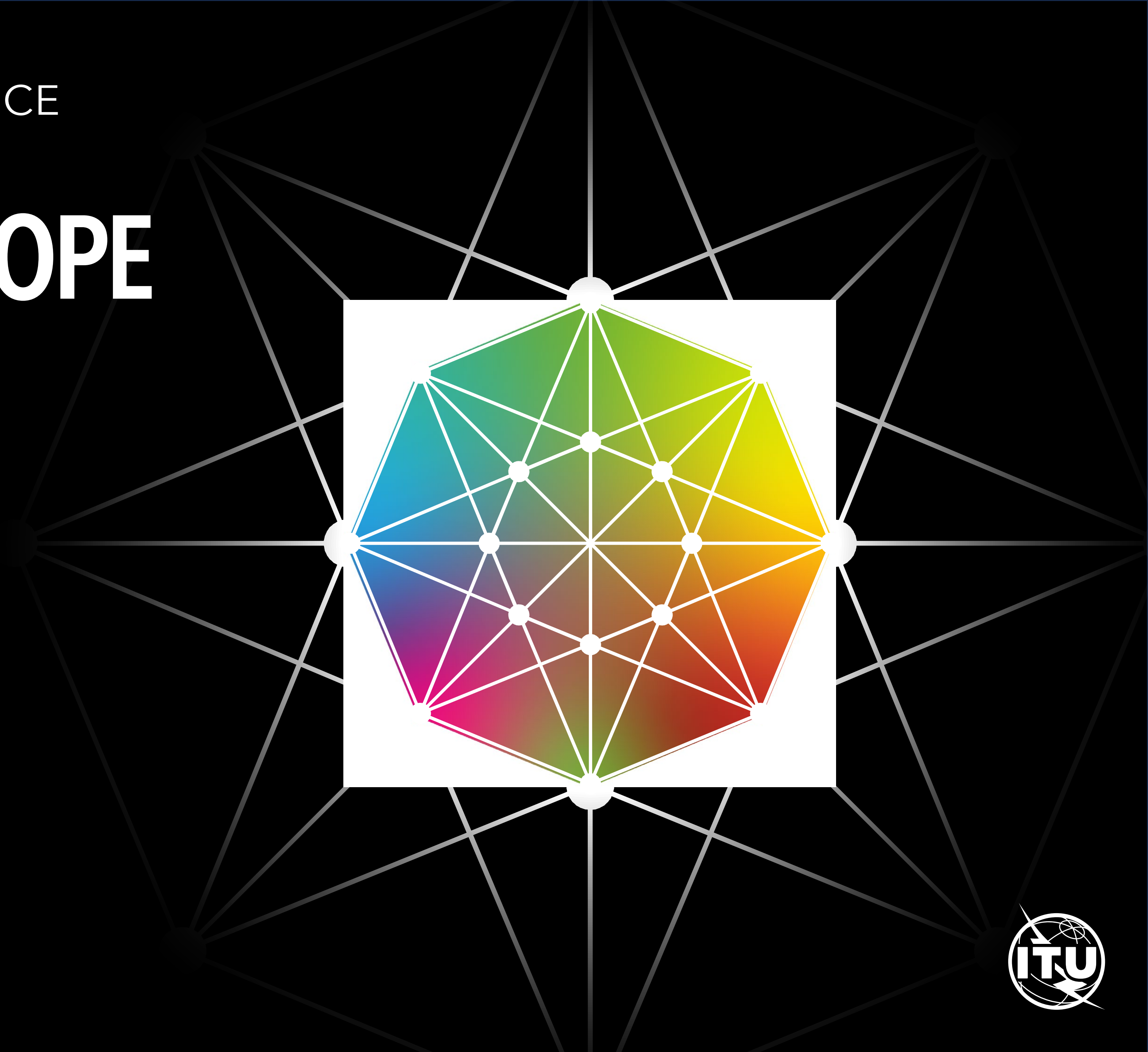
16TH ITU ACADEMIC CONFERENCE

ITU KALEIDOSCOPE
GENEVA2026

AI and frontier technologies for good

7-9 July 2026
Geneva, Switzerland

Hosted by AI for Good Global Summit

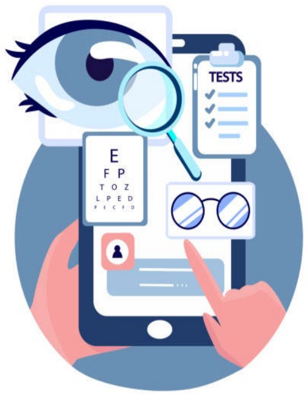


Pocket Diagnosis: Ex-YOLO-Driven Real-Time Ophthalmic diagnosis with Smartphone Applications

Wednesday 8th July 2026

Presenter:
Dr. Kyamelia Roy
Lecturer, Dept. of ETCE
Siliguri Govt. Polytechnic

Paper Session 3- AI in Healthcare and well-being applications
Day 1- Tuesday 7th July 2026



Pocket Diagnosis: Ex-YOLO-Driven Real-Time Ophthalmic diagnosis with Smartphone Applications

Problem :

Accurate early detection of retinal diseases from OCT scans remains challenging due to dependence on expert ophthalmologists, high computational requirements, and limited accessibility in resource-constrained regions.

