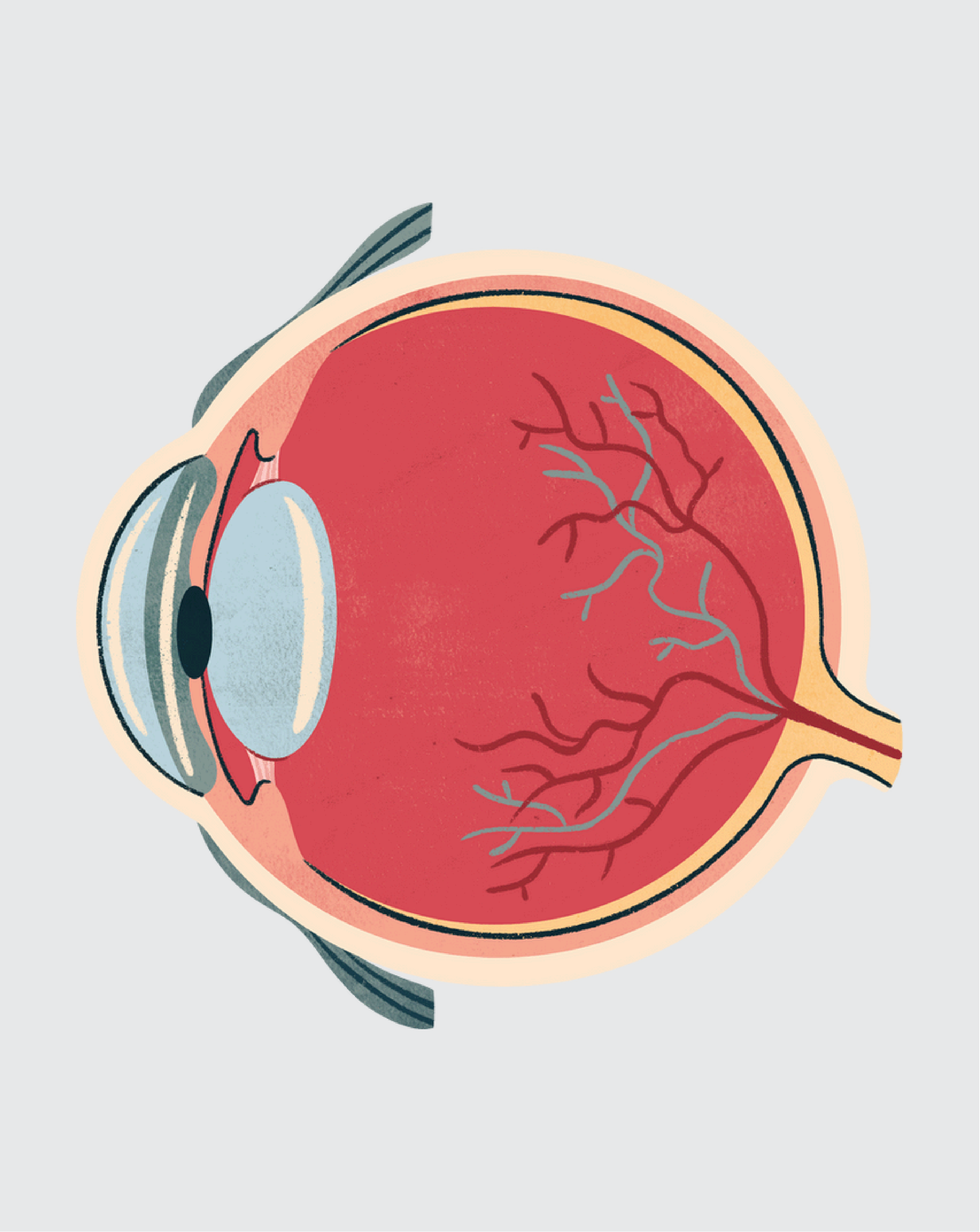
CONTENTS

INTRODUCTION



In the healthcare domain, early detection and effective management of diseases are pivotal. One such critical area is the detection of Diabetic Retinopathy, a condition that affects the eyes of individuals with diabetes. With the rising prevalence of diabetes globally, the need for efficient, early-stage detection of Diabetic Retinopathy has become increasingly vital.

So with the use of modern technologies, such as Computer Vision & Deep Learning, our project aims to utilize image samples of retinas for early detection of Diabetic Retinopathy. This would help healthcare professionals intervene promptly and potentially stop vision loss in people with diabetes.

PROBLEM STATEMENT

The Center for Disease Control and Prevention (CDC) estimates that 29.1 million people in the India have diabetes and the World Health Organization estimates that 347 million people have the disease worldwide.

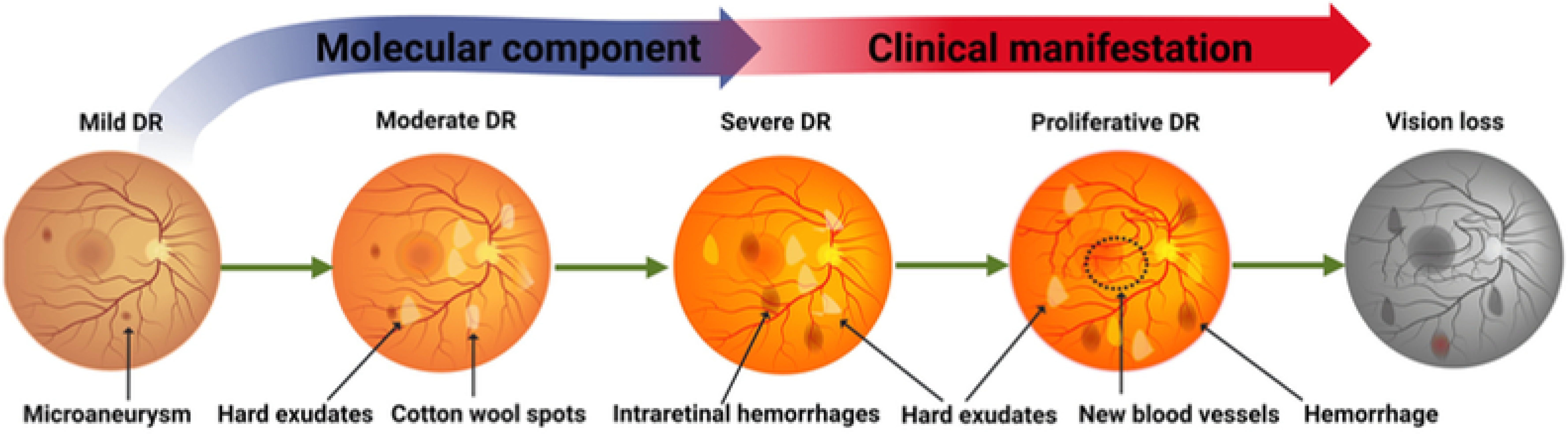
Currently, detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital color fundus photographs of the retina.

WHAT ACTUALLY IS DIABETIC RETINOPATHY ?

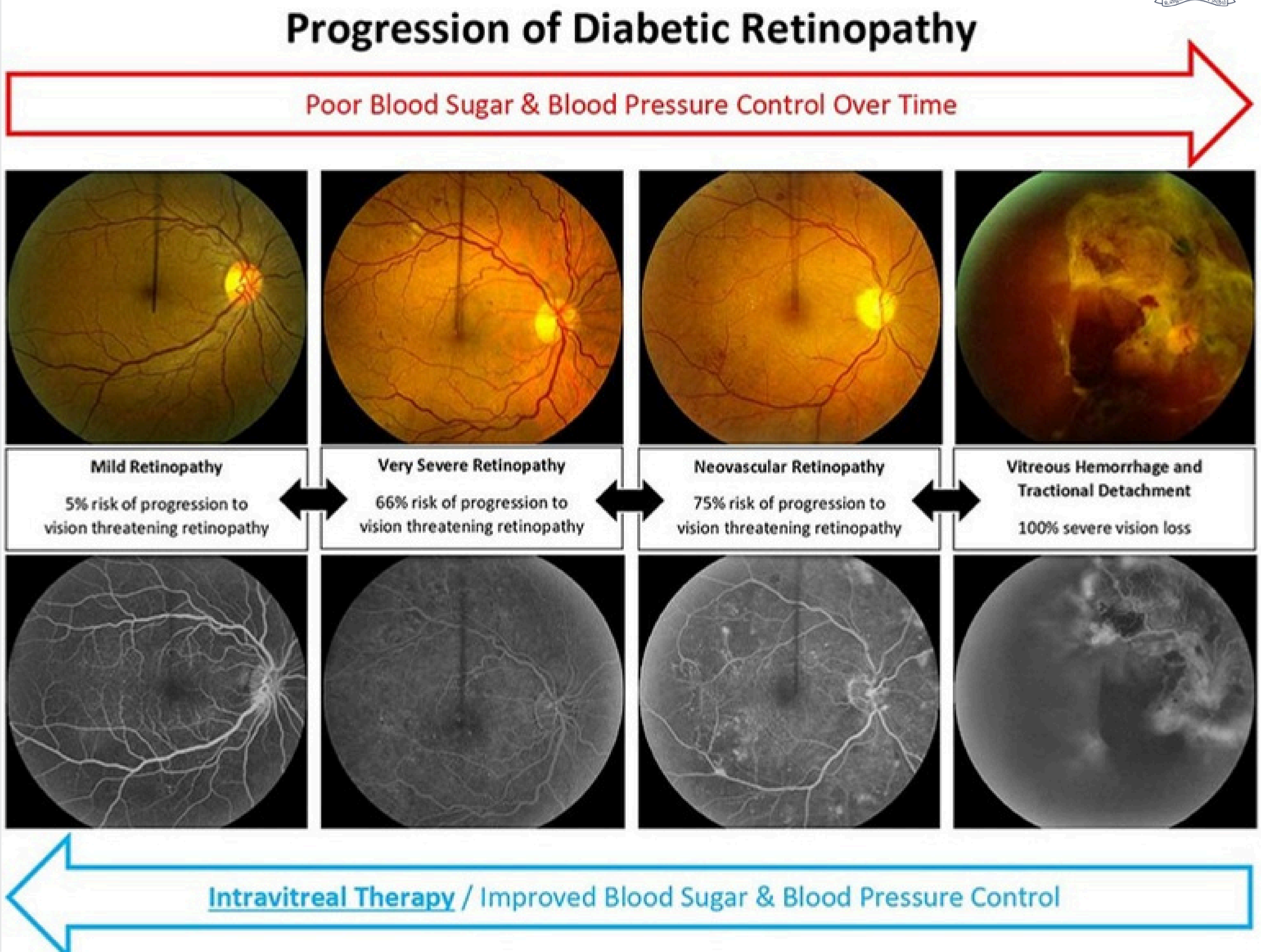
1. Diabetic retinopathy is primarily caused by high levels of glucose (sugar) in the blood over an extended period of time. Prolonged elevated blood sugar levels can damage the small blood vessels in the retina, leading to diabetic retinopathy.

