

M.Sc. *Informatics Engineering*Deep Learning class 2024/2025

Multi-Label Classification of Retinal Diseases from Fundus Photography

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Objectives

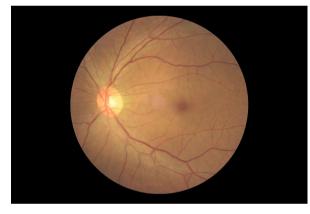
- Develop a model for multi-label classification of retinal diseases using fundus photography.
- Explore dual-branch architectures for joint analysis of left and right eye images.
- Compare **CNN** and **Transformer-based** models in terms of performance on the ODIR-5K dataset.

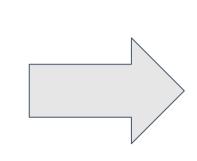
Problem

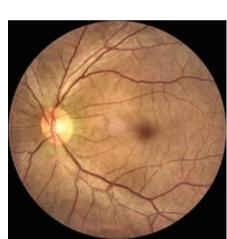
- Retinal diseases are often diagnosed manually, which is resource-intensive and requires expert knowledge.
- Many patients show multiple concurrent conditions; hence, single-label classification is insufficient.
- Often, other exams such as Dilated Eye Exam, Optical Coherence Tomography (OCT) and Fluorescein Angiography are needed. Developing a model that relies only on fundus images could streamline diagnosis.

Methodology

- Preprocessing:
 - Crop retina region via bounding box detection
 - Apply CLAHE for local contrast enhancement
 - Resize to 224x224 and normalize using ImageNet statistics

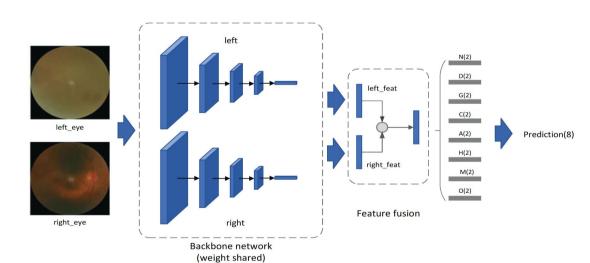






• Models:

- CNNs: EfficientNetB0, EfficientNetB4, ResNet18
 (Pretrained on ImageNet & RetinaMNIST)
- o Transformers: ViT-b16, ViT-b32
- Architecture: Adapted existing models into a dual-branch structure to process left and right eye images independently but jointly



https://arxiv.org/pdf/2102.07978

• Training:

- Optimizer: Adam with weight decay (1e-5)
- Loss: Sigmoid Focal Loss for class imbalance
- Early stopping based on validation loss

References

[1] Guo, Chen & Yu, Minzhong & Li, Jing. (2021). Prediction of Different Eye Diseases Based on Fundus Photography via Deep Transfer Learning - jcm-10-05481-2. Journal of Clinical Medicine. 10. http://dx.doi.org/10.3390/jcm10235481 [2] Shumoos Al-Fahdawi, Alaa S. Al-Waisy, Diyar Qader Zeebaree, Rami Qahwaji, Hayder Natiq, Mazin Abed Mohammed, Jan Nedoma, Radek Martinek, Muhammet Deveci. (2024).

Fundus-DeepNet: Multi-label deep learning classification system for enhanced detection of multiple ocular diseases through data fusion of fundus images https://doi.org/10.1016/j.inffus.2023.102059

[3] Hu, W., Li, K., Gagnon, J., Wang, Y., Raney, T., Chen, J., Chen, Y., Okunuki, Y., Chen, W., & Zhang, B. (2025). FundusNet: A Deep-Learning Approach for Fast Diagnosis of Neurodegenerative and Eye Diseases Using Fundus Images. Bioengineering, 12(1), 57. https://doi.org/10.3390/bioengineering12010057
[4] National Institute of Health Data Science at Peking University (NIHDS-PKU),