Motivation:

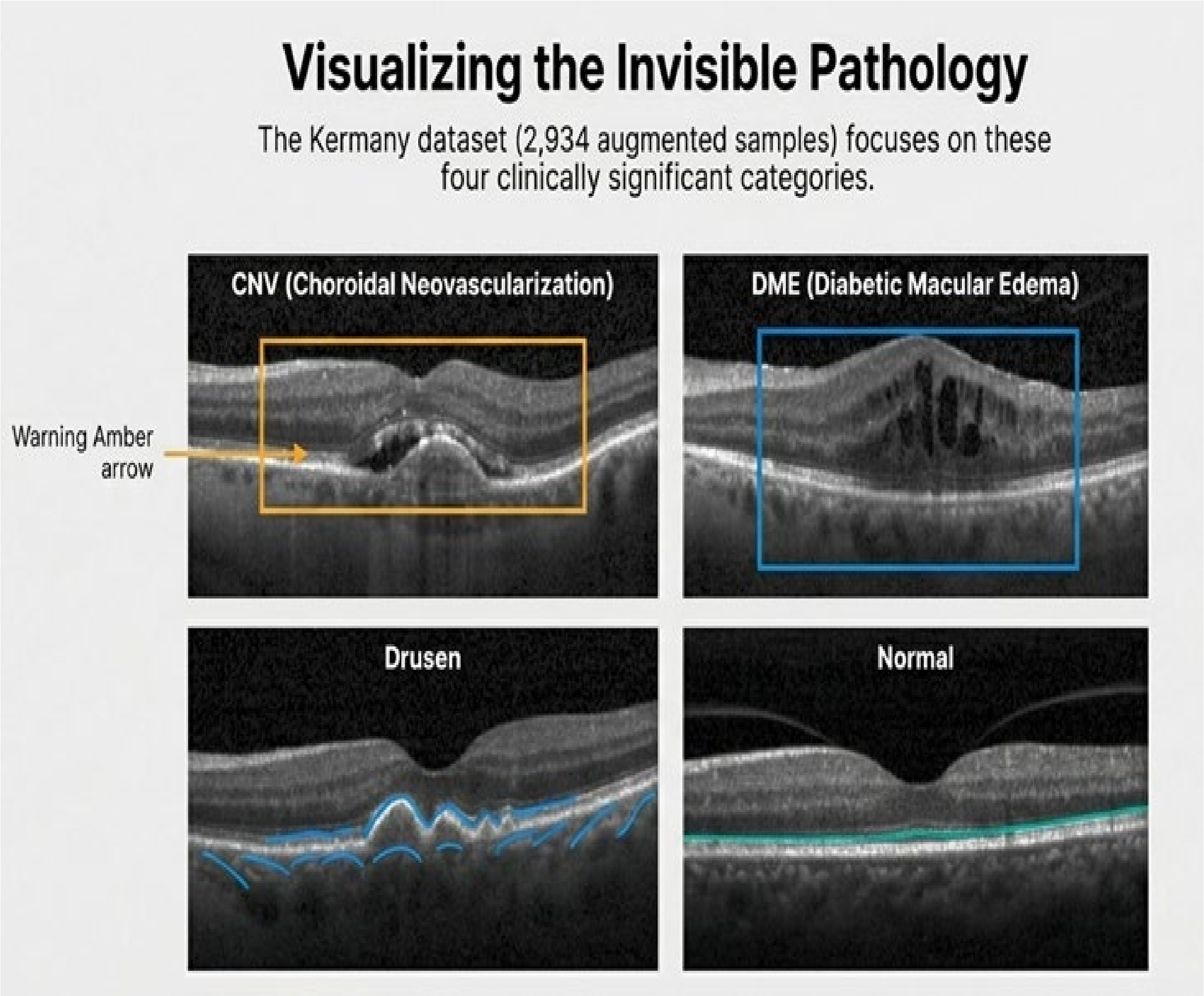
- *To enable rapid and accurate early screening of retinal diseases for timely treatment and prevention of vision loss.*
- *To develop a lightweight and accessible AI-based diagnostic system that reduces dependence on expensive clinical infrastructure and expert ophthalmologists.*

Objectives

- Develop lightweight retinal disease detection framework
- Use Edge-AI optimized architecture
- Compare multiple YOLO versions
- Improve performance using SE attention
- Deploy on Android smartphone