2. There are two main types of diabetic retinopathy:
   - Non-proliferative diabetic retinopathy (NPDR)
   - Proliferative diabetic retinopathy (PDR)

STAGES OF DIABETIC RETINOPATHY



DIABETIC RETINOPATHY IN RETINAL DATASET



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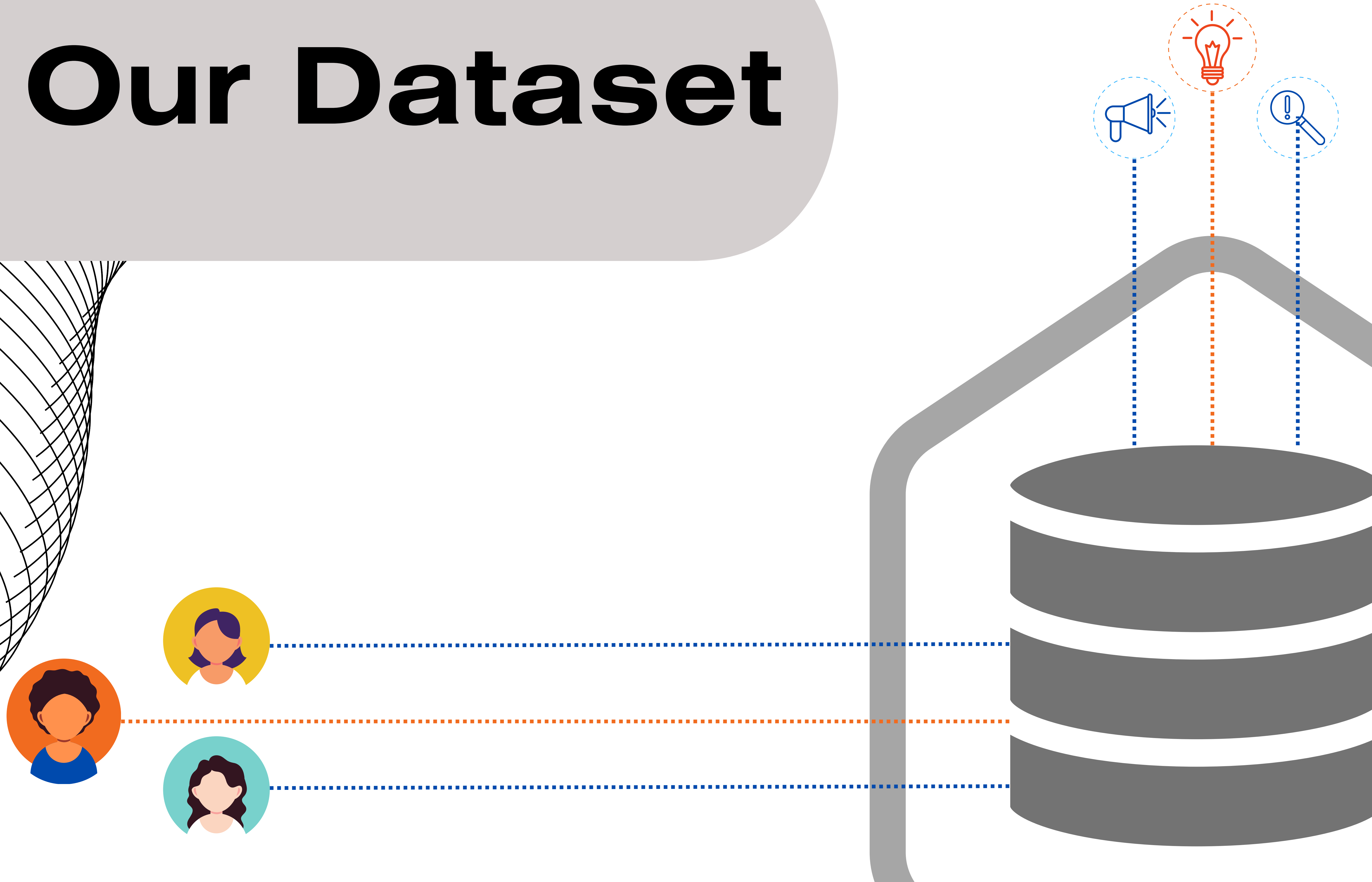
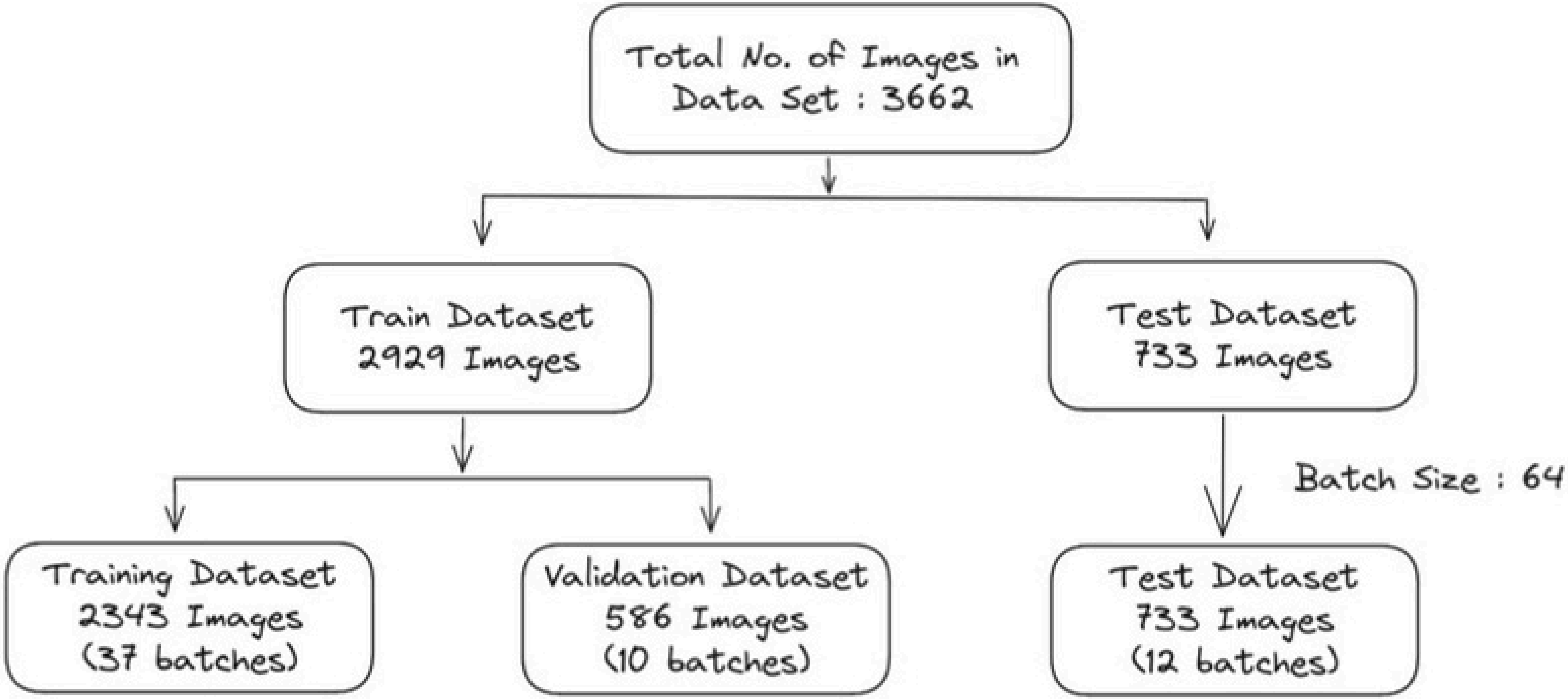
www.vitbhopal.ac.in

About Our Dataset




Total No. of Images in Data Set : 3662
Train Dataset 2929 Images
Test Dataset 733 Images
Batch Size : 64
Training Dataset 2343 Images (37 batches)
Validation Dataset 586 Images (10 batches)
Test Dataset 733 Images (12 batches)

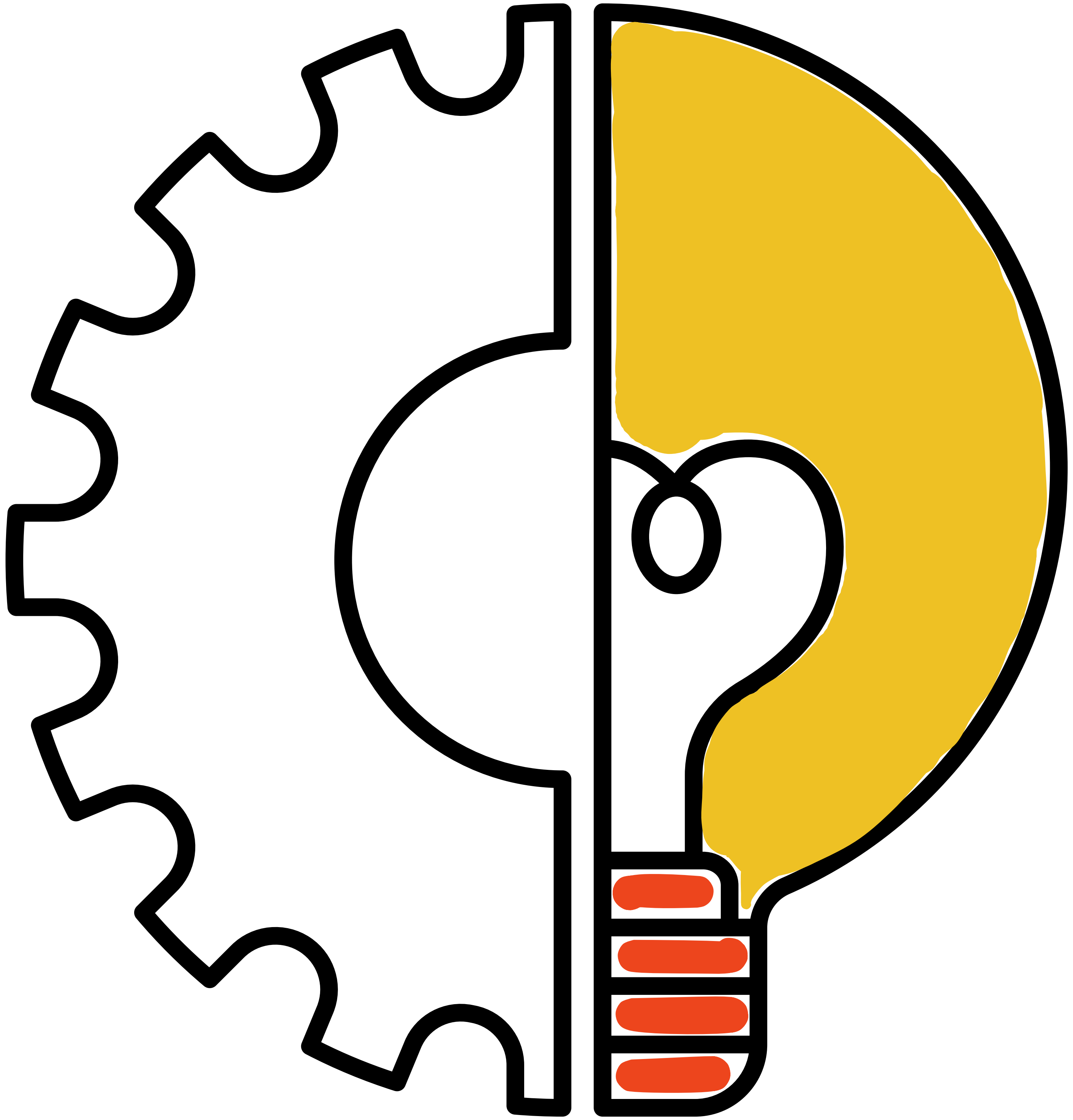
1. **Dataset size**
A large dataset is generally preferred as it provides more diverse samples for the model to learn from, leading to better generalization. However, the dataset should also be manageable in terms of computational resources required for training.

