#### ****Dataset Collection and Annotation:****

We curated a large and diverse retinal fundus image dataset across eight diagnostic classes: Age-related Macular Degeneration (AMD), Cataract, Diabetic Retinopathy (DR), Glaucoma, Hypertensive Retinopathy, Myopia, Normal, and Other. Each image was manually reviewed and annotated by domain experts to ensure high-quality, consistent labeling. This helped reduce bias and enhanced the model's ability to generalize across varied patient populations.

#### ****Data Preprocessing and Augmentation****

To overcome class imbalance and improve the robustness of the model, a detailed preprocessing and augmentation pipeline was implemented:

* **Data Cleaning:** Removal of duplicates, corrupt, or low-quality images.
* **Data Splitting:** Stratified 80/20 split for training and testing, with 10% of training data used for validation per epoch.
* **Augmentation Techniques:**
  + Geometric: horizontal/vertical flips, 90° and 270° rotations
  + Photometric: CLAHE (Contrast Limited Adaptive Histogram Equalization), contrast and brightness adjustments (±20%)
  + Noise: Gaussian noise injection (σ ≤ 0.05)

These augmentations were essential for improving generalization and reducing overfitting, especially in smaller or underrepresented classes.

#### ****Prescription Analysis Pipeline****

When a patient uploads a fundus image, the system first preprocesses the image and feeds it into the trained hybrid CNN model. If the model predicts a retinal disease class with confidence above a defined threshold, the system automatically queries the Gemini API to fetch detailed information about the detected disease. This includes relevant safety precautions, lifestyle advice, treatment awareness, and follow-up care recommendations. The patient receives a preliminary AI-generated diagnosis enriched with this contextual information.

In contrast, when a doctor uploads an image, the system simply processes the image through the same hybrid model and returns the predicted disease class without additional API-enriched context.

#### ****Hybrid CNN Model Architecture****

Our model consists of a dual-branch hybrid CNN, optimized for multiscale feature extraction:

**InceptionV3 Branch**: Trained from scratch to extract fine-grained details critical for detecting small or subtle lesions.

**ResNet50 Branch**: Initialized with pretrained ImageNet weights to capture deeper and broader residual features.

The outputs from both branches are pooled using **Global Average Pooling**, concatenated, and passed through **Swish-activated Dense layers** before classification via a softmax head.

This design ensures the model captures both micro and macro patterns across diverse retinal abnormalities.

#### ****Model Training and Tuning****

* **Optimizer:** Adam (Learning Rate = 1e‑4)
* **Loss Function:** Categorical Cross-Entropy
* **Callbacks:** Early stopping and model checkpointing based on validation accuracy.
* **Cross-Validation:** 5-fold stratified cross-validation was conducted to fine-tune hyperparameters like batch size, learning rate, and dropout rate.

#### ****Evaluation and Reporting****

The final model was tested on a held-out test set and evaluated using:

* **Metrics:** Accuracy, weighted precision, recall, F1-score
* **Tools:** Confusion matrix to assess misclassifications across classes

The best-performing model was integrated into the system backend for real-time AI-assisted fundus analysis.