Smart Retinal Scan: AI-Driven Diagnostic Tool for Early Detection

GROUP 8

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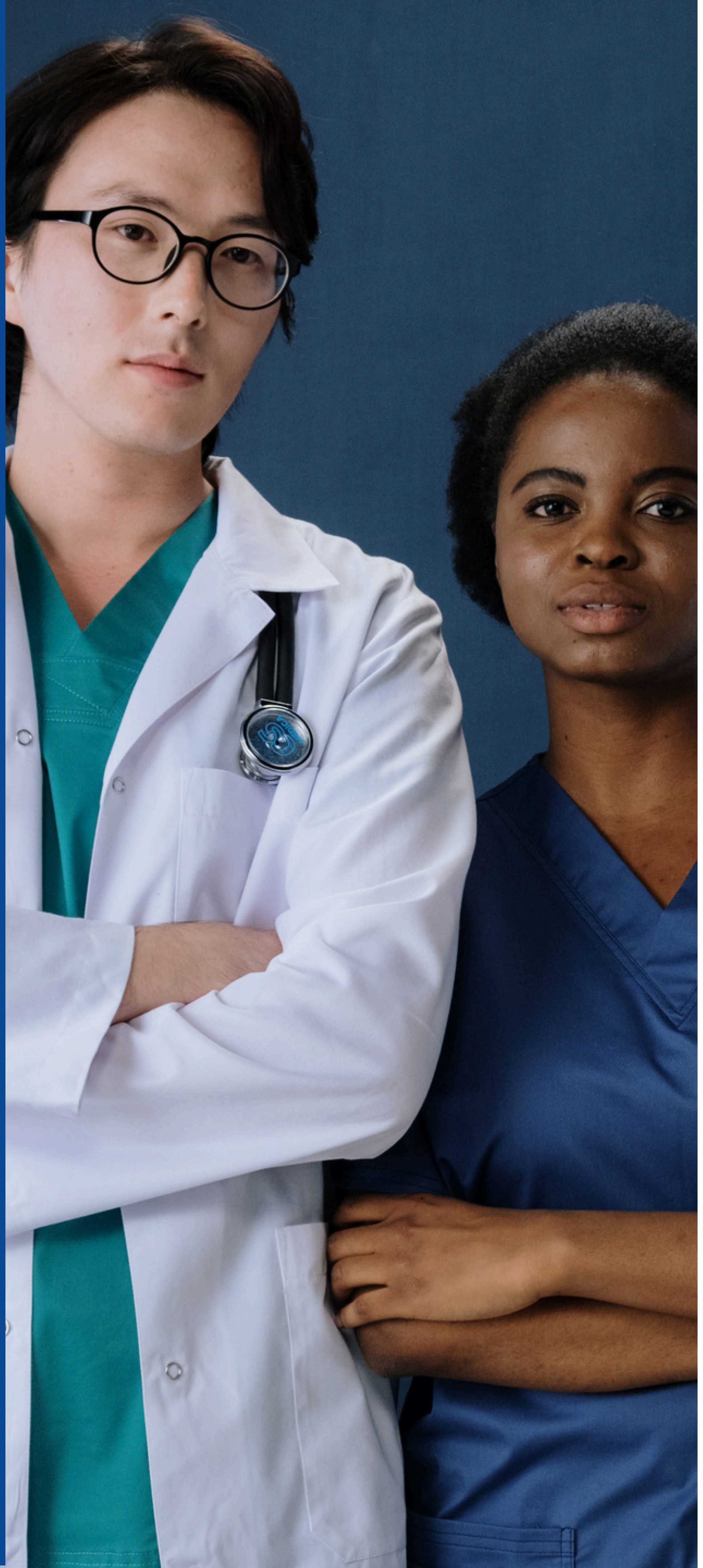
Introduction

Diabetic Retinopathy represents a critical global health challenge, affecting over 93 million people worldwide and standing as the primary cause of vision loss in working-age adults.

This eye disease, associated with chronic diabetes, develops when high blood sugar levels damage the blood vessels in the retina.