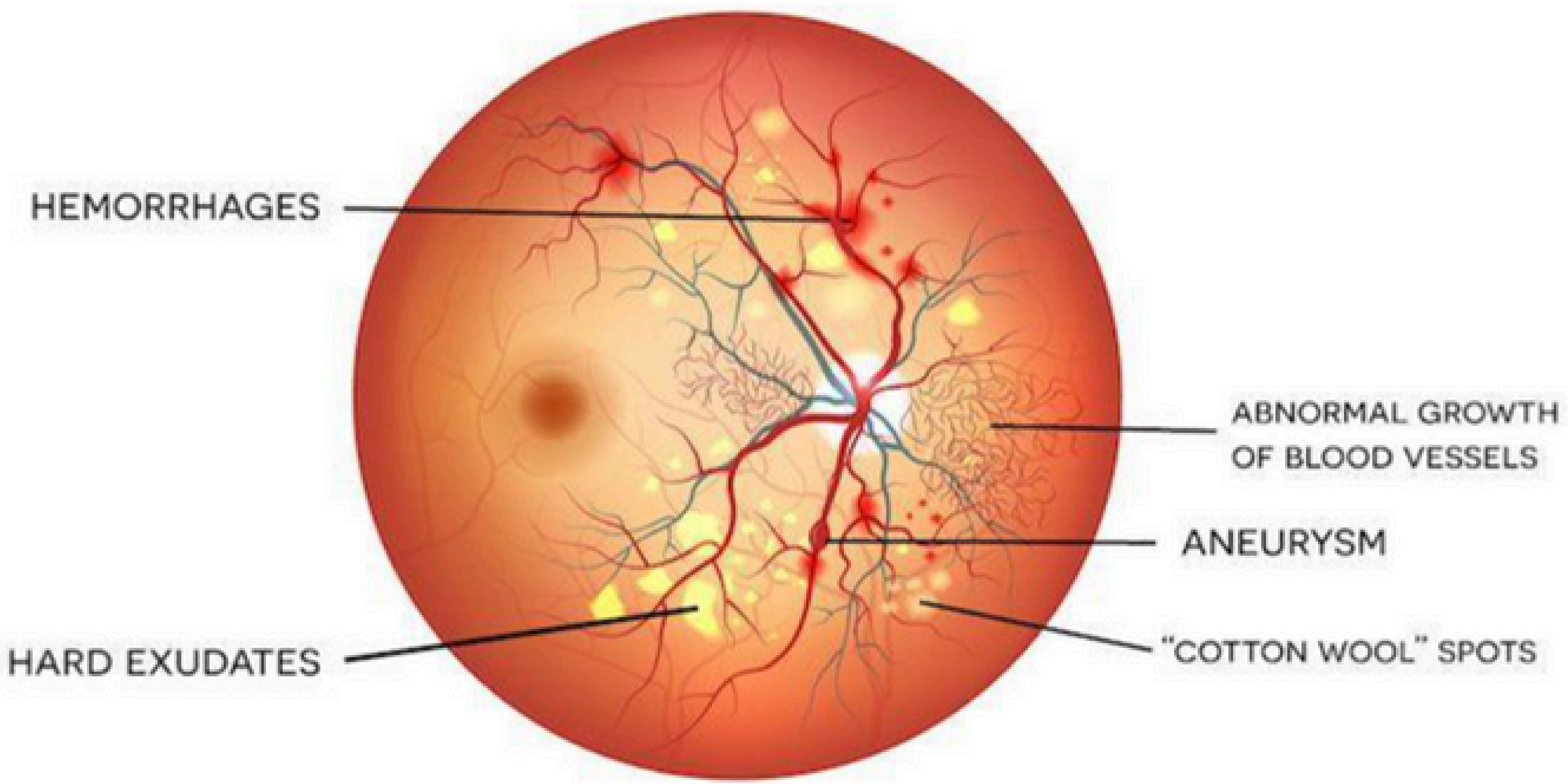
2. **Class balance**
The dataset should have a balanced distribution of samples across different classes or stages of diabetic retinopathy. Imbalanced data can lead to biased model predictions favoring the majority class.

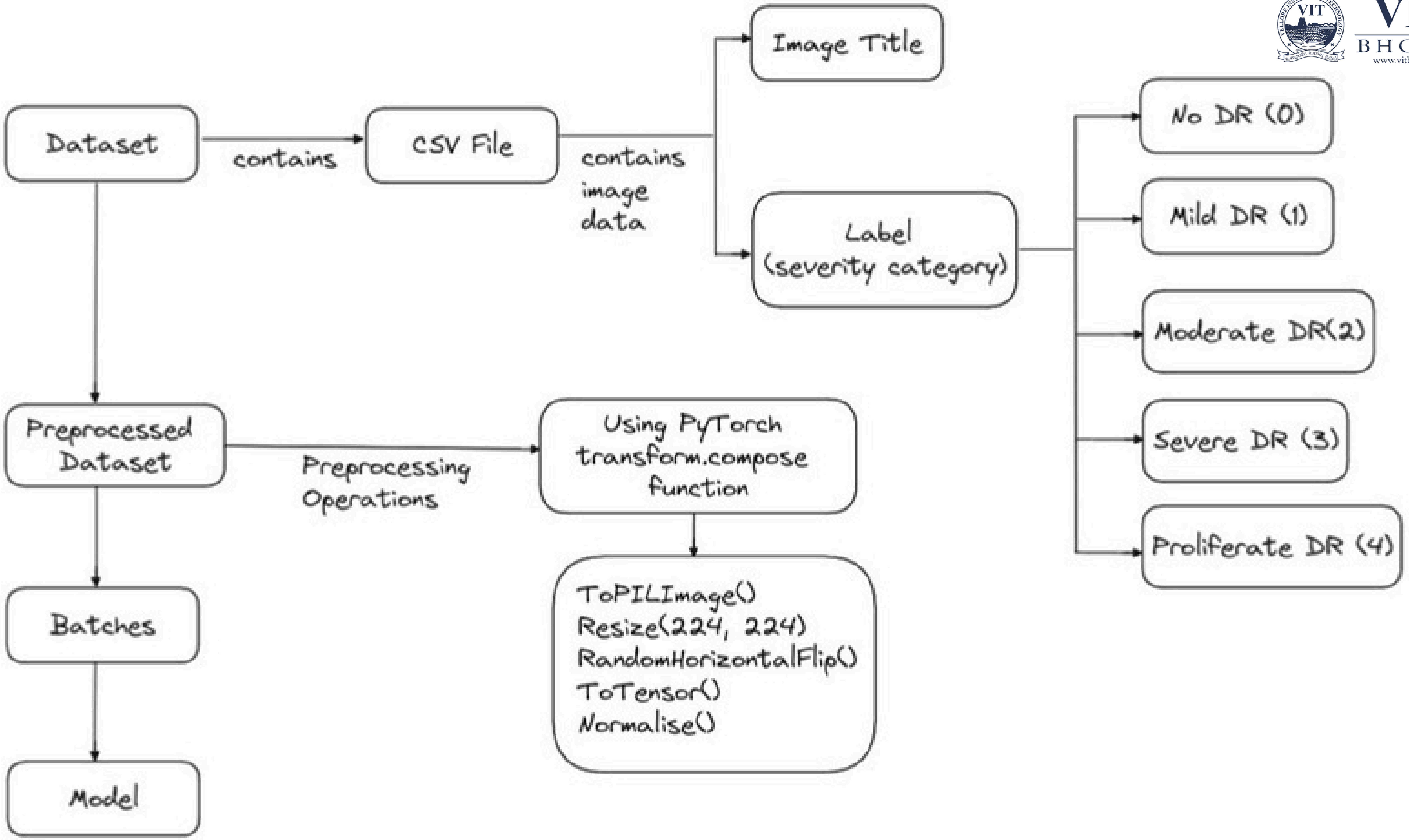
3. **Ethical considerations**
The dataset should be collected and used in an ethical manner, respecting patient privacy and adhering to relevant regulations and guidelines. Proper anonymization and consent procedures should be followed.

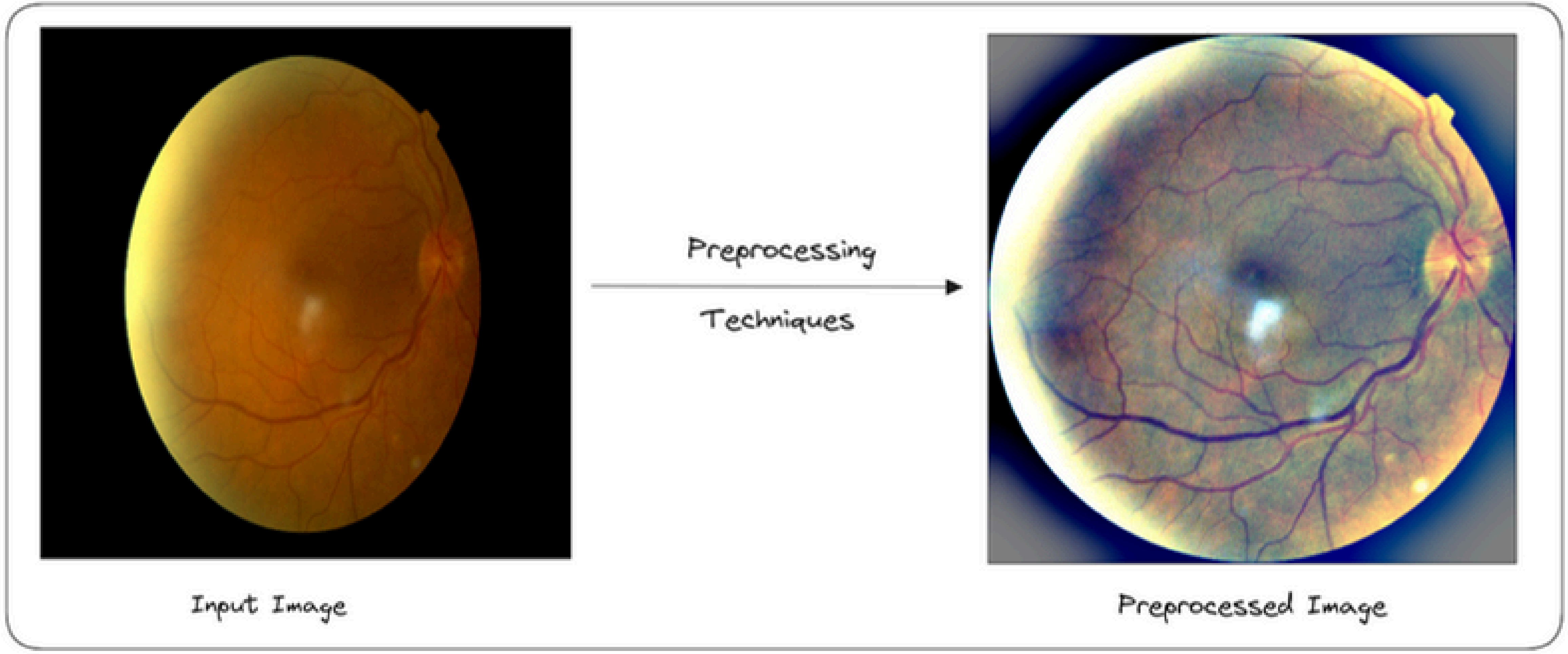
4. **Why we chose this Dataset**
After extensive trials and testing, the chosen dataset was found to have an optimal size, balanced class distribution, and sufficient computational resources were available for model training.

