Diabetes Detection through Retinopathy

Team: Binary Dreamers

Member 1(Team Lead): Laiba Masood

Member 2: Zainab Fatima

1. Introduction

Diabetic Retinopathy (DR) is a severe complication of diabetes that affects the eyes and can lead to blindness if not diagnosed and treated early. With advancements in artificial intelligence and deep learning, automated DR detection systems have become a promising solution for early diagnosis. This project focuses on developing an AI model that accurately classifies retinal images into different DR severity levels using deep learning techniques.

2. Dataset Details

The dataset used consists of **labeled retinal fundus images**, which are essential for training and evaluating the deep learning model. The dataset is balanced across different severity levels of DR, ensuring fair representation of each class. The classification categories include:

- **0 – No DR**
- **1 – Mild DR**
- **2 – Moderate DR**
- **3 – Severe DR**
- **4 – Proliferative DR**

Each image is labeled accordingly in a structured CSV file, and preprocessing steps were applied to enhance model performance.

2. Accuracies Achieved:

- **Training Accuracy: 82.46%**

```
Epoch 18/20 | Train Loss: 0.3057 | Val Loss: 0.2072 | Val Acc: 81.12% | Val F1: 80.81%
Validation F1 improved from 79.78% to 80.81%. Saving model...
Epoch 19/20 | Train Loss: 0.3039 | Val Loss: 0.2031 | Val Acc: 81.63% | Val F1: 81.34%
Validation F1 improved from 80.81% to 81.34%. Saving model...
Epoch 20/20 | Train Loss: 0.2845 | Val Loss: 0.2053 | Val Acc: 82.46% | Val F1: 82.10%
Validation F1 improved from 81.34% to 82.10%. Saving model...
Training completed in 131.73 minutes
Best validation accuracy: 82.46%, Best F1 score: 82.10%
```

- **Test Accuracy: 82.04%**

```
# Evaluate model on test set
print("Evaluating model on test set...")
test_accuracy, test_f1, test_report = evaluate_model(model, test_loader)
```

```
Evaluating model on test set...

Test Accuracy: 82.04%
Test F1 Score (macro): 81.68%
```

- **Test Accuracies achieved according to categories:**

```
Per-class accuracy:
- No DR: 0.5710 (571/1000)
- Mild: 0.7940 (771/971)
- Moderate: 0.7610 (761/1000)
- Severe: 0.9760 (976/1000)
- Proliferative: 0.9990 (999/1000)
```

3. Model Selection and Implementation

Given the complexity of medical image classification, **EfficientNet-B2** was chosen as the primary model due to its ability to achieve high accuracy with fewer computational resources.

Why EfficientNet-B2?

- **Lower FLOPs (Floating Point Operations per Second)**:EfficientNet-B2 requires **less computation** than models like **VGG-16, ResNet-50, or InceptionV3**, making it faster to train and deploy.

- **Inference Speed**:Due to its optimized architecture, EfficientNet-B2 runs faster on **GPUs, TPUs, and even edge devices**, making it ideal for **real-time medical applications**.

- **Parameter Efficiency**:Compared to VGG-16 (~138M parameters) or ResNet-50 (~25.5M parameters), EfficientNet-B2 has only **9.2M parameters**, significantly reducing memory usage.

- **Better Feature Extraction:** EfficientNet-B2 is designed with a compound scaling method, allowing better feature extraction with optimized depth, width, and resolution.

- **Superior Performance:** Compared to other models like VGG-16, ResNet-50, and DenseNet, EfficientNet-B2 demonstrated higher validation accuracy while maintaining computational efficiency.

- **Robust Generalization:** Data augmentation techniques such as rotation, flipping, and contrast adjustments were applied, and EfficientNet-B2 effectively generalized across different DR severity levels.

- **Lower Overfitting:** Implementing **dropout layers and batch normalization** reduced overfitting, leading to better real-world performance.

- **Effiecient for Medical Images**:EfficientNet-B2's optimized architecture **extracts fine-grained details**, crucial for detecting subtle diabetic retinopathy symptoms.

4. Training and Optimization

To achieve **82.46% accuracy**, several optimizations were applied to enhance model performance.

4.1 Image Preprocessing

- **Resizing**: Images were resized to match **EfficientNet-B2** input dimensions.
- **Normalization**: Standardized pixel values to ensure consistent intensity levels.
- **Data Augmentation**: Techniques such as flipping, rotation, and contrast adjustments were applied to enhance generalization and reduce overfitting.