Global Statistics:

- **347 million people globally are diabetic**

In the US:

- **29.1 million people have diabetes**
- **40-45% show some stage of DR**
- **Over 4.4 million Americans aged 40+ had DR during 2005-2008**
- **Approximately 0.7 million have advanced DR risking severe vision loss**

Current Challenges

Manual Detection Process:
The traditional diagnostic approach faces several critical limitations:

- Requires specialized ophthalmologists to examine digital color fundus photographs
- Manual diagnosis typically takes 7-14 days
- Limited availability of trained clinicians in high-need areas
- Time-intensive evaluation process for identifying vascular abnormalities

Current Implications

Vision impairment progression can be controlled if detected early, however:

- The disease often shows minimal symptoms until advanced stages
- Delayed diagnosis can lead to irreversible vision damage
- Limited access to specialists results in missed treatment opportunities

Project Goals

Automated Solution:
Our project aims to develop an AI-driven diagnostic tool that will:

- Analyze fundus images with varying illumination and fields of view
- Generate accurate severity grades for DR classification
- Provide rapid screening results to enable timely interventions
- Achieve classification accuracy matching human expert performance

This automated approach promises to revolutionize DR screening by making it more accessible, efficient, and timely, particularly in regions with limited healthcare resources.

Data Exploration

Dataset Source:

- Messidor Database of retinal fundus images.
- Total: 35,126 high-resolution images (~88 GB).
- Includes images of both left and right eyes.

Training Dataset:

- Due to computational constraints, the model was trained on 3,700 images (~9 GB).
- Images were preprocessed and saved on Google Drive for efficient access and storage.

Rationale for Reduced Dataset:

- Handling the full dataset was impractical with available resources.
- Focused on achieving a balance between quality and computational feasibility.

Architecture Design

Model Used:

- ResNet50 for base feature extraction.
- Additional fully connected layers to classify into 5 DR severity levels.
- Dropout layers to prevent overfitting.

Pipeline Details:

- Input: Preprocessed retinal fundus images.
- Backbone: ResNet50 with modifications in final dense layers.
- Output: Probability distribution across 5 severity classes (0: No DR to 4: Proliferative DR).

Metrics Monitored:

- Accuracy

Why ResNet Pre-trained Models?

- **ResNet (Residual Networks) resolves vanishing gradient issues using skip connections.**
- **Proven effective for image classification, even on medical datasets.**
- **Pre-trained weights on ImageNet accelerate convergence and improve feature extraction.**

Experimental Approaches

- Attempt with Autoencoders:

Purpose: Used autoencoders for feature extraction and dimensionality reduction to simplify the classification task.

Results:

1. Achieved 28% accuracy, indicating suboptimal performance.
2. Highlights the limitations of unsupervised pre-training for this complex classification problem.

- Insights from Autoencoder Experiment:

Challenges Identified:

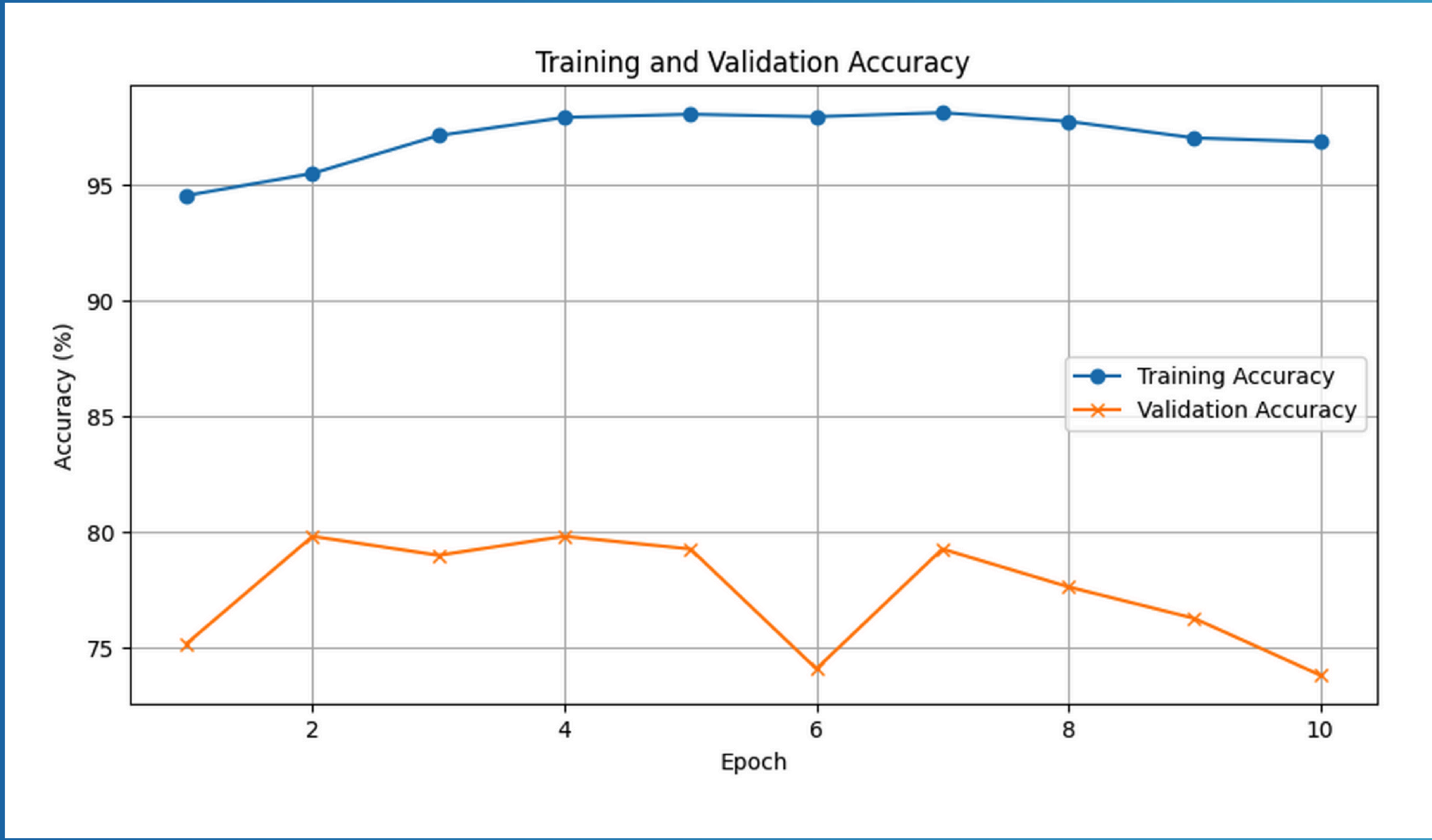
1. High variability and noise in retinal images.
2. Autoencoders struggled to capture meaningful features distinguishing severity levels.

Conclusion: A supervised learning approach with pre-trained models like ResNet proved more effective.

Prediction, Inference and Other goals (1)