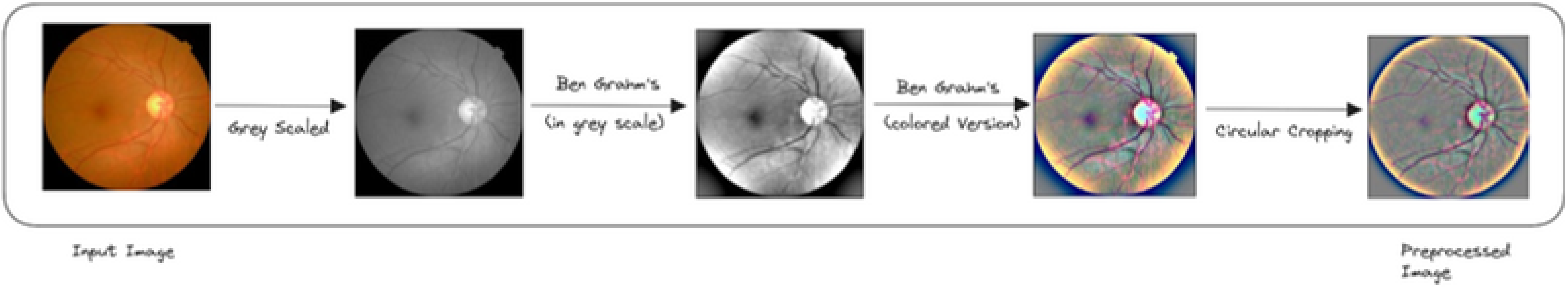
HOW DID WE PRE-PROCESS OUR DATASET ?




HEMORRHAGES
ABNORMAL GROWTH
OF BLOOD VESSELS
ANEURYSM
HARD EXUDATES
"COTTON WOOL" SPOTS


Dataset
contains
CSV File
contains image data
Image Title
Label (severity category)
No DR (0)
Mild DR (1)
Moderate DR(2)
Severe DR (3)
Proliferate DR (4)
Preprocessed Dataset
Preprocessing Operations
Using PyTorch transform.compose function
ToPILImage()
Resize(224, 224)
RandomHorizontalFlip()
ToTensor()
Normalise()
Batches
Model


Preprocessing
Techniques
Input Image
Preprocessed Image


Grey Scaled
Ben Graham's
(in grey scale)
Ben Graham's
(colored Version)
Circular Cropping
Input Image
Preprocessed
Image

EXISTING APPROACHES

S. No.	Paper Title	Methodology	Dataset	Innovation	Unique Idea	Result & Accuracy
1	Using a Deep Learning Algorithm and Integrated Gradients Explanation to Assist Grading for Diabetic Retinopathy	Inception v4 model trained	Dataset of 1,796 retinal fundus images from 1,612 diabetic patients	Integrated Gradients explanation, heatmap assistance	Combination of algorithm predictions with explanatory heatmaps	Overall accuracy: 88.4%
2	Computer-Assisted Diagnosis for Diabetic Retinopathy Based on Fundus Images Using Deep Convolutional Neural Network	DCNNs with fractional max-pooling, SVM classifier	Kaggle DR detection database	Fractional max-pooling layers,	Combination of DCNNs and SVM optimized by TLBO	Accuracy: 86.17%
3	Automated Diabetic Retinopathy Detection Based on Binocular Siamese-like Convolutional Neural Network	Siamese-like CNN architecture	Kaggle Diabetic Retinopathy Detection competition dataset	Binocular fundus image input, Siamese-like architecture	Binocular model inspired by human diagnostic process	AUC: 0.951, Sensitivity: 82.2%, Specificity: 70.7%

EXISTING APPROACHES

S. No.	Paper Title	Methodology	Dataset	Innovation	Unique Idea	Result & Accuracy
4	Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning models	Synergic Deep Learning (SDL) model	MESSIDOR dataset with around 1200 color fundus images	Synergic Deep Learning model, SDL architecture	Synergic Deep Learning (SDL) model	Accuracy: 99.28%, Sensitivity: 98.54%, Specificity: 99.38%
5	Detection of Diabetic Retinopathy Using Bichannel Convolutional Neural Network	Bichannel CNN model	Kaggle Diabetic Retinopathy dataset	Bichannel CNN architecture, entropy images	Utilizing entropy images of gray level and green component	Accuracy: 87.83%, Sensitivity: 77.81%, Specificity: 93.88%
6	Computer-aided diagnosis of retinal diseases using multidomain feature fusion	SVM-based learning algorithm	Dataset from PSG Institute of Medical Science and Research	Feature fusion, SVM classifier	Combined transform and spatial domain features	Accuracy: 96.3%, Sensitivity: 95.8%, Specificity: 97.8%

SHORT COMINGS OF EXISTING APPROACHES

SHALLOW NETWORKS

LIMITED FEATURE ENGINEERING

DIFFICULTY IN LEARNING HIERARCHIAL REPRESENTATIONS

LIMITED SCALABILITY

1. **Shallow Networks**

Traditional machine learning approaches or shallow neural networks may struggle to capture the intricate and nuanced patterns present in retinal fundus images. They may lack the capacity to learn complex features hierarchically, leading to suboptimal performance.

2. **Limited Feature Extraction**

Shallower networks may have limited ability to extract high-level features relevant to diabetic retinopathy detection. This could result in less discriminative feature representations, leading to decreased classification accuracy.

3. **Manual Feature Engineering**

Many traditional methods rely on manual feature engineering, where domain experts manually design features based on their understanding of the problem. This approach can be time-consuming, labor-intensive, and may not capture all relevant features effectively.

4 Difficulty in Learning Hierarchical Representations

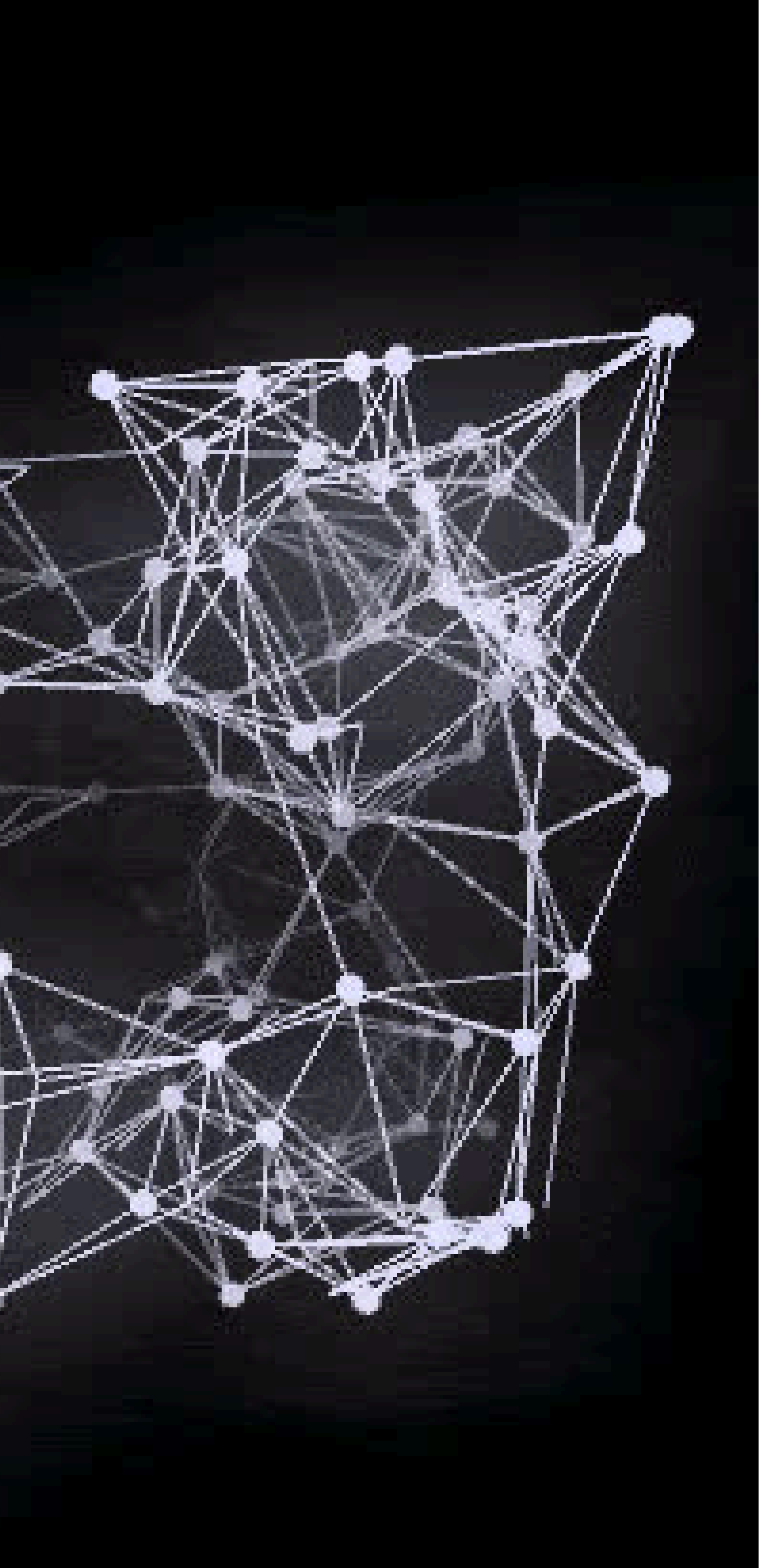
Shallow networks struggle to learn hierarchical representations of features, which are crucial for understanding complex patterns present in retinal images. As a result, they may not achieve the same level of performance as deep learning models like ResNet.

5 Susceptibility to Overfitting

Traditional machine learning approaches may be more susceptible to overfitting, especially when dealing with high-dimensional data like retinal images. This can lead to poor generalization performance on unseen data.