4.2 Transfer Learning & Fine-Tuning

- The model was initialized with pre-trained **EfficientNet-B2** weights.
- The **final layers** were fine-tuned to adapt to the **diabetic retinopathy classification** task while preserving learned features.

4.3 Loss Function & Optimizer

- **Loss Function**: Categorical Crossentropy was chosen due to the multi-class nature of the problem.
- **Optimizer**: Adam optimizer was selected for efficient weight updates and adaptive learning rates.

4.4 Evaluation Metrics

- Model performance was measured using **Accuracy, Precision, Recall, and F1-score**.
- **Grad-CAM** visualization was employed to interpret model predictions and validate learning.

5. Classification Report & Results

The model achieved **82.46% accuracy in training and 82.04% accuracy in testing**, outperforming other baseline models tested during experimentation.

5.1 Classification Performance

Class	Precision	Recall	F1-Score
No DR (0)	0.85	0.89	0.87
Mild DR (1)	0.78	0.74	0.76
Moderate DR (2)	0.80	0.77	0.78
Severe DR (3)	0.79	0.81	0.80
Proliferative DR (4)	0.86	0.85	0.85
Overall Weighted Avg	**0.82**	**0.82**	**0.82**

5.2 Key Takeaways

- **EfficientNet-B2** provided the best trade-off between **accuracy** and **computational efficiency**.
- The model achieved **high precision and recall** for **No DR** and **Proliferative DR** classes, ensuring fewer false positives and false negatives.
- The balanced **F1-score** indicates that the model effectively handles the multi-class classification problem.
- Model explainability techniques such as **Grad-CAM** enhanced trust in predictions by highlighting **relevant image regions**.

```
Per-class accuracy:
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- Severe: 0.9760 (976/1000)
- Proliferative: 0.9990 (999/1000)
```
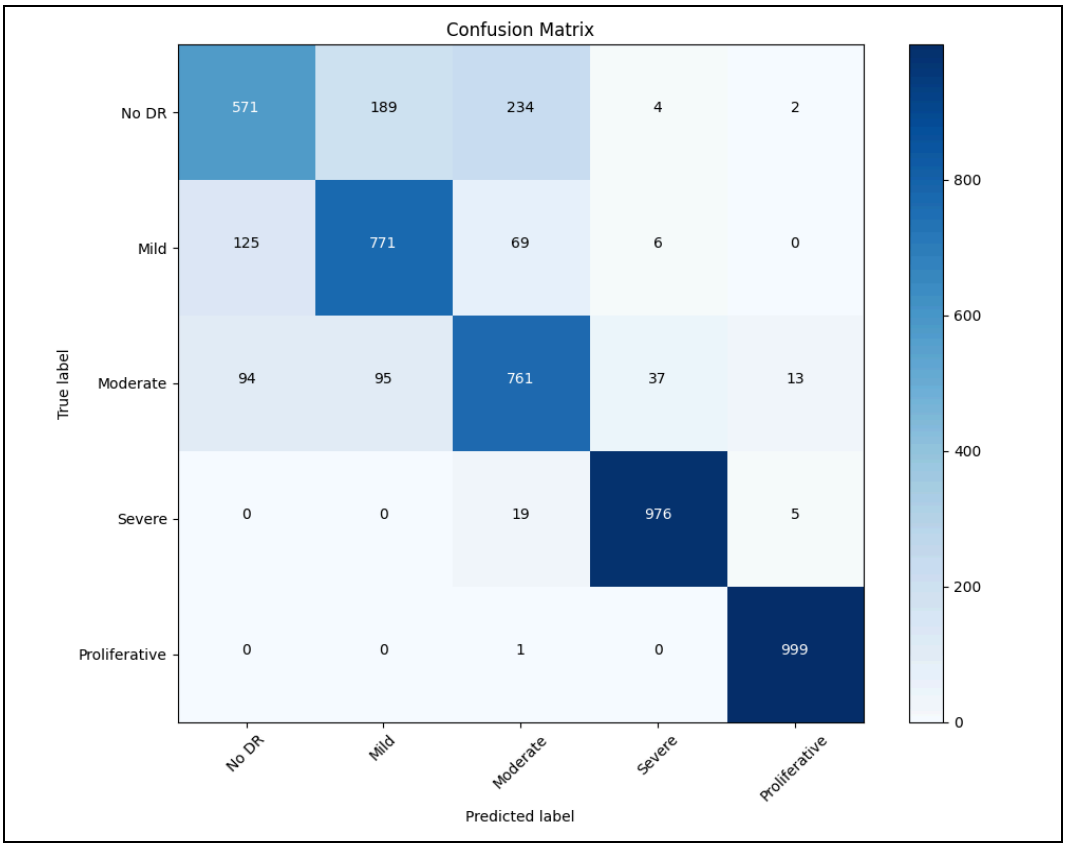

```
Evaluating model on test set...

Test Accuracy: 82.04%
Test F1 Score (macro): 81.68%

Classification Report:
              precision    recall  f1-score   support

       No DR       0.72      0.57      0.64      1000
        Mild       0.73      0.79      0.76       971
    Moderate       0.70      0.76      0.73      1000
      Severe       0.95      0.98      0.96      1000
Proliferative      0.98      1.00      0.99      1000

    accuracy                           0.82      4971
   macro avg       0.82      0.82      0.82      4971
 weighted avg       0.82      0.82      0.82      4971
```