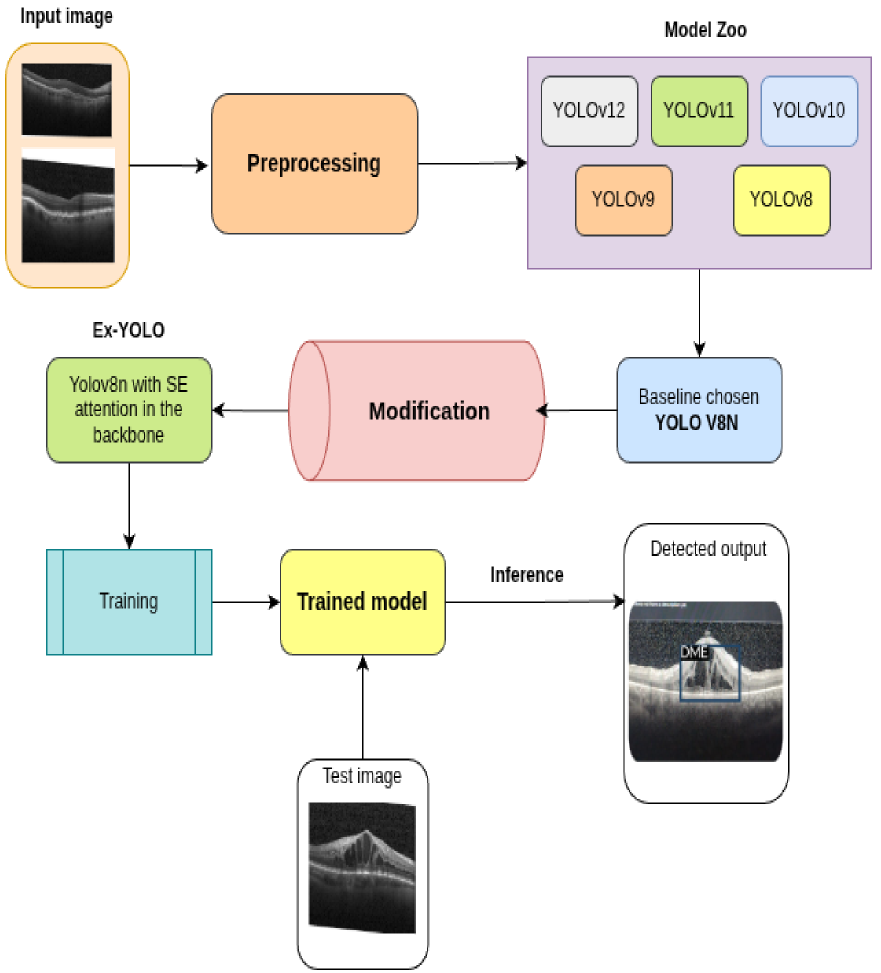
Dataset(Kermany OCT)

- 998 original images
- Augmented to 2,934 images
- Augmentation: rotation, flipping, intensity variation



Methodology

- **Dataset Preparation & Preprocessing:** resizing, annotation, normalization, and augmentation
- **Model Benchmarking & Selection:** Evaluated multiple YOLO architectures (YOLOv8–YOLOv12) based on accuracy, recall, mAP, and computational efficiency, selecting YOLOv8n as the optimal baseline.
- **Proposed Ex-YOLO Development:** Enhanced YOLOv8n by integrating Squeeze-and-Excitation (SE) attention blocks to improve retinal feature extraction while maintaining lightweight computation.
- **Evaluation & Mobile Deployment:**