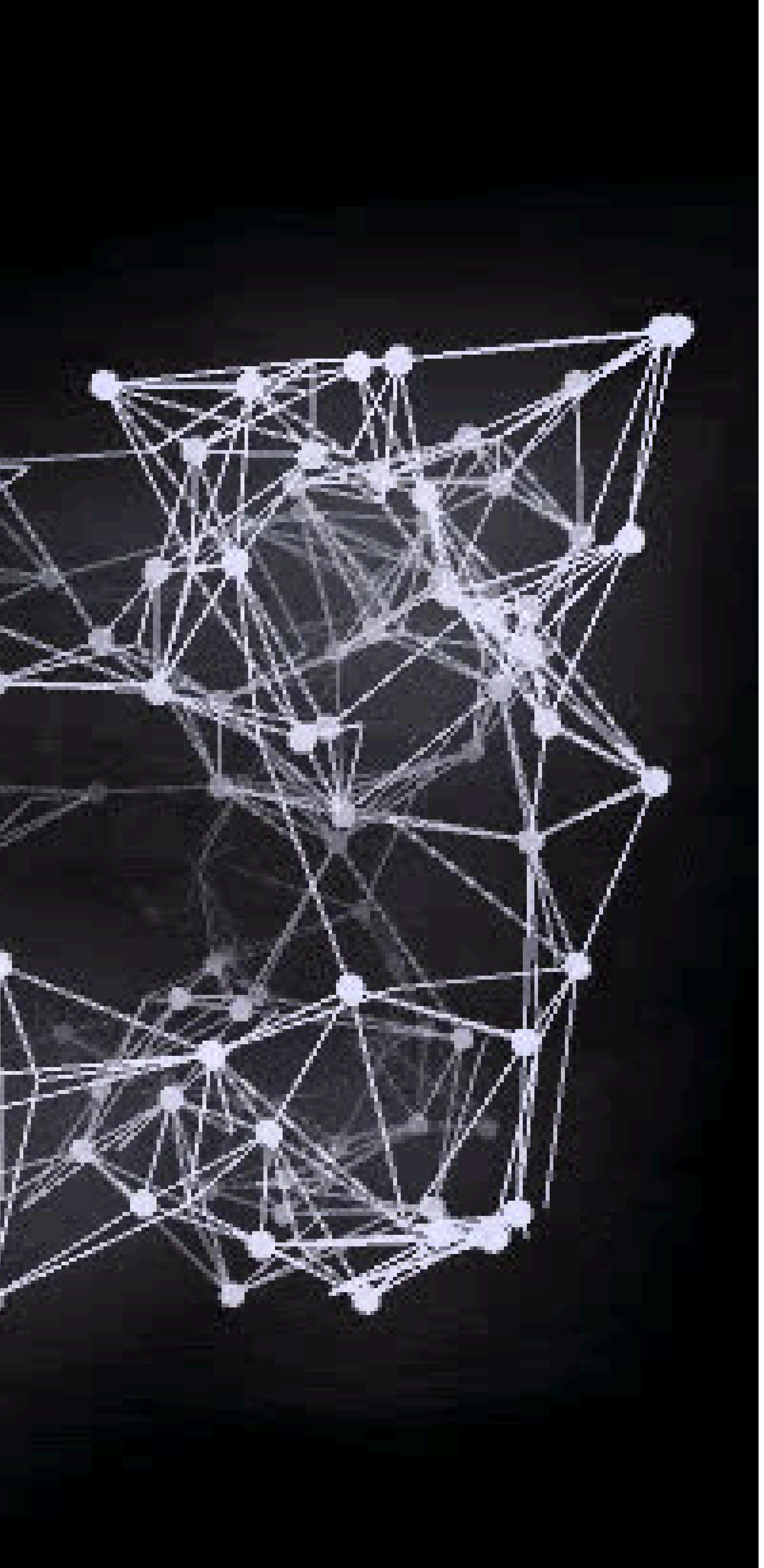
6 Limited Scalability

Shallow networks or traditional methods may have limited scalability when dealing with large datasets or complex tasks. They may not be able to leverage the computational power of modern hardware efficiently, leading to longer training times or decreased performance.



METHODOLOGY

- We have employed the ResNet-152 architecture for the detection and classification of diabetic retinopathy severity levels from retinal fundus images in the APTOS dataset.
- The methodology begins with preprocessing the retinal images through resizing and normalization to ensure uniformity in input dimensions.
- Subsequently, the model architecture, consisting of residual blocks with batch normalization and ReLU activations, is used.
- Batch normalization stabilizes the training process by reducing internal covariate shift, while ReLU activations introduce non-linearity, enabling the model to learn complex patterns.



METHODOLOGY

- Residual connections within the architecture allow gradients to bypass certain layers during backpropagation, addressing the vanishing gradient problem and facilitating the training of the 152-layer deep network.
- Following feature extraction, a global average pooling layer aggregates salient features into a compact vector representation, which is then processed by fully connected layers for classification into five severity classes.
- During training on the labeled APTOS dataset, the model's parameters are optimized using backpropagation and categorical cross-entropy loss function

PROPOSED SOLUTION

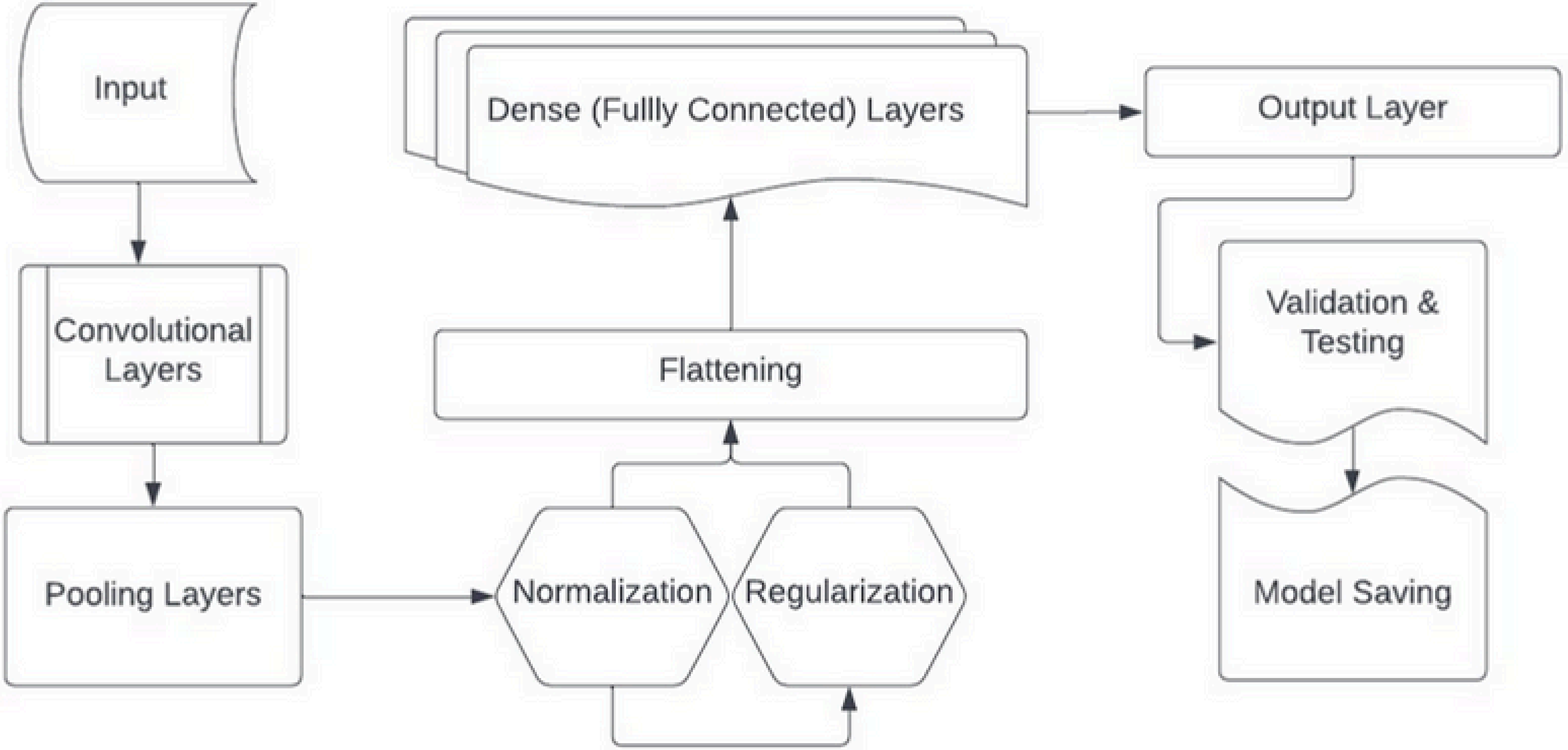
- We realized the need and tried to address the globally acknowledged necessity for a thorough and automated approach to Diabetic Retinopathy (DR) Screening.

- Hence we had started to Research and Develop a Deep Learning based ResNet Model according to comprehension that can effectively identify DR by analyzing the presence of lesions associated with vascular abnormalities caused by the disease.

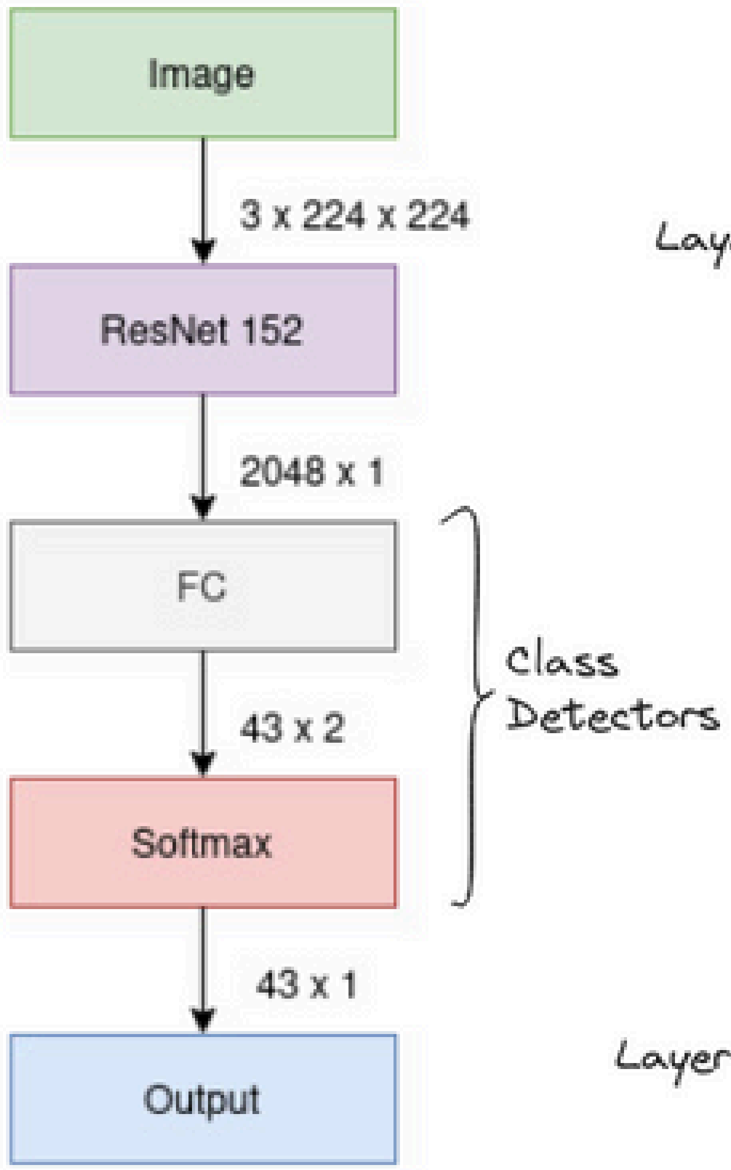
- This model is capable of classifying images into multiple classes of ['No DR', 'Mild', 'Moderate', 'Severe', 'Proliferative DR'] based on different severity level of the Disease

