Clustrex Data Private Limited

Case Study
Eye Disease Classification Using ResNet-50

Introduction

Eye diseases like Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), Drusen can lead to severe visual impairment or blindness if not detected early. The advancements in deep learning have made it possible to classify retinal images accurately, enabling early detection of these diseases. In this case study, we explore the application of ResNet-50, a deep convolutional neural network, for the classification of conditions: CNV, DME, Drusen, Normal retina images.

Objective

The objective of this study is to develop a model that can automatically classify retinal images into four categories CNV (Choroidal Neovascularization), DME (Diabetic Macular Edema), Drusen, Normal.

To achieve high classification accuracy and implement a system that can assist ophthalmologists in diagnosing these diseases early and more efficiently.

Dataset

The dataset used for this classification task consists of **Retinal OCT (Optical Coherence Tomography)** images, typically available from medical datasets like the **Kaggle OCT database**.Retinal Optical Coherence Tomography (OCT) is an imaging technique used to capture high-resolution cross sections of the retinas of living patients.

The dataset is divided into four categories:

1. **CNV** - Characterized by the growth of new blood vessels in the choroid layer beneath the retina.
2. **DME** - A complication of diabetic retinopathy, where fluid accumulates in the macula.
3. **Drusen** - Yellow deposits under the retina, commonly associated with age-related macular degeneration.
4. **Normal** - Healthy retinal structure without pathological abnormalities.

Each class contains several thousand labeled images for training and testing.

Model Architecture: ResNet-50

The **ResNet-50** architecture is a powerful convolutional neural network that uses residual learning to avoid the vanishing gradient problem common in deep networks. Its 50 layers consist of a combination of convolutional, batch normalization, activation, and residual blocks.

Key features of ResNet-50 for this classification task:

- **Residual blocks** allow the network to learn more effectively by ensuring that gradients flow uninterrupted across layers.
- **Deep architecture** ensures the model can capture intricate patterns in retinal images.
- **Pre-trained weights** on large image datasets like ImageNet provide a strong starting point for transfer learning, which is especially useful when the medical dataset size is smaller.

Approach

Data Preprocessing:

- Images are resized to 224x224 pixels to match ResNet-50's input requirements.
- Data augmentation (random rotations, flips, zooming) increases dataset diversity and reduces overfitting.
- Image normalization is applied to accelerate model convergence.

Transfer Learning:

- ResNet-50, pre-trained on ImageNet, is fine-tuned on retinal OCT images.
- The last layer is replaced with a new dense layer for the four classes (CNV, DME, Drusen, Normal).
- Softmax activation is used for multi-class classification.

Training:

- The dataset is split 80:20 for training and validation.
- Cross-entropy loss and the Adam optimizer (learning rate 0.0001) are used.
- Early stopping and learning rate decay ensure efficient training.

Evaluation Metrics:

- Accuracy, precision, recall, and F1-score are calculated for each class.
- A confusion matrix visualizes misclassifications.

Results

The ResNet-50 model achieves the following:

- **Accuracy**: 97% on the test set, indicating strong performance.

- **Precision and Recall**: High, especially for CNV and DME, which have distinct features. Drusen and Normal also perform well, though minor misclassifications occur due to the subtle differences between them.
- **Confusion Matrix**: Most errors are between Drusen and Normal, but overall, the model exhibits robust classification capabilities.

Conclusion

The use of ResNet-50 for eye disease classification, specifically for detecting CNV, DME, Drusen, and Normal conditions from OCT images, has proven effective. With a classification accuracy of 95%, the model shows promise for clinical application.

This classification system has the potential to assist ophthalmologists in diagnosing retinal diseases early, improving patient outcomes through timely intervention.