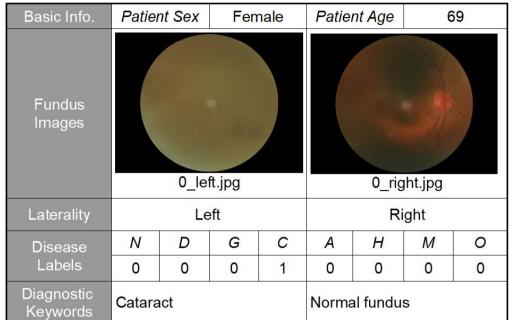
https://odir2019.grand-challenge.org/#ocular-disease-intelligent-recognition-odir-2019

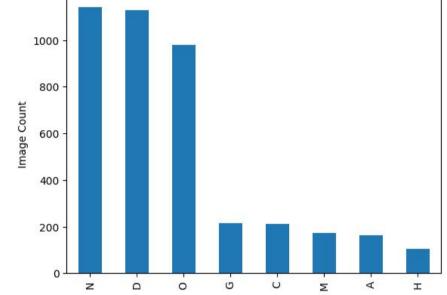
[5] Our Google Colab Notebook https://colab.research.google.com/drive/1vaWRuVwJHS9Gteg-Lnyrk-q7oERCsJ9G

Dataset

• ODIR-5K Dataset:

- ~5,000 patient samples
- Each sample includes left and right fundus images
- 8 disease labels: Normal (N), Diabetes (D), Glaucoma (G), Cataract (C), Age-related Macular Degeneration (A), Hypertension (H), Myopia (M), Other(O)
- Split: 60% Train, 20% Validation, 20% Test
- Labels are multi-label binary vectors

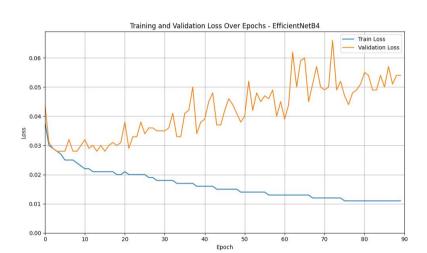




Class Distribution

https://odir2019.grand-challenge.org/dataset/

Results

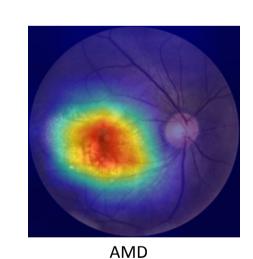


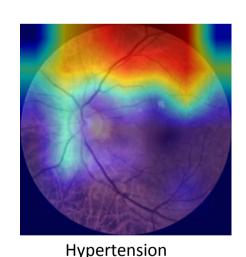


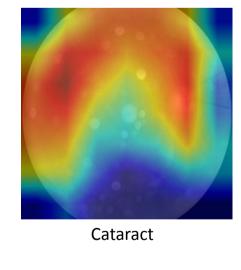
Model	Avg Loss	Accuracy	AUC	F1	Precision	Recall	PR AUC
EfficientNetB0(ImageNet)	0.0273	0.8750	0.8345	0.5371	0.5322	0.6065	0.5736
EfficientNetB4(ImageNet)	0.0298	0.8786	0.8434	0.5685	0.5221	0.6608	0.5825
ViT_b_32(ImageNet)	0.0326	0.8527	0.6613	0.3332	0.2454	0.7227	0.2689

Class	Precision	Recall	F1 Score	PR-AUC
N	0.483	0.675	0.563	0.534
D	0.652	0.590	0.619	0.729
\mathbf{G}	0.466	0.692	0.557	0.531
\mathbf{C}	0.825	0.767	0.795	0.840
A	0.297	0.688	0.415	0.484
H	0.096	0.529	0.162	0.207
M	0.875	0.848	0.862	0.887
O	0.403	0.681	0.506	0.446

EfficientNetB4 per-class Metrics







Conclusions

- Deep learning models can perform multi-label classification of retinal diseases using paired fundus images, with CNNs currently outperforming transformer-based architectures under limited training conditions.
- ViT showed **underfitting**, likely due to insufficient data.
- Preprocessing steps significantly enhanced model learning and convergence.

Future Directions

- Address class imbalance using techniques like focal loss tuning, or SMOTE.
- Apply more aggressive regularization to CNN models to mitigate overfitting.
- Investigate hybrid or ensemble models that combine CNNs and transformers.

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