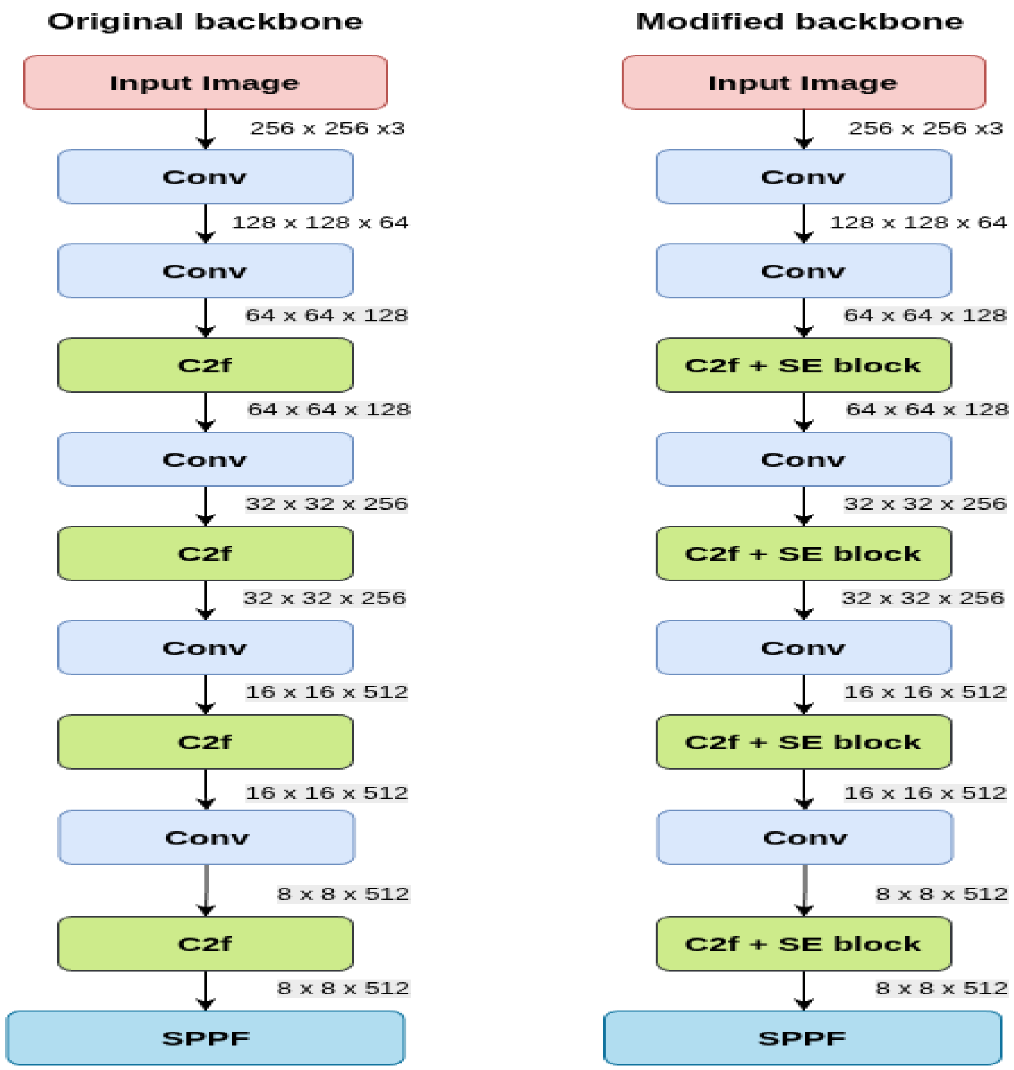
The Best Baseline Model

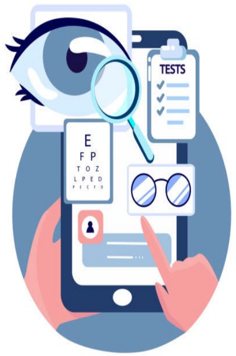
The Model Zoo Shootout: Finding the Baseline

Despite the theoretical advancements of v11 and v12, YOLOv8n delivered superior recall and overall mAP@0.50, proving its unmatched ability to recover relevant disease features.

Model	Precision	Recall	mAP@0.50
YOLOv12n	0.7090	0.5586	0.6264
YOLOv11n	0.7150	0.5872	0.6432
YOLOv10n	0.4797	0.5677	0.5392
YOLOv9t	0.6919	0.6014	0.6695
YOLOv8n	0.6798	**0.6366**	**0.6810**