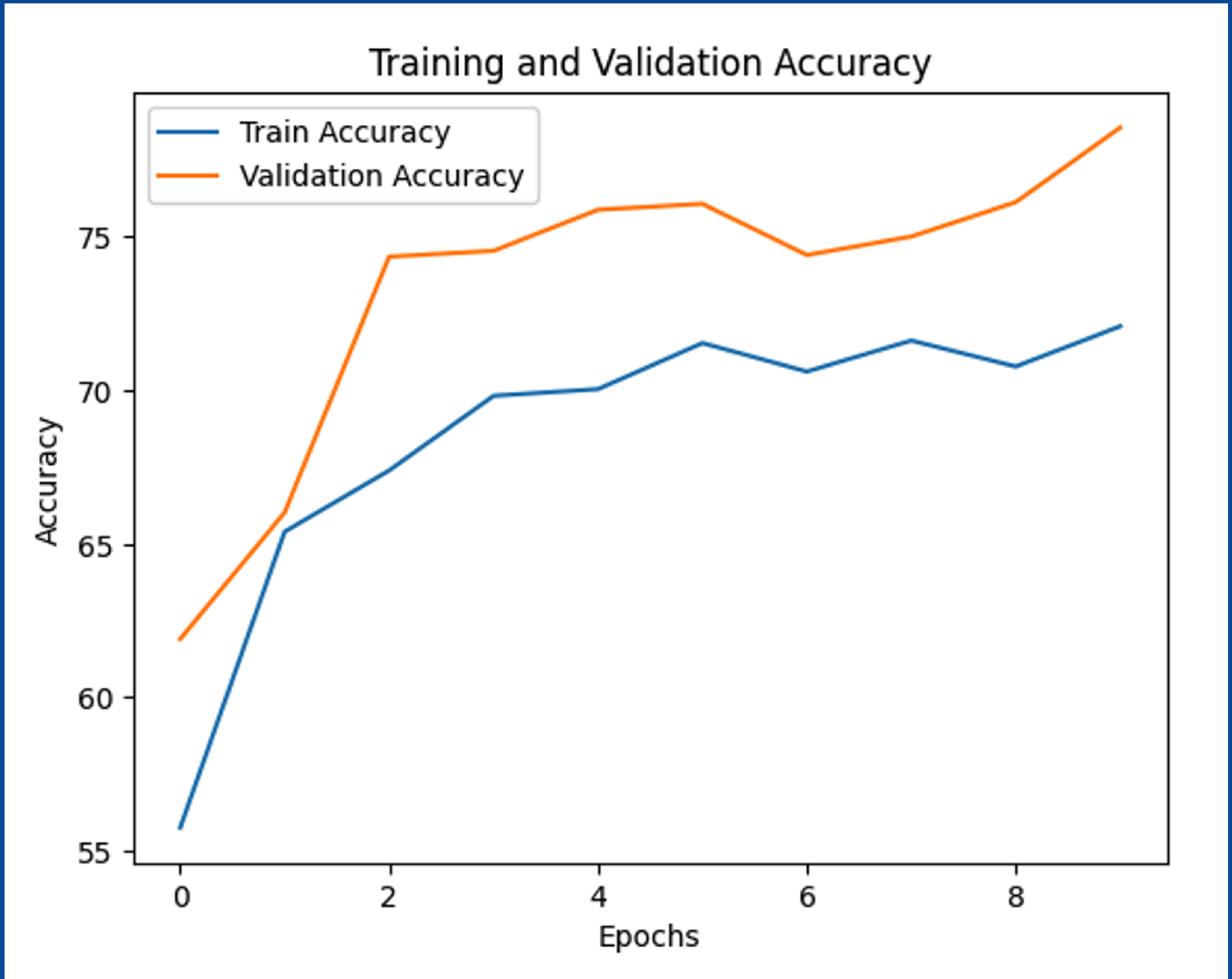
The CNN model aims to classify diabetic retinopathy DR into 5 severity levels

Method	Validation Accuracy
Resizing	78.14%
Early stopping	79.51%
Resized, Flipped, Color Jitter	78.56%
Auto-encoder	28%