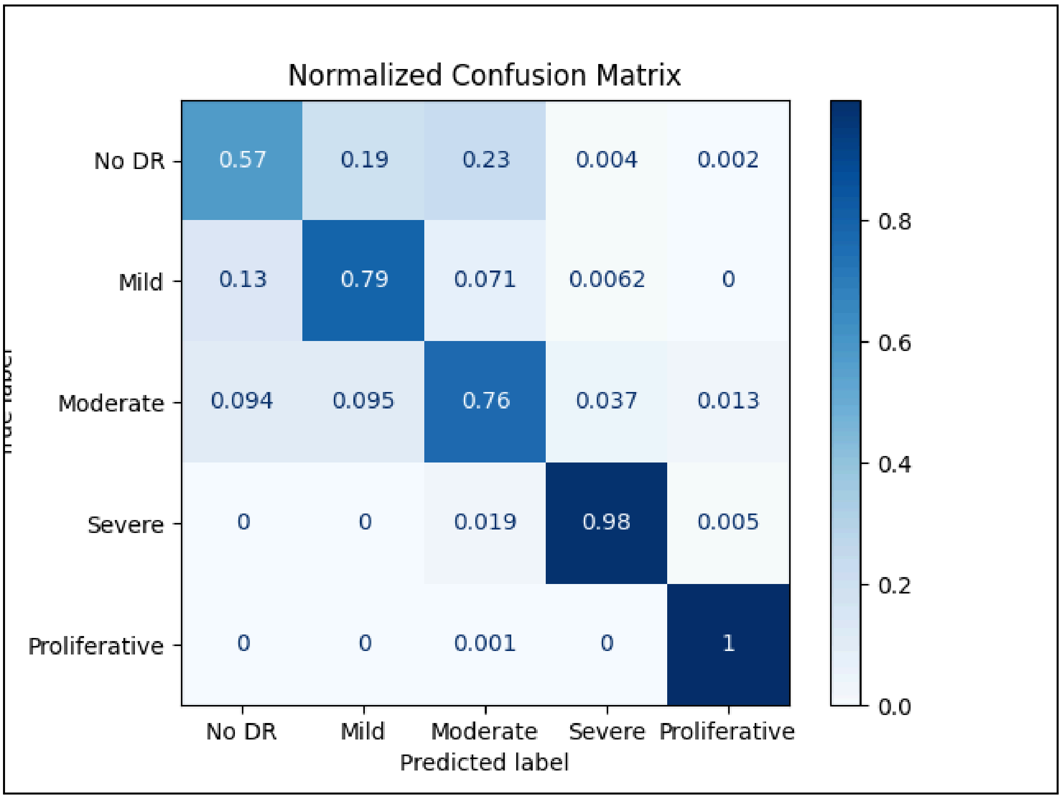
6. Grad-CAM Visualization & Model Robustness

