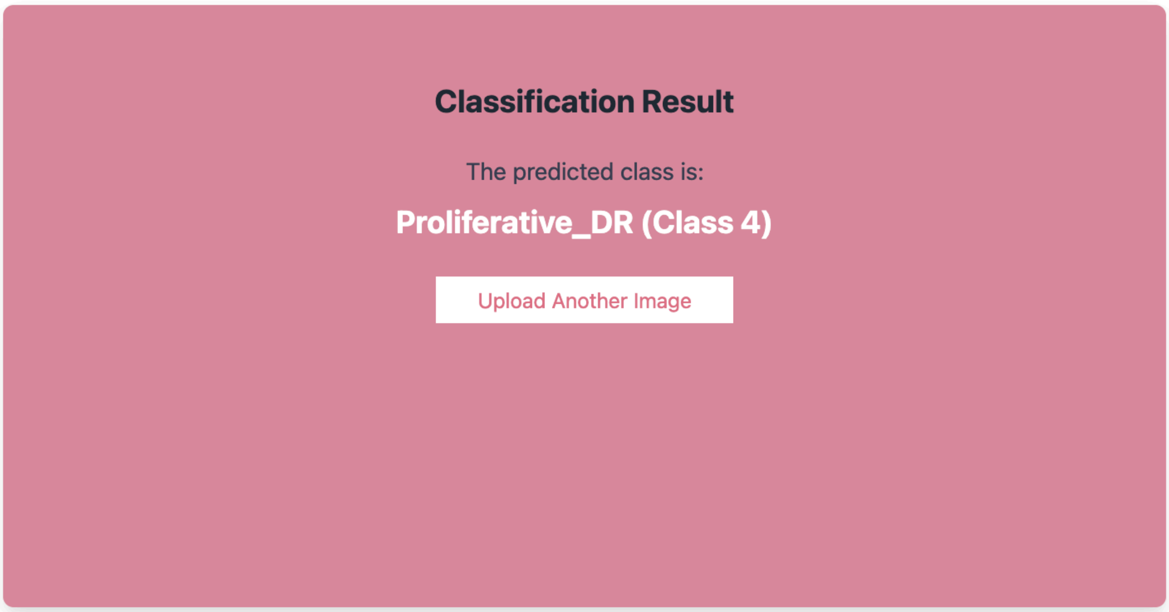
4. Class 3


Diabetic Retinopathy Classification
Upload an Image
Browse... No file selected.
Classify
3
Search
Today
99_left._aug_20.jpeg
99_right._aug...0._aug_0.jpeg
163_left._aug_8._aug_17.jpeg
163_right.jpeg
352_left._aug_7.jpeg


Classification Result
The predicted class is:
Severe (Class 3)
Upload Another Image

5. Class 4


Diabetic Retinopathy Classification
Upload an Image
Browse... No file selected.
Classify
4
Search
Today
test
train
val
0
1
2
3
4
217_left._aug_21._a
217_right._aug_8.jp
294_left._aug...._au
294_right._au..._au
294_right._aug_31.


Classification Result
The predicted class is:
Proliferative_DR (Class 4)
Upload Another Image

CONCLUSION

Our deep learning-based approach successfully demonstrated the potential of AI in early diabetic retinopathy detection. With further improvements, this system can significantly assist medical professionals in diagnosing the disease efficiently.