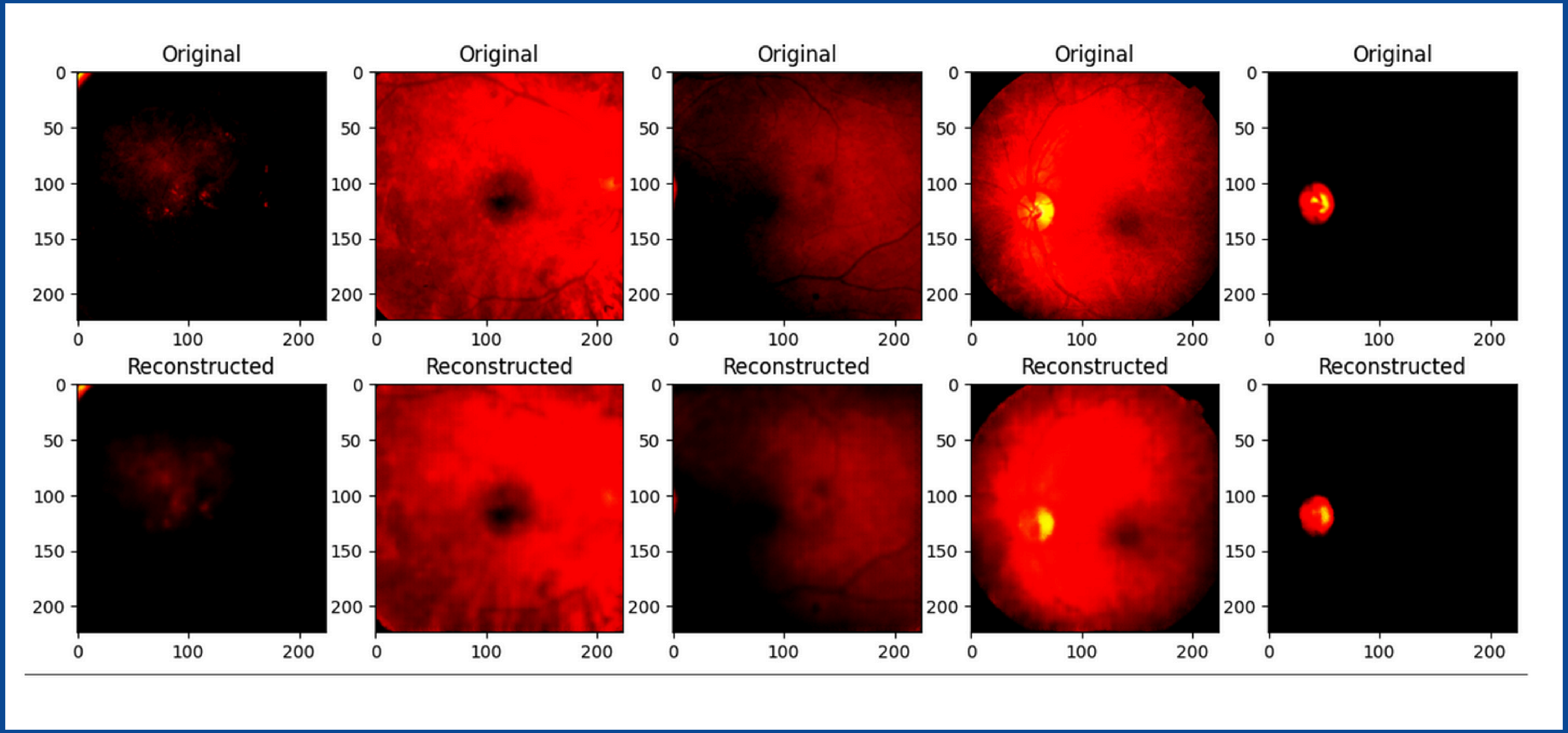
Prediction, Inference and Other goals (2)

- Used early stopping to improve the validation accuracy to 79.1% from 78.14%
- Further augmentation by resizing and changing the degrees of rotation with early stopping resulted in a validation accuracy of 78.56%. The plot ⇒



Problems Encountered

- The data was imbalanced for DR(Diabetic Retinopathy) and NDR (No Diabetic Retinopathy)
- We tried using autoencoders for resizing the images but that greatly reduced the accuracy values.’
- Noticeable noise was observed in retinal scans.



Key Understanding

Model Selection:

- ResNet18 with pre-trained weights on ImageNet achieved the best performance with **79.23% validation accuracy** and **81.47% test accuracy**.
- Pre-trained architectures effectively addressed the challenges of limited training data and complex feature extraction.

Data Challenges:

- Imbalanced dataset impacted classification accuracy, especially for higher severity levels (3 and 4).
- Noise in retinal images and variability in resolution posed significant preprocessing challenges.

Techniques Tried:

- Early stopping improved validation accuracy from **78.14% to 79.51%**.
- Augmentations (resizing, flipping, color jitter) showed mixed results, with validation accuracy stabilizing around **78.56%**.
- Autoencoders were less effective, achieving only **28% accuracy**, underscoring the importance of supervised learning for this task.

Future Directions:

1. **Data Enhancement:**
   - Augment the dataset to address class imbalance, particularly for severity levels 3 and 4.
   - Incorporate more diverse retinal images for better generalization.
2. **Model Optimization:**
   - Experiment with deeper ResNet variants (e.g., ResNet50) or ensemble learning approaches.
   - Fine-tune hyperparameters such as learning rate, dropout, and optimizer.