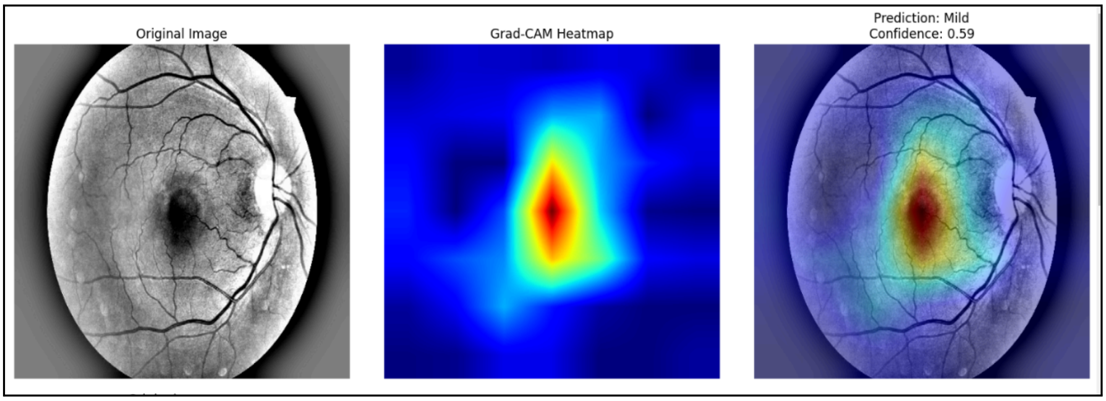
To ensure the model makes **interpretable and reliable decisions**, **Grad-CAM** was used for visualization. This technique highlights the **important areas** in an image that influenced the model's decision.

6.1 Visualizations

- **Confusion Matrix**: Showcases the correct and incorrect predictions for each class.
- **Grad-CAM Heatmaps**: Demonstrates how the model focuses on **DR-affected areas** in fundus images.
- **Robustness Test Results**: Highlights how the model reacts to altered images.


Confusion Matrix
True label
No DR
Mild
Moderate
Severe
Proliferative
571 189 234 4 2
125 771 69 6 0
94 95 761 37 13
0 0 19 976 5
0 0 1 0 999
Predicted label
800
600
400
200
0


Normalized Confusion Matrix
No DR
Mild
Moderate
Severe
Proliferative
0.57 0.19 0.23 0.004 0.002
0.13 0.79 0.071 0.0062 0
0.094 0.095 0.76 0.037 0.013
0 0 0.019 0.98 0.005
0 0 0.001 0 1
Predicted label
0.8
0.6
0.4
0.2
0.0