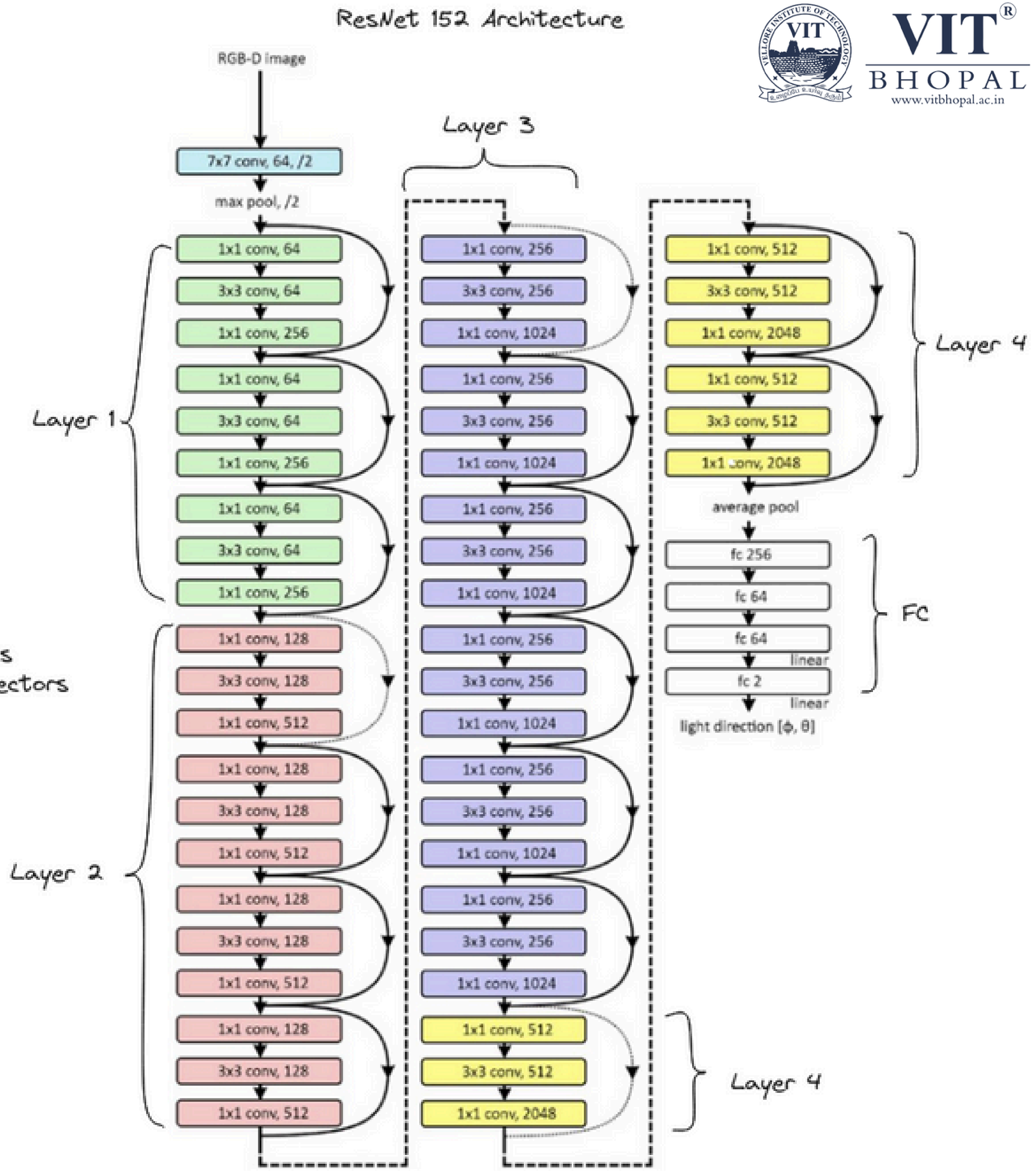
- The automated DR detection model is made in accordance to benefit individuals with diabetes by providing early and accurate screening for potential vision-threatening complications.

