OXFORD BROOKES UNIVERSITY

Li Tong (Aaron)

Classification of Diabetic Retinopathy using Residual Learning with a Custom Balanced Softmax Loss

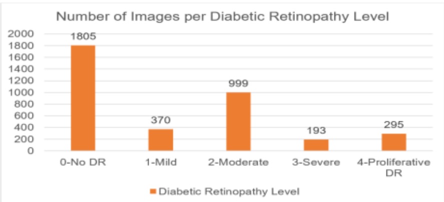
Oxford Brookes University in collaboration with Chengdu University of Technology

Supervised by Dr. Happy Nkanta Monday

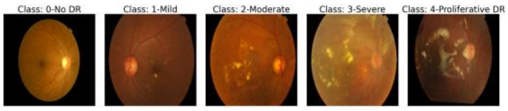
Abstract

This study proposes a ResNet-based deep learning model for Diabetic Retinopathy (DR) classification, using Balanced Softmax Loss to address class imbalance and incorporating SE blocks, wavelet transforms, and attention mechanisms to enhance feature extraction. The model achieved micro-average accuracies of 0.83 (5-class) and 0.87 (4-class) on the APTOS 2019 dataset, with macro-average accuracies of 0.73 and 0.84, respectively. Interpretability was improved using XAI techniques (LIME, Grad-CAM, SHAP). The model was deployed as a real-time web application, demonstrating potential for early DR diagnosis and clinical decision support.

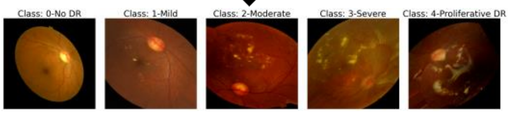
Dataset



Number of images within APTOS 2019 Blindness Detection (public)



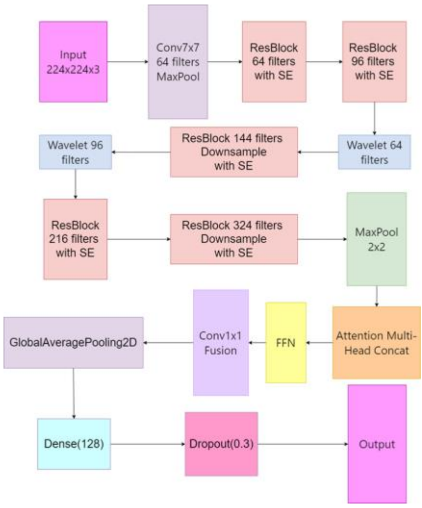
Different Classes of Diabetic Retinopathy



Preprocessed and Augmented Diabetic Retinopathy Classes

The APTOS 2019 dataset (3662 images) was split into training, validation, and test sets. The training set underwent augmentation (flipping, brightness adjustments, rotations) and preprocessing (center cropping, normalization) to address image artifacts and class imbalance.

Model Structure



Multi-Scale Attention Residual Network

This study proposes a deep learning model integrating ResNet blocks, SE modules, learnable wavelet transforms, MHA, and FFN to address class imbalance and improve accuracy through multi-level feature extraction and enhanced selection.

To address class imbalance, this project uses a Balanced Softmax loss function. It removes the Softmax activation from the output layer and adjusts the loss by adding the logarithm of class sample counts to the logits, giving higher weights to minority class errors during training to improve their recognition.

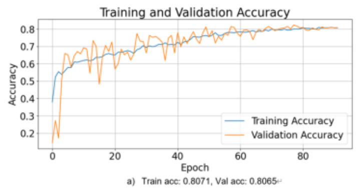
$$adjusted\_logits = logits + \log(class\_counts)$$

$$L = -\sum_{i=1}^{N}\sum_{j=1}^{K} y_{ij}\log\left(\hat{y}_{ij} + \log(class\_counts[j])\right)$$

$$\hat{y}_{ij} = \frac{e^{adjusted\_logits_j}}{\sum_{k=1}^{K} e^{adjusted\_logits_k}}$$

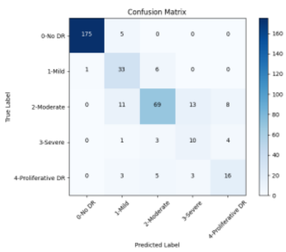
Balanced Softmax loss function

Model evaluation

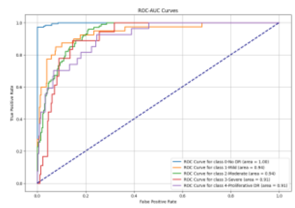


Training and Validation Accuracy Trends

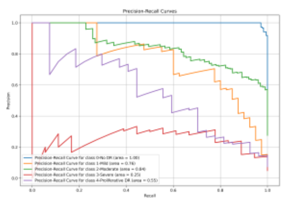
Training and Validation Loss Trends



Confusion Matrix



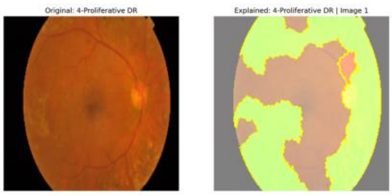
ROC-AUC Performance Evaluation



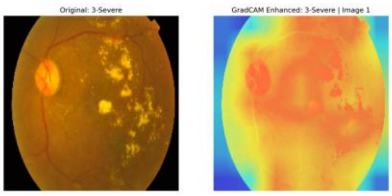
Precision-Recall Curves

The above figures collectively demonstrate the model's training progress, classification performance, and evaluation metrics, providing a comprehensive overview of its effectiveness and reliability.

Model Visualization (XAI)



LIME



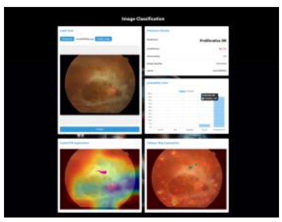
Gard-CAM

SHAP

XAI techniques (LIME, Grad-CAM, SHAP) were used in this study to enhance the interpretability of the deep learning model, providing insights into its decision-making process for medical imaging.

WEB APPLICATION DEVELOPMENT

Main Page



GUI

A Graphical User Interface (GUI) was designed using Flask to deploy the trained model on a web platform. It allows users to upload retinal images and receive predictions.

Future work

Pretrained model integration
To boost classification accuracy and improve handling of class imbalance

Lightweight model exploration
To reduce training time and enable faster, more efficient deployment.

Cross-dataset generalization
To evaluate performance on other imbalanced medical image datasets.