Model Architecture and Modification

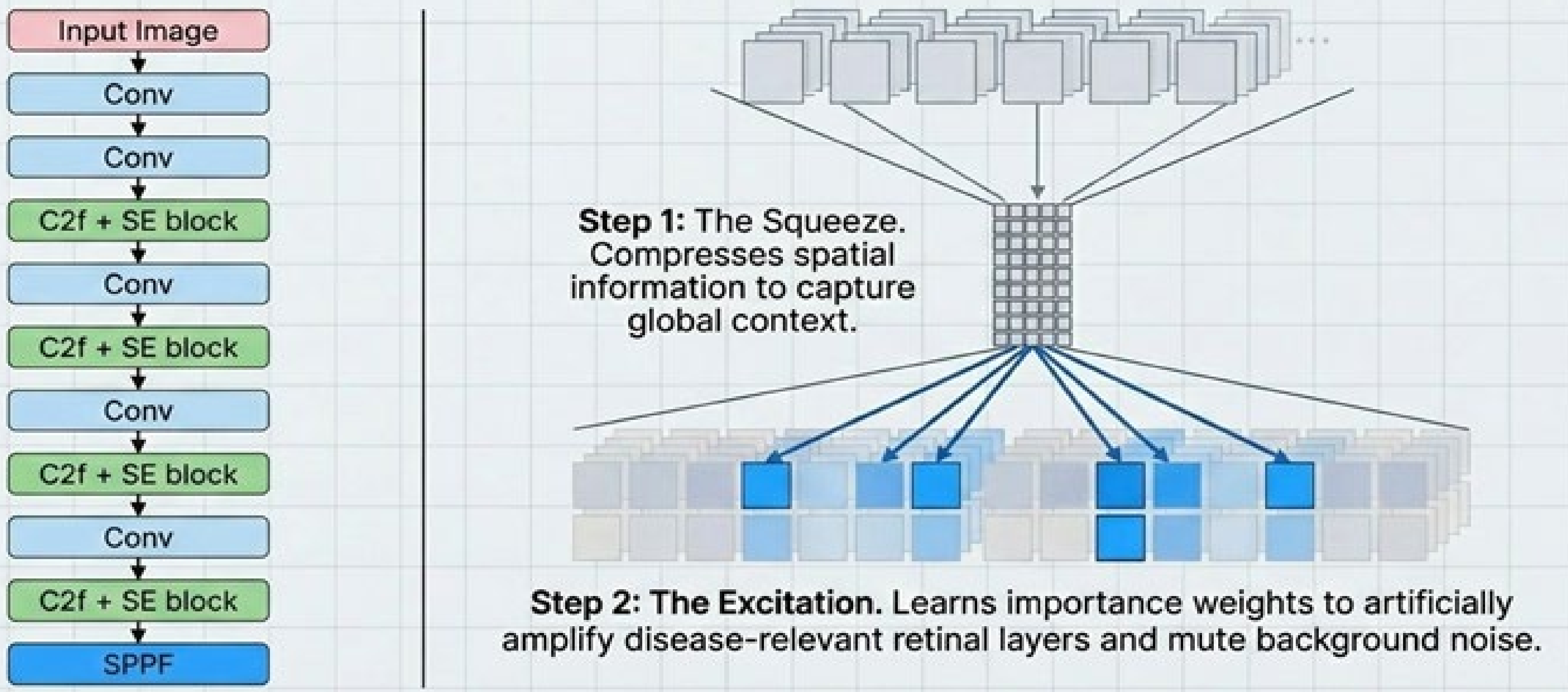




Model Architecture and Modification

Deconstructing Squeeze-and-Excitation (Ex-YOLO)

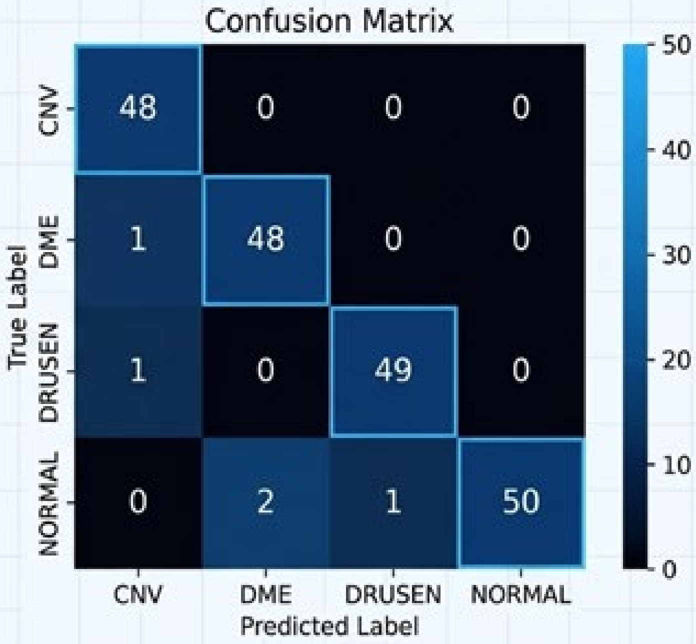
Result: Integrated directly into the YOLOv8n C2f feature aggregation module.
Massive boost in subtle class variations with a near-zero computational penalty.

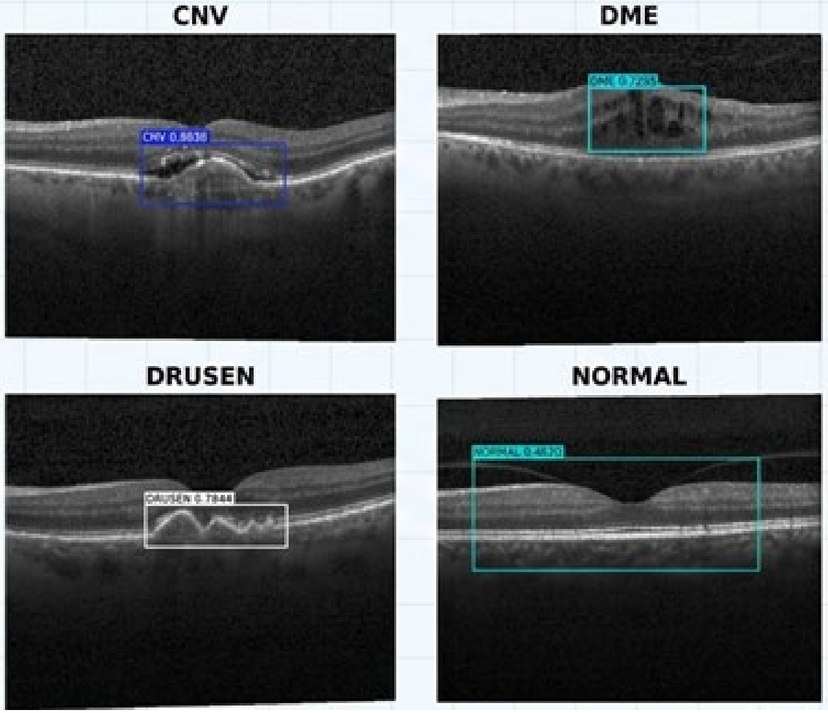


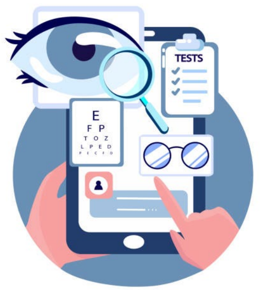
Results

Mapping Diagnostic Reliability

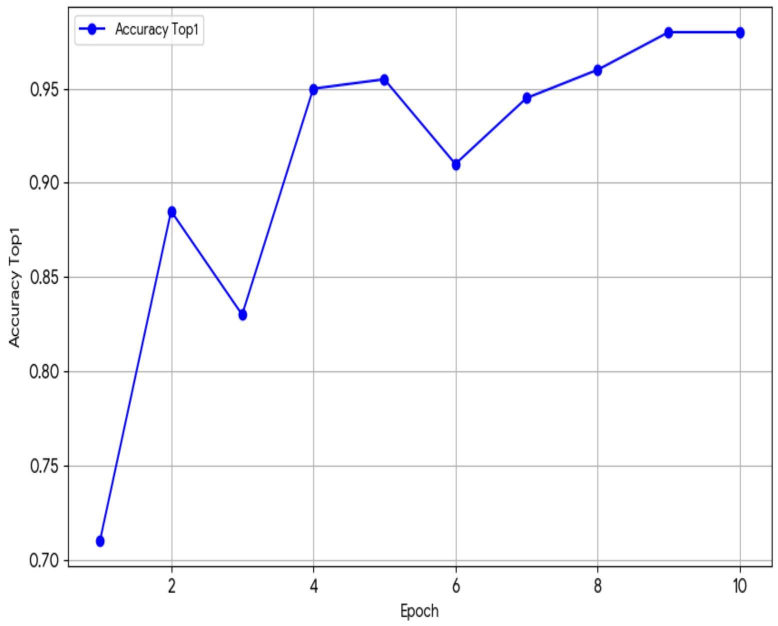
The Ex-YOLO framework reliably distinguishes between minute pathological differences, achieving an overall precision of 0.742 and an mAP@0.50 of 0.7451 across the multi-class anomalies.