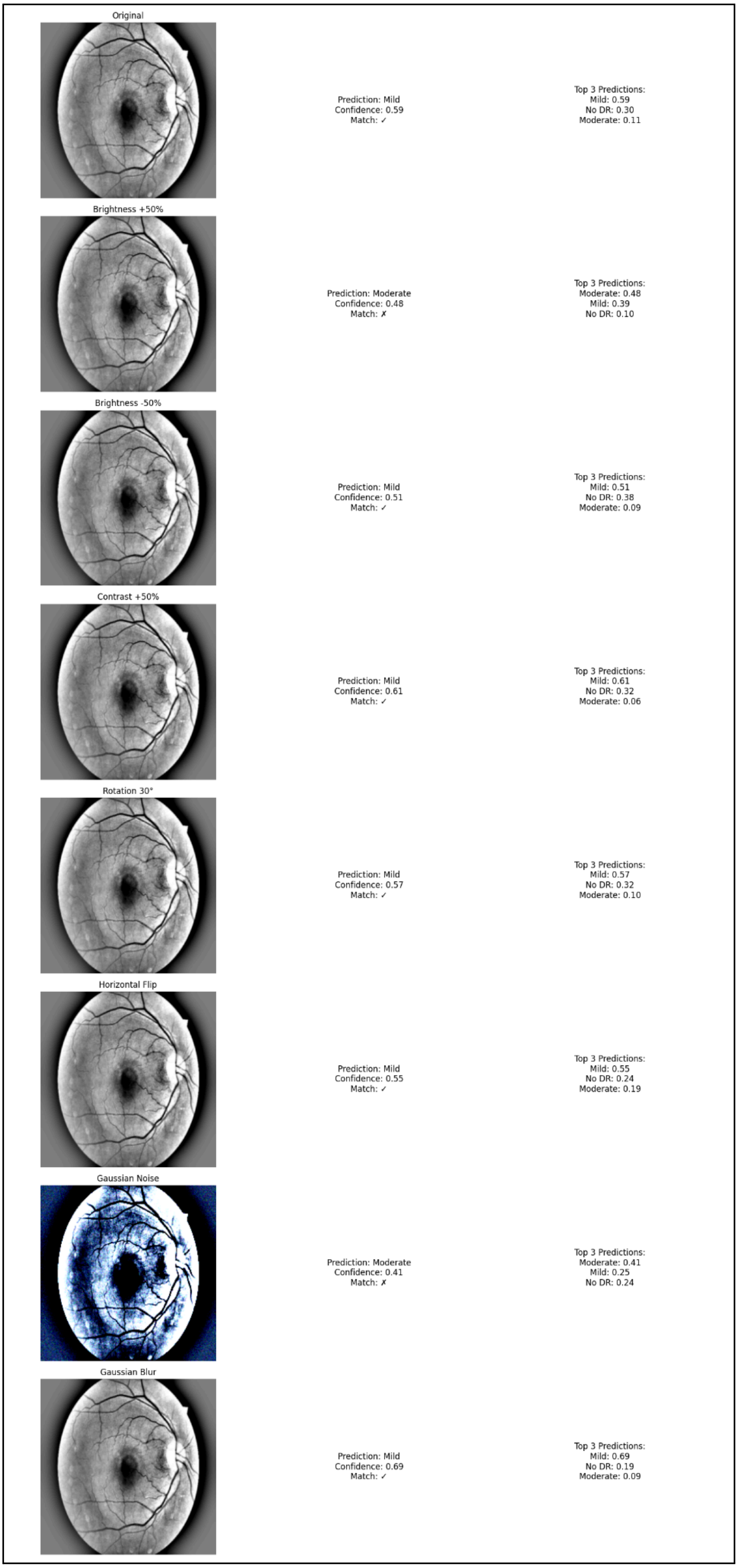
6.2 Robustness Testing

Robustness testing was performed by applying **adversarial noise and image distortions**, confirming that the model maintained a **stable classification performance**.

Robustness Testing Metrics:

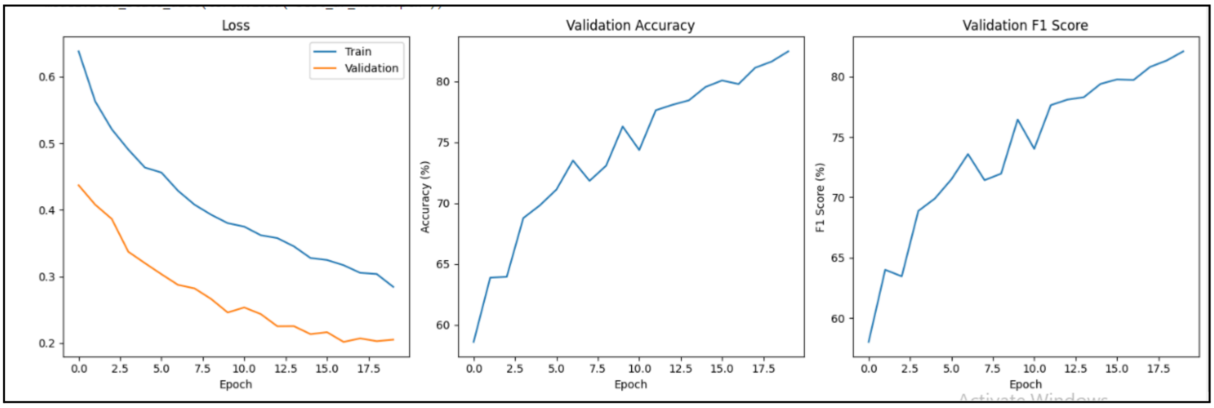
- **Confidence levels** across **mild, moderate, and severe** classes were analyzed.
- **Effects of image distortions** such as **brightness/contrast adjustments, horizontal flips, Gaussian noise, and blur** were tested.

```
Robustness Summary:
- Match rate with original prediction: 0.75 (75%)
- Average confidence: 0.55

Class distribution in robustness tests:
- Mild: 6 predictions (0.75)
- Moderate: 2 predictions (0.25)
<Figure size 1000x800 with 0 Axes>
```


