Advancing Diabetic Retinopathy Detection: Reducing Misdiagnosis Using Deep Ensemble Learning

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Diabetic retinopathy (DR), a primary cause of vision loss worldwide, is projected to affect 130 million individuals by 2030. Difficulties related to diagnosis have led to an estimated underdiagnosis rate of 25%. Leveraging Machine Learning (ML) models in diagnosis workflows can increase accessibility and lower costs associated with DR diagnosis. However, in high-risk medical applications, it is imperative that model confidence is quantifiable, and that only high confidence predictions be used to guide patient care. This study aims to increase the reliability and accuracy of DR detection by introducing a novel deep ensemble learning architecture with uncertainty estimation. The ensemble is formed from a variety of sub-models of various architectures, including ResNet-50, DenseNet-121, MobileNetV3 Small, MobileNetV3 Large, EfficientNetB0, EfficientNetB2, and EfficientNetB3. The final output class is determined by an accuracy-weighted majority vote, and uncertainty is estimated using a probability-weighted entropy score. This uncertainty score was demonstrated to be useful as a tunable filter, where low-confidence samples can be dropped to boost reliability. In practice, these dropped samples would be flagged for further review. The ensemble was trained and validated on a dataset containing 35,000 retinal images from Kaggle and had an unfiltered accuracy of 0.9370 with F1 score of 0.9376, and an uncertainty-filtered accuracy of up to 0.9944 with F1 score of up to 0.9932. This study demonstrates the utility of ensemble-based uncertainty estimations to boost the reliability of ML models, a method that can be extended to many other high-risk medical applications.