Retinal Image Classification

Part 1: Image Preprocessing

Description: I developed a Python-based image preprocessing tool designed to enhance the quality of retinal images before training the AlexNet neural network for the classification of glaucoma, normal vision, and diabetic retinopathy. The tool utilizes OpenCV and NumPy libraries to perform essential preprocessing tasks, ensuring that the images are in optimal condition for effective model training.

Key Features:

User -Friendly Interface: The application features a simple graphical user interface (GUI) built with Tkinter, allowing users to easily select image directories and processing options.

Image Format Flexibility: Users can specify the image format (e.g., JPG, PNG, BMP) for batch processing, accommodating various types of retinal images.

Multiple Processing Options:

Resizing: Images can be resized to the required dimensions of 227x227 pixels, which is essential for input into the AlexNet architecture.

Colormap Application: Grayscale images can be converted to color using a customizable colormap, enhancing visual features that may be critical for classification tasks.

Cropping: The tool can automatically crop out black borders from images, focusing on the relevant areas and improving the dataset's quality.

Technical Implementation:

The preprocessing tool reads images from a specified directory, applies the selected processing option, and saves the modified images back to the original location. The code is structured to handle various image formats and includes error handling to ensure robustness.

The preprocessing steps are crucial for improving the accuracy of machine learning models in diagnosing eye diseases, ultimately contributing to better patient outcomes.

Part 2: Training and Validation

Description: I developed a deep learning model using PyTorch to classify retinal images into three categories: glaucoma, normal vision, and diabetic retinopathy. Leveraging the power of transfer learning with a pretrained AlexNet architecture, I aimed to enhance the accuracy of diagnosing eye diseases, which is crucial for timely medical intervention.

Key Features:

Data Preparation: The dataset consisted of 3,000 retinal images, with 2,400 images allocated for training and 600 for validation. I implemented data augmentation techniques such as random horizontal flipping, rotation, and color jittering to improve model robustness and generalization.

Model Architecture: I utilized the AlexNet model, known for its effectiveness in image classification tasks. The final layer of the model was customized to match the number of classes in the dataset, allowing for accurate predictions.

Training and Optimization: The model was trained for 12 epochs using the Adam optimizer with a learning rate scheduler to adjust the learning rate based on validation loss. This approach helped achieve a high level of convergence and performance.

Performance Metrics: The model achieved an impressive validation accuracy of 90.83% and a recall of 91.05%, indicating its effectiveness in correctly identifying the presence of eye diseases.

Technical Implementation:

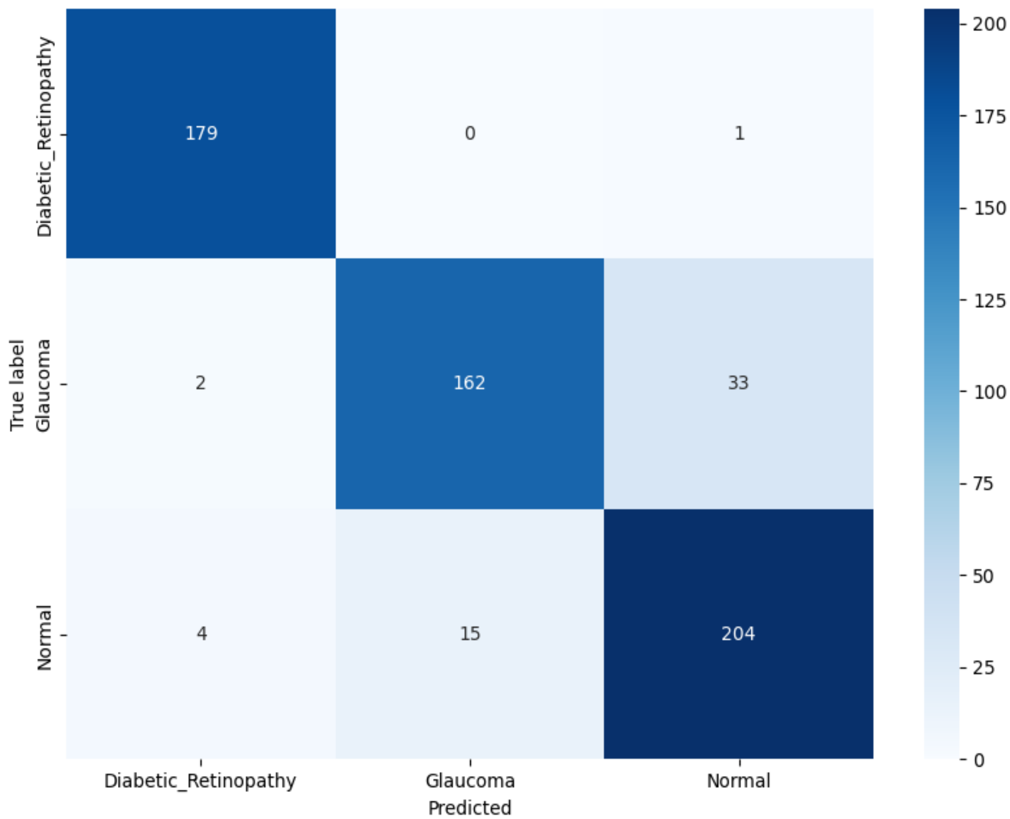
The project involved the following steps:

Data Loading and Transformation: Utilized PyTorch's ImageFolder to load images and applied transformations for both training and validation datasets.

Model Training: Implemented a training loop that included loss calculation, backpropagation, and optimization. The model's performance was monitored using a learning rate scheduler.

Validation and Evaluation: After training, the model was evaluated on the validation set, and metrics such as accuracy and recall were computed. A confusion matrix was generated to visualize the model's performance across different classes.

By improving the accuracy of retinal image classification, this work contributes to better diagnostic tools for eye diseases, ultimately enhancing patient care



Confusion Matrix