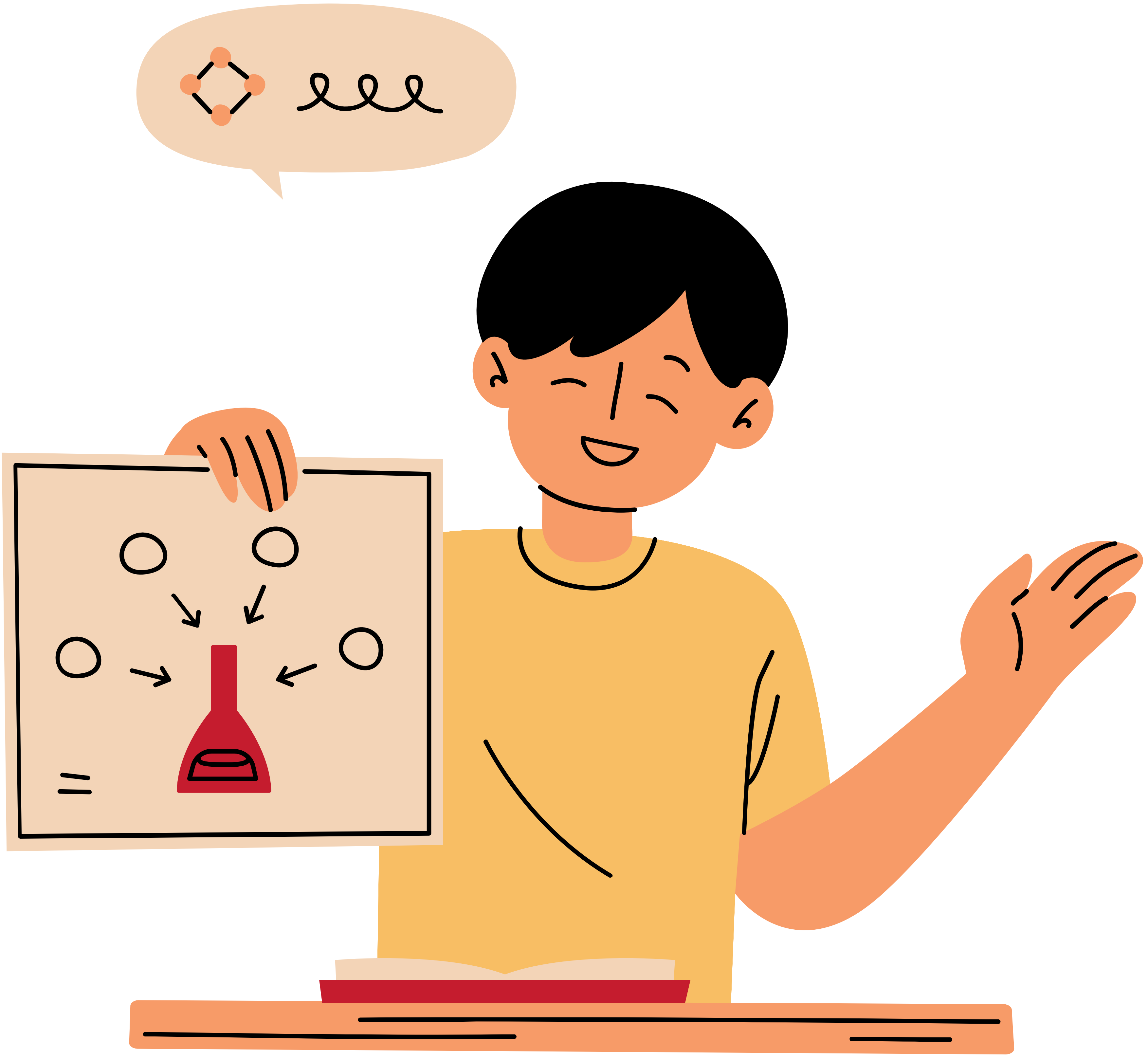
MODEL ARCHITECTURE



ResNet-152 Architecture



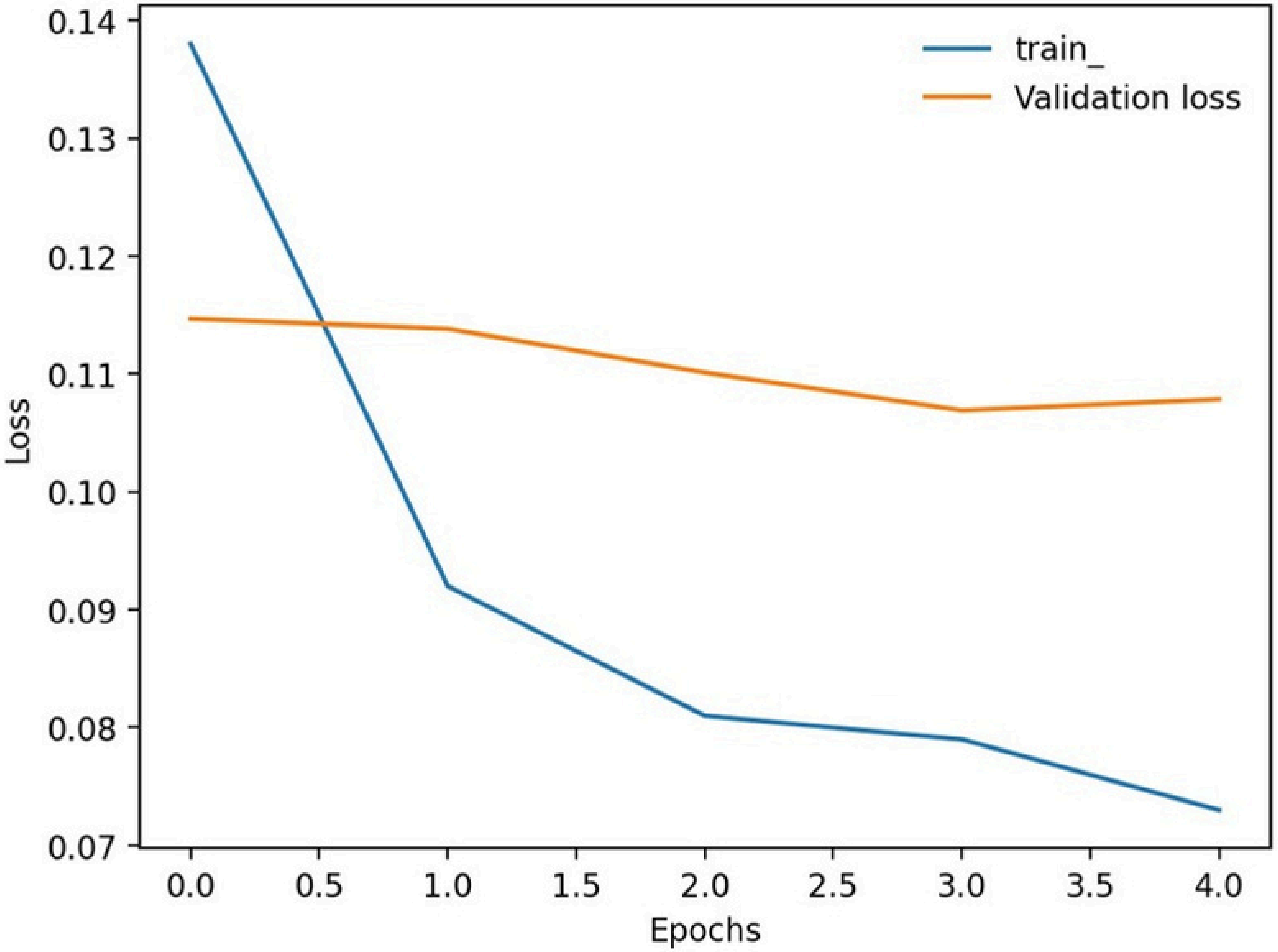




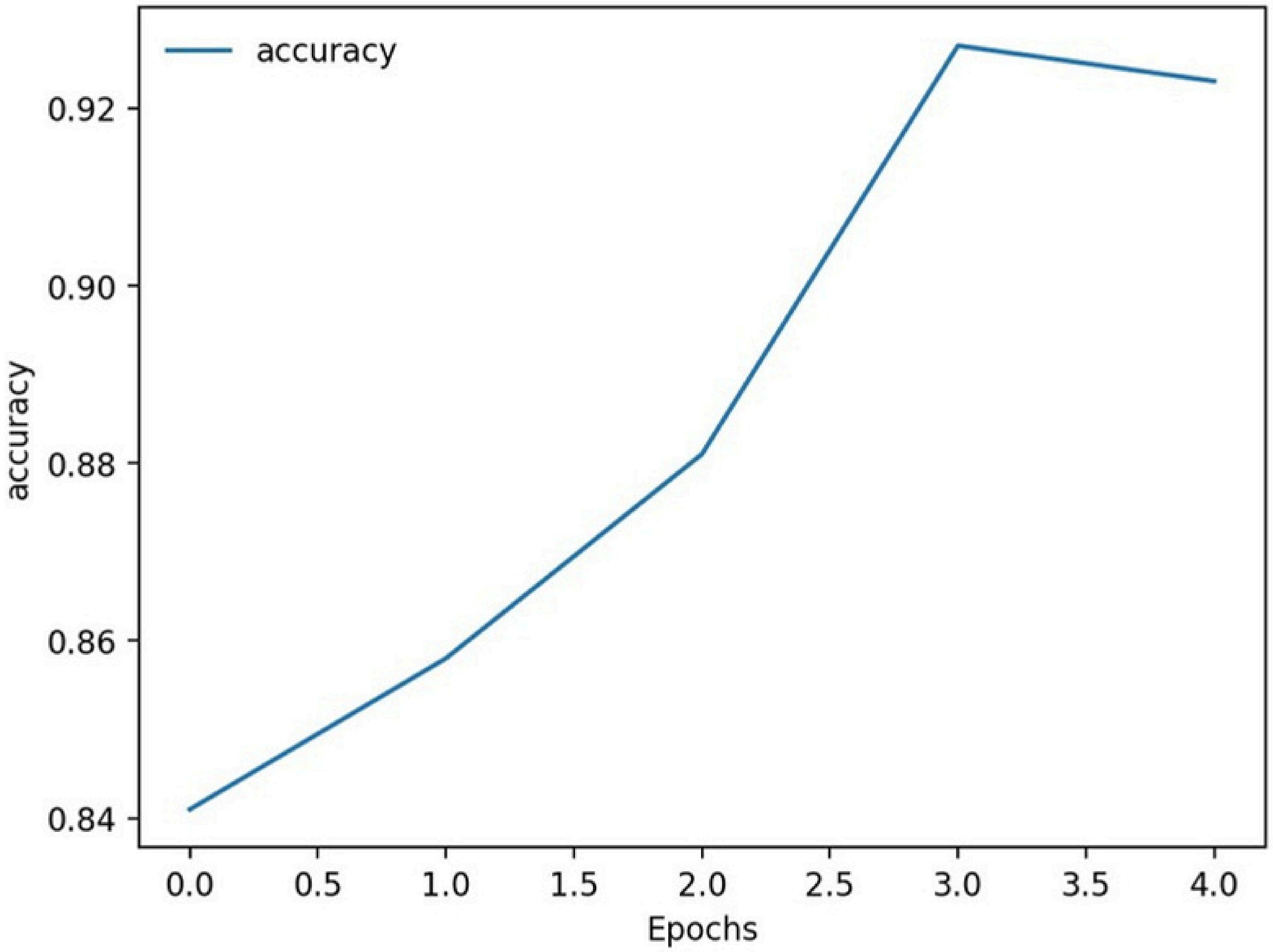
EVIDENTIAL GRAPHS AND PLOTS

Dataset Categorical Distribution

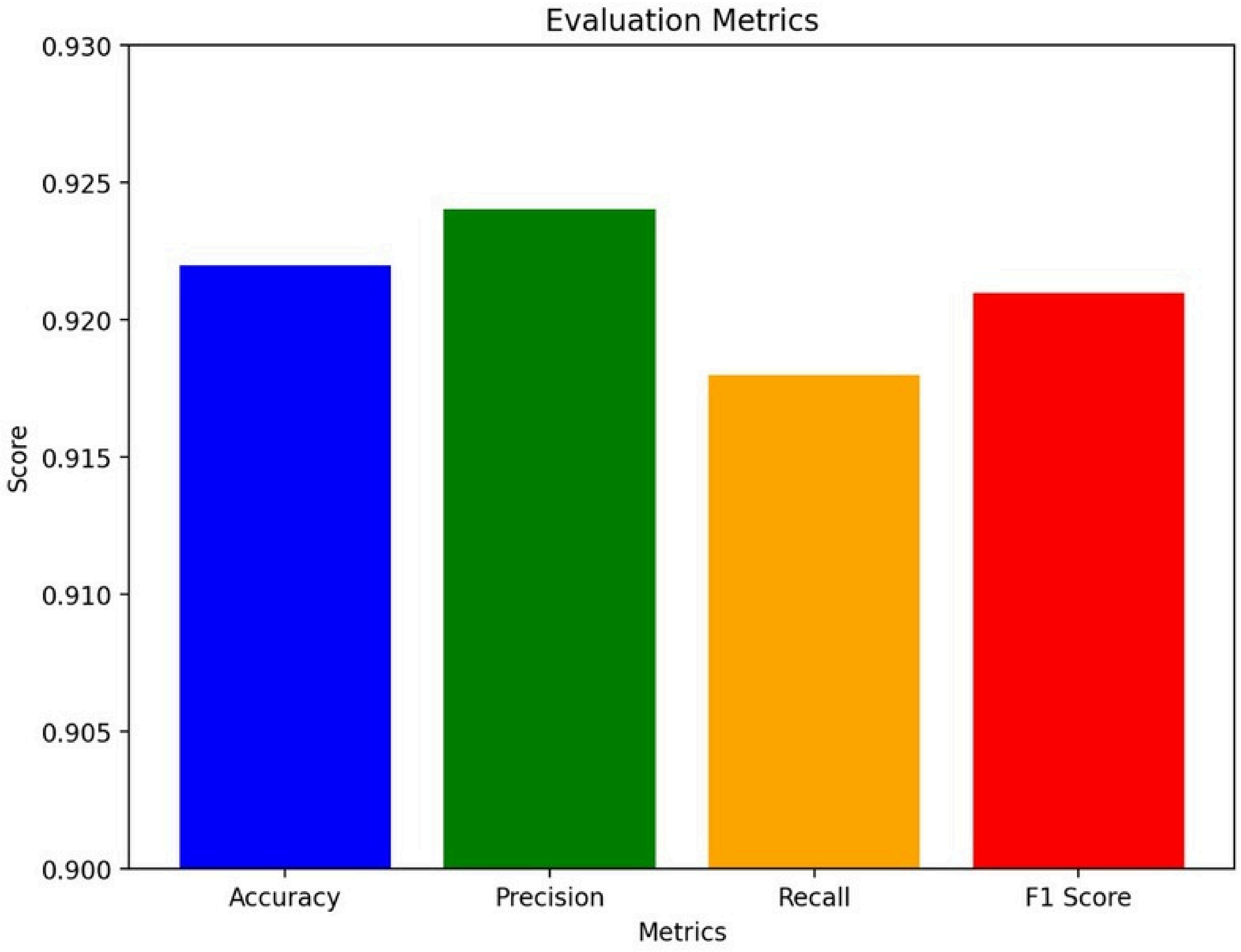
Training & Validation Loss



Training Accuracy



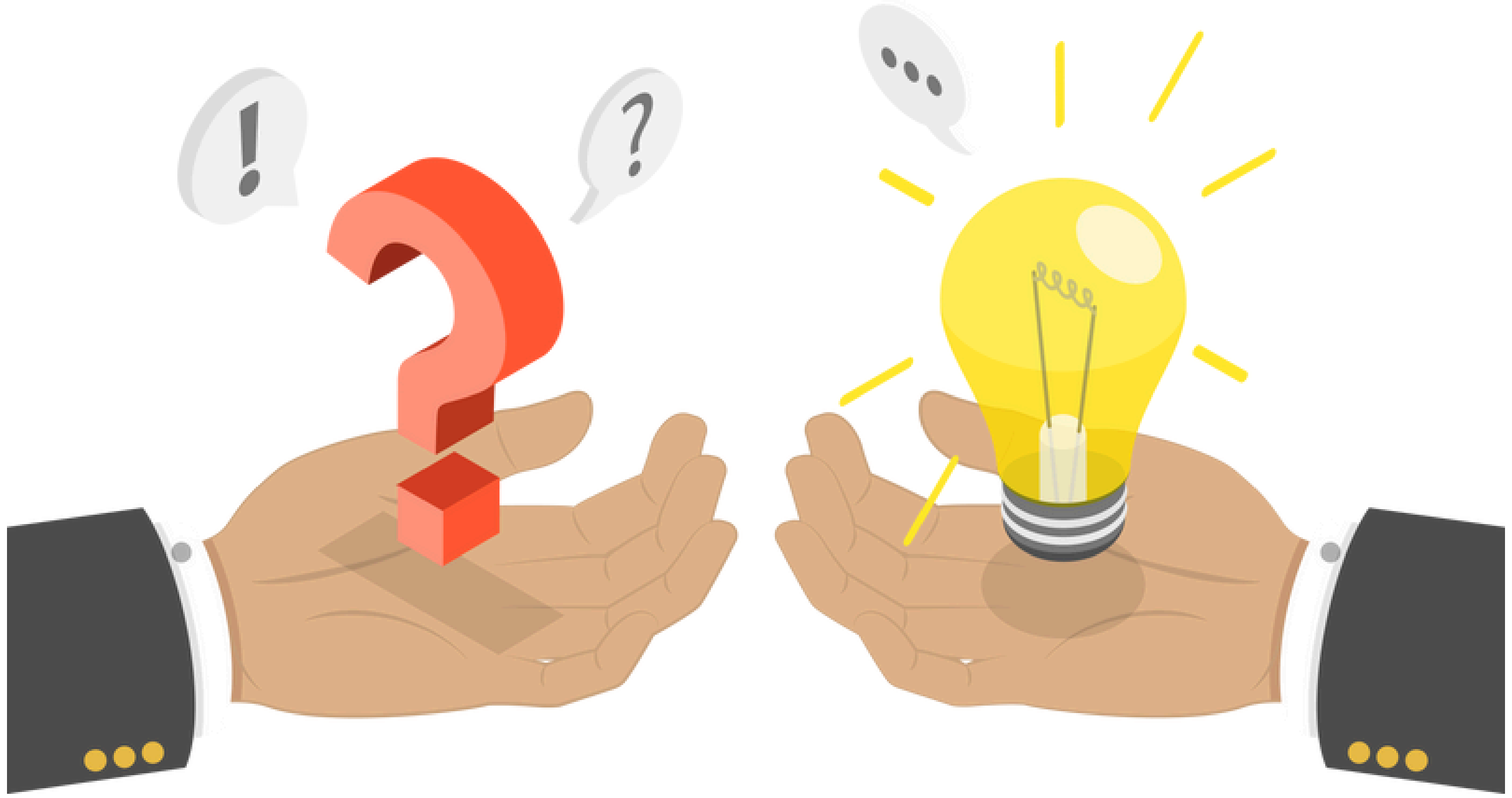
Evaluation Metrices




```python
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