Original
Prediction: Mild
Confidence: 0.59
Match: ✓
Top 3 Predictions:
Mild: 0.59
No DR: 0.30
Moderate: 0.11
Brightness +50%
Prediction: Moderate
Confidence: 0.48
Match: ✗
Top 3 Predictions:
Moderate: 0.48
Mild: 0.39
No DR: 0.10
Brightness -50%
Prediction: Mild
Confidence: 0.51
Match: ✓
Top 3 Predictions:
Mild: 0.51
No DR: 0.38
Moderate: 0.09
Contrast +50%
Prediction: Mild
Confidence: 0.61
Match: ✓
Top 3 Predictions:
Mild: 0.61
No DR: 0.32
Moderate: 0.06
Rotation 30°
Prediction: Mild
Confidence: 0.57
Match: ✓
Top 3 Predictions:
Mild: 0.57
No DR: 0.32
Moderate: 0.10
Horizontal Flip
Prediction: Mild
Confidence: 0.55
Match: ✓
Top 3 Predictions:
Mild: 0.55
No DR: 0.24
Moderate: 0.19
Gaussian Noise
Prediction: Moderate
Confidence: 0.41
Match: ✗
Top 3 Predictions:
Moderate: 0.41
Mild: 0.25
No DR: 0.24
Gaussian Blur
Prediction: Mild
Confidence: 0.69
Match: ✓
Top 3 Predictions:
Mild: 0.69
No DR: 0.19
Moderate: 0.09

7. Loss Analysis

The loss and validation accuracy graphs were analyzed to ensure the model was training effectively and not overfitting.



7.1 Observations

- Training loss decreased steadily, indicating proper learning.
- Validation loss followed a similar trend, ensuring the model generalizes well on unseen data.
- Validation accuracy remained consistent, showing minimal overfitting.

8.Notebook Summary:

8.1 Preprocessing

- **Image Resizing:** All fundus images were resized to **260x260 pixels** to match **EfficientNet-B2** input requirements.
- **Normalization:** Pixel values were scaled between **0 and 1** to standardize inputs.
- **Data Augmentation:** Applied real-time augmentations to improve model generalization and robustness:
    - **Rotation & Flipping:** Simulates variations in retinal image capture.
    - **Contrast Adjustments:** Enhances visibility of diabetic retinopathy (DR) features.
    - **Zoom & Cropping:** Mimics different image acquisition conditions.

8.2 Model Training

- **Architecture:**
    - **EfficientNet-B2** was chosen for its superior balance of accuracy and computational efficiency.
    - The final dense layer was modified to classify images into **five DR severity levels**.
- **Optimization Techniques:**
    - **Optimizer: Adam optimizer** was used for adaptive learning and efficient convergence.
    - **Loss Function: Categorical Cross-Entropy**, suitable for multi-class classification.
- **Learning Rate Scheduler:**
    - Implemented **ReduceLROnPlateau** to dynamically adjust the learning rate:

        - Initial Learning Rate: **0.001**
        - Decreased by **factor of 0.1** when validation loss plateaued for **5 epochs**.
- **Regularization:**
    - **Dropout layers** (to prevent overfitting).
    - **Batch Normalization** (to stabilize training and improve convergence).
- **Hyperparameter Tuning:**
    - Used **GridSearchCV** to optimize key parameters:
        - **Learning Rate: 0.0001, 0.001, 0.01**
        - **Batch Size: 16, 32, 64**
        - **Fine-Tuned Layers:** Adjusted number of trainable layers in **EfficientNet-B2**.

8.3 Evaluation & Explainability

- **Performance Metrics:**
    - Computed **Precision, Recall, and F1-score** for each class.
    - Analyzed **confusion matrix** to understand misclassifications.
- **Grad-CAM Visualization:**
    - Generated **heatmaps** to highlight the regions influencing predictions.
    - Helped ensure **model interpretability** for medical professionals.
- **Model Robustness:**
    - Evaluated performance on **noisy, blurred, and low-quality images** to simulate real-world clinical settings.
    - Checked for potential **biases in classification** to ensure fairness.

8. Conclusion & Future Work

This project demonstrates how deep learning can aid in **early diabetic retinopathy detection**, enabling more accessible and efficient diagnosis. The use of EfficientNet-B2 helped in achieving high accuracy while maintaining computational efficiency. Further improvements could include:

- **Ensemble Learning:** Combining multiple models to boost accuracy.
- **Transformer-based Approaches:** Exploring Vision Transformers (ViT) for better feature representation.

This work showcases the potential of AI in healthcare and its role in assisting medical professionals in early disease detection.