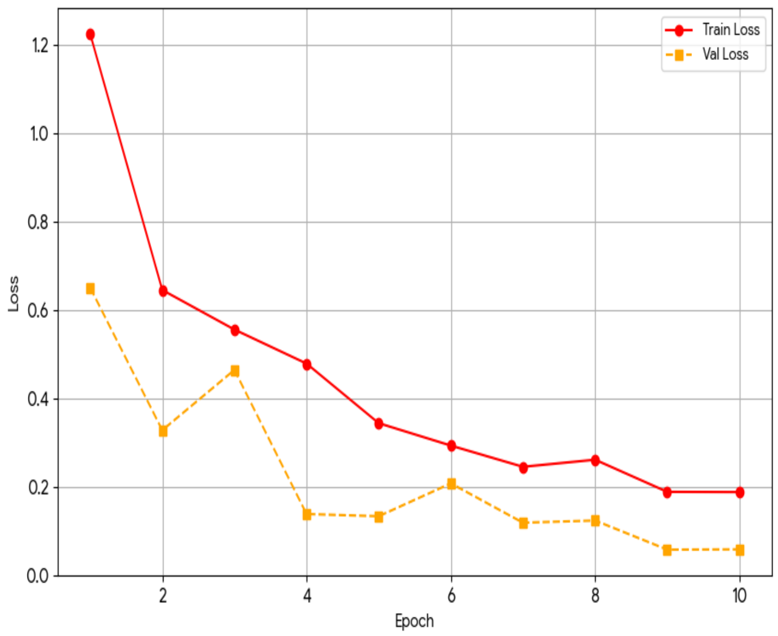




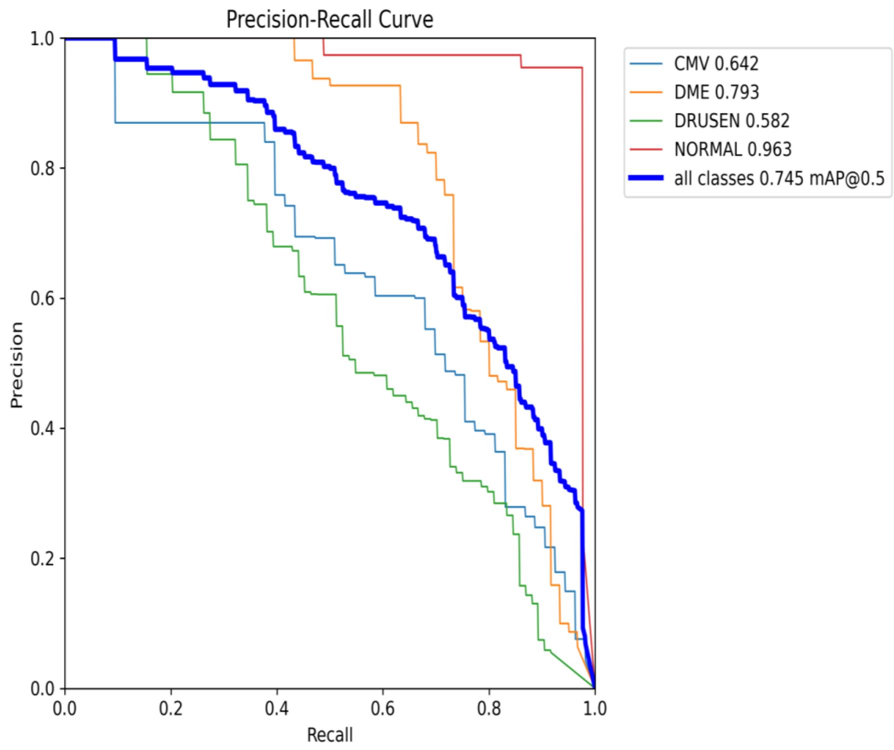

TESTS

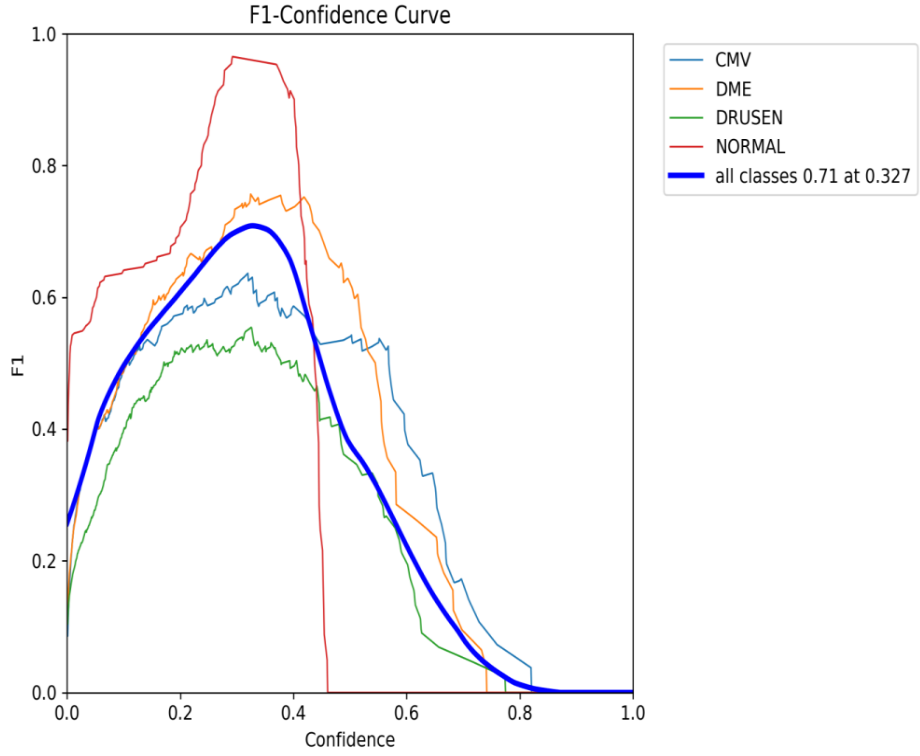
Results


Accuracy Top1
0.95
0.90
0.85
0.80
0.75
0.70
Accuracy Top1
2
4
6
8
10
Epoch

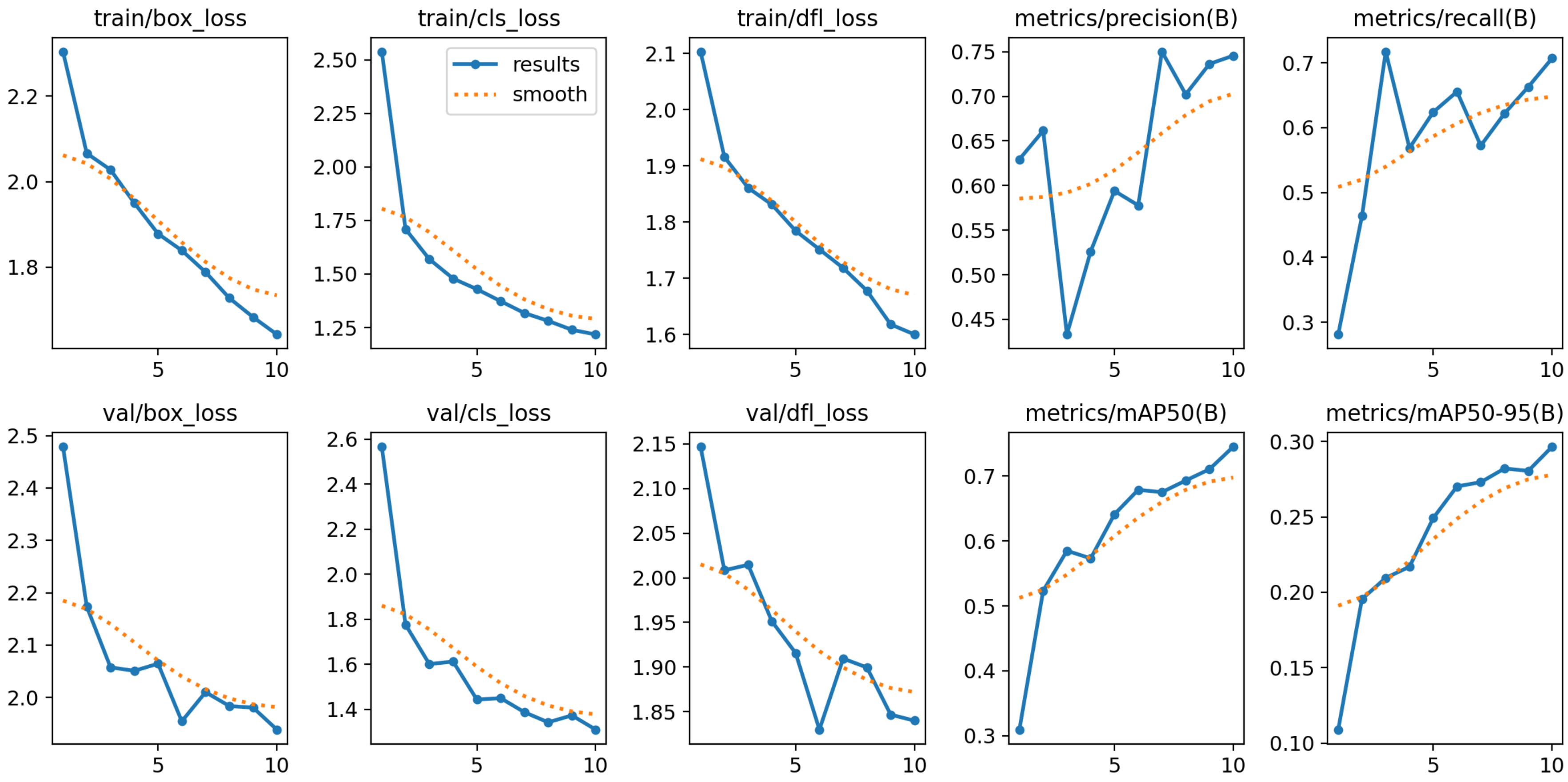

Train Loss
Val Loss
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Loss
2
4
6
8
10
Epoch

Results


Precision-Recall Curve
Precision
Recall
CMV 0.642
DME 0.793
DRUSEN 0.582
NORMAL 0.963
all classes 0.745 mAP@0.5


F1-Confidence Curve
F1
Confidence
CMV
DME
DRUSEN
NORMAL
all classes 0.71 at 0.327

Results


train/box_loss
train/cls_loss
train/dfl_loss
metrics/precision(B)
metrics/recall(B)
results
smooth
val/box_loss
val/cls_loss
val/dfl_loss
metrics/mAP50(B)
metrics/mAP50-95(B)

Results

- The proposed Ex-YOLO model achieved strong detection performance while maintaining very low inference latency, which is essential for real-time deployment.

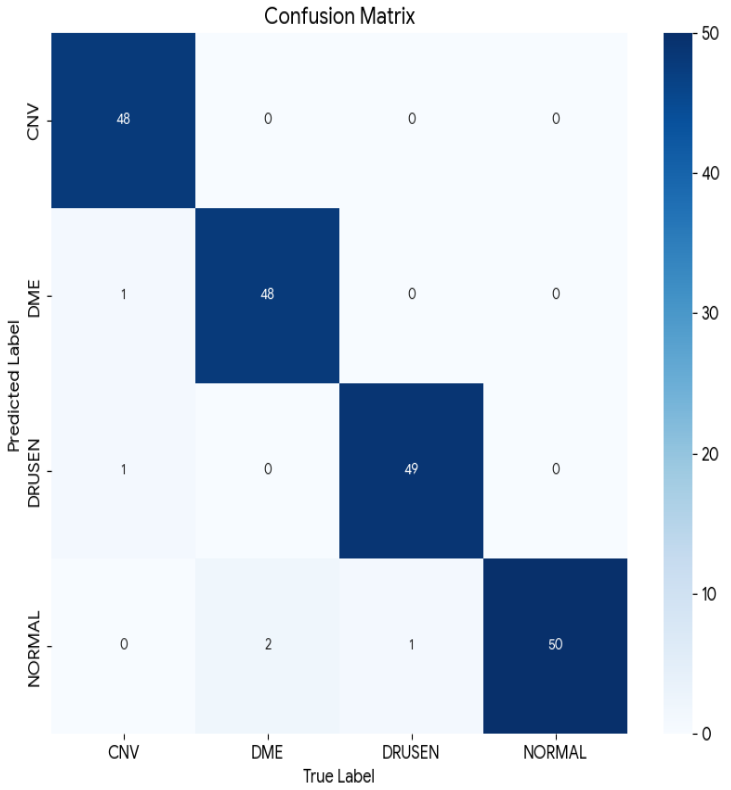
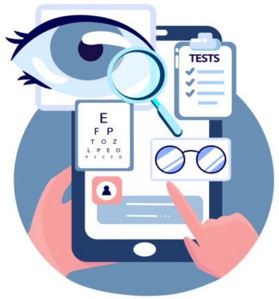