```
Accuracy: 0.921993178717599
Precision: 0.9240332034223382
Recall: 0.917993178717599
F1 Score: 0.9210008789408223
```

“HOW OUR PROPOSED METHODOLOGY ADDRESSES THE SHORTCOMINGS OF EXISTING APPROACHES”



1 Deep Architecture

ResNet-152 has a much deeper architecture compared to traditional methods, allowing it to learn more complex and hierarchical representations of features from retinal fundus images.

2 Automatic Feature Extraction

ResNet-152 can automatically learn discriminative features directly from the data, eliminating the need for manual feature engineering, which is required in traditional methods.

3 Residual Connections

The inclusion of residual connections in ResNet-152 addresses the vanishing gradient problem, enabling effective training of very deep networks. This allows ResNet-152 to capture intricate details and patterns present in retinal images more effectively.

4 Hierarchical Feature Learning

ResNet-152 learns hierarchical representations of features through its deep architecture, enabling it to capture both low-level details (such as edges and textures) and high-level semantic information (such as lesions and abnormalities) simultaneously.

5 Generalization Performance

ResNet-152's ability to learn complex features and hierarchical representations results in superior generalization performance compared to traditional methods. It can adapt well to variations in image quality, illumination, and other factors present in real-world data.

6 Scalability and Efficiency

Despite its depth, ResNet-152 is highly scalable and efficient, leveraging parallel processing capabilities of modern hardware effectively. This allows for faster training times and efficient inference, making it suitable for large-scale applications.

7 Fine-grained Severity Classification

ResNet-152 enables fine-grained classification of diabetic retinopathy severity into five distinct stages: No DR, Mild, Moderate, Severe, and Proliferative. This granularity provides clinicians with more detailed information about the progression of the disease, facilitating better patient management and treatment planning at various stages of diabetic retinopathy.

8 Effective Data Preprocessing

ResNet-152 incorporates robust data preprocessing techniques, such as resizing and normalization of retinal fundus images. These preprocessing operations ensure uniformity in input dimensions and enhance the quality of input data, resulting in improved model performance and generalization to unseen data. Additionally, preprocessing steps like noise reduction and contrast enhancement have been employed, further improving the model's ability to extract meaningful features from retinal images.

PROGRESS ON PROPOSED SOLUTION

- Transitioned to the versatile ResNet 152 architecture, leveraging its vast capacity of 58,970,117 parameters.
- Significantly increased the dataset size from 1GB to 8GB, incorporating a comprehensive collection of over 3,000 retinal images.
- Implemented better data preprocessing techniques, like auto cropping, circle cropping, Normalization which improves previous method for achieving higher data quality and model performance.
- Upgraded the model from binary classification to multi-class classification.
- Leveraged the Hugging Face platform to deploy the model and create an easily integrable API, enabling seamless integration with web and mobile applications.

PROJECT DEPLOYMENT

Why Hugging Face ?

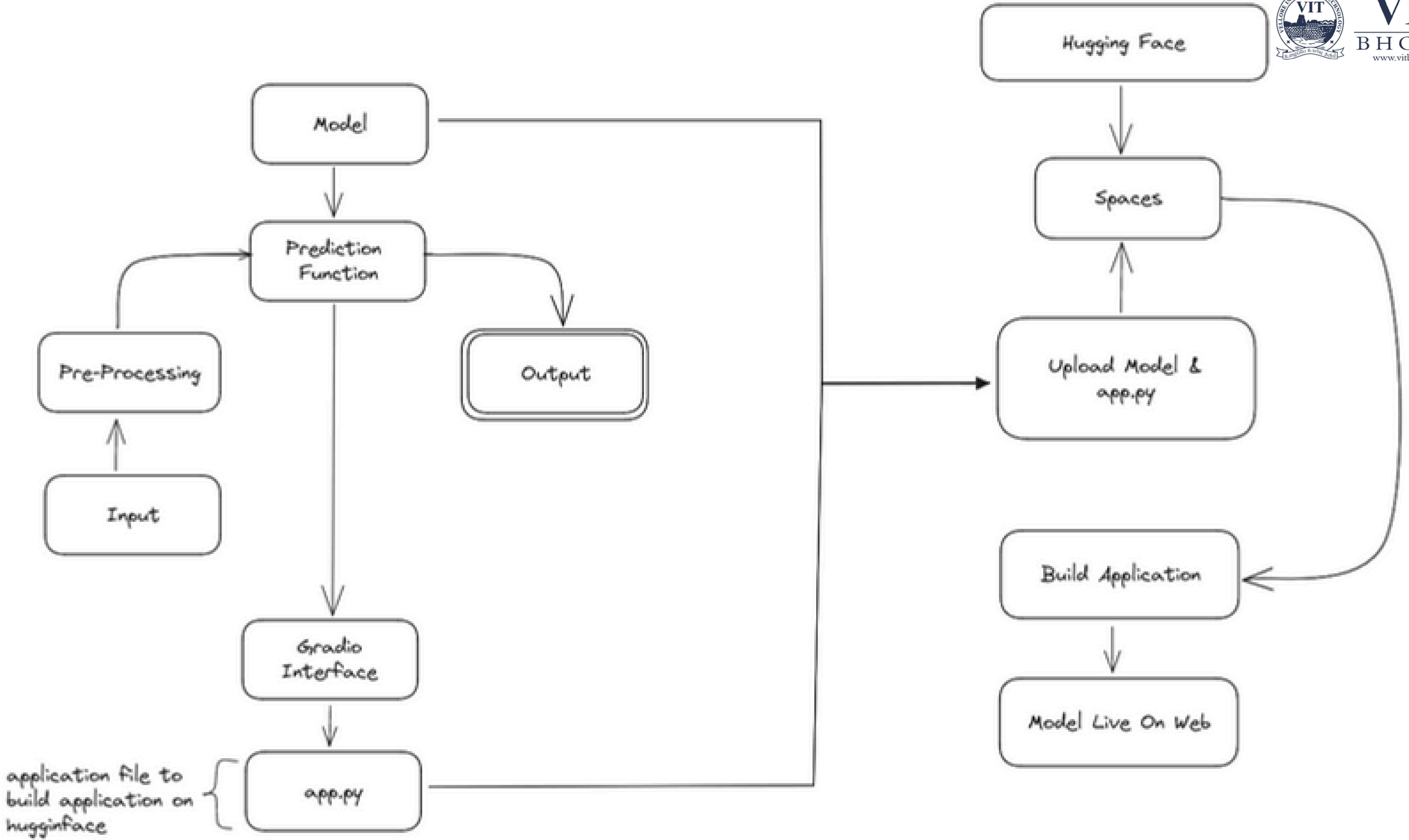
1. Hugging Face provides a user-friendly platform for deploying machine learning models. It allows developers, researchers, and businesses to easily access and interact with models through APIs.

2. Hugging Face's infrastructure is designed to handle large-scale deployments and high-volume API requests. Automatic scaling of resources ensures optimal performance and cost-efficiency.

3. Allows seamless integration with frameworks like PyTorch and TensorFlow. Furthermore it is easier deployment of models trained using these frameworks.

4. Hugging Face promotes collaboration and sharing within the machine learning community. Deployed models can be shared, allowing for feedback and potential collaboration.

5. Option to monetize deployed models by allowing users to purchase access to the API. Potential revenue stream for researchers, developers, or businesses.


Hugging Face
Model
Spaces
Prediction Function
Pre-Processing
Output
Upload Model & app.py
Input
Build Application
Gradio Interface
Model Live On Web
application file to build application on hugginface
app.py

TIMELINE OF OUR PROJECT

REVIEW-0

- Finalized Project Proposal, Outline and Objectives
- Conducted Literature Review on Relevant Theories and Concepts

REVIEW-1

- Focused on Dataset selection by reviewing relevant Research Papers.
- Explored various Data Preprocessing methods to facilitate better feature extraction.

REVIEW-2

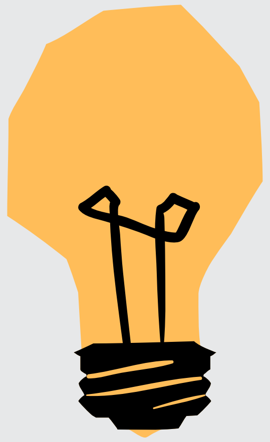
- Explored various popular models with different datasets.
- Decided upon ResNet-152 Architecture for it versatile nature.

FINAL REVIEW

- Decided upon the APTOS Dataset because of its diverse collection of images.
- Deployed the Model on Hugging Face using API.

COMPARISION WITH EXISTING APPROACHES

Author	Year	Target Condition	Training Dataset	Validation Dataset	Method	Accuracy
Pratt et al.	2016	DR: 0-4	Kaggle dataset EyePACS	Kaggle dataset EyePACS	Novel CNN model	75%
Gulshan et al.	2016	rDR, rDME	Kaggle dataset EyePACS and 3 hospitals in India	EyePACS-1 , Messidor-2	CNN: Inception-v3	AUC: 0.974
Abramoff et al.	2016	noDR, rDR, vtDR	Eyecheck project and University of Iowa	Messidor-2	Hybrid model of multiple CNNs (AlexNet, VGGNet) and random forest classifiers	AUC: 0.980 (CI: 0.968-0.992)
Ting et al.	2017	rDR, vtDR, referable glaucoma and referable AMD	SIDRP 2010-13	SIDRP 2014-15 and 10 external multiethnic datasets	CNN: VGGNet	AUC: rDR = 0.879, vtDR = 0.908 (CI: 95%)
Gargeya et al.	2017	rDR	Kaggle dataset EyePACS	Messidor-2, Eoptha	CNN with decision tree classifier	AUC: 0.949
Our Project	2024	DR: 0-4	APTOS-19 Dataset	APTOS-19 Dataset	ResNet-152	92.32%



BENEFITS OF OUR SOLUTION

HIGH ACCURACY

We have achieved an impressive test accuracy of 92% by using ResNet-152 Architecture over fundic diabetic retinopathy dataset.

TRANSFER LEARNING

Our methodology uses ResNet-152 Architecture which leverages pre-trained weights and adapts well to Deep Learning specific tasks.

ROBUST FEATURE EXTRACTION

ResNet-152’s deep architecture allows it to learn intricate features from retinal images, capturing subtle patterns associated with Diabetic Retinopathy.

REDUCED VANISHING GRADIENT

The residual connections in ResNet-152 mitigate the vanishing gradient issue, enabling efficient training even for very deep networks.

SCALABILITY

ResNet-152 can handle large datasets and complex image features, making it suitable for real-world applications.

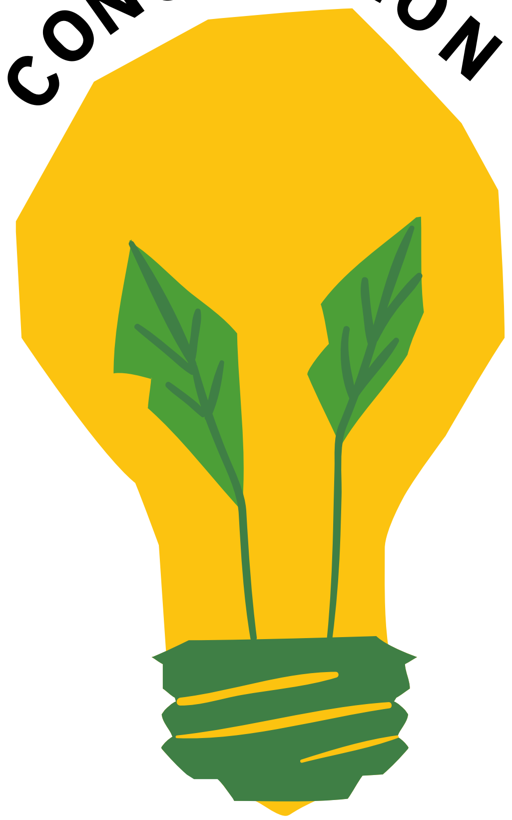
IMAGE AUGMENTATION

Image augmentation enhances ResNet-152's generalization by transforming training images, improving performance on varied retinal image data.

LIGHT WEIGHT

ResNet-152 quantization and compression facilitate resource-limited device deployment, aiding community screening and providing access to large pool of users.

CONCLUSION



In conclusion, our ResNet model demonstrated impressive performance, achieving a training accuracy of 93%, validation accuracy of 93.2%, and minimal loss of 0.136. Although there was a slight decrease in test accuracy (92.19%) and an increase in loss (0.149) on the test set, the model's ability to generalise to unseen data remained commendable, indicating its potential for reliable DR detection in real-world scenarios. Ultimately, the Diabetic Retinopathy Detection Support System Model was successfully deployed on Hugging Face, creating an easily integrable API for automated diagnosis and screening of this prevalent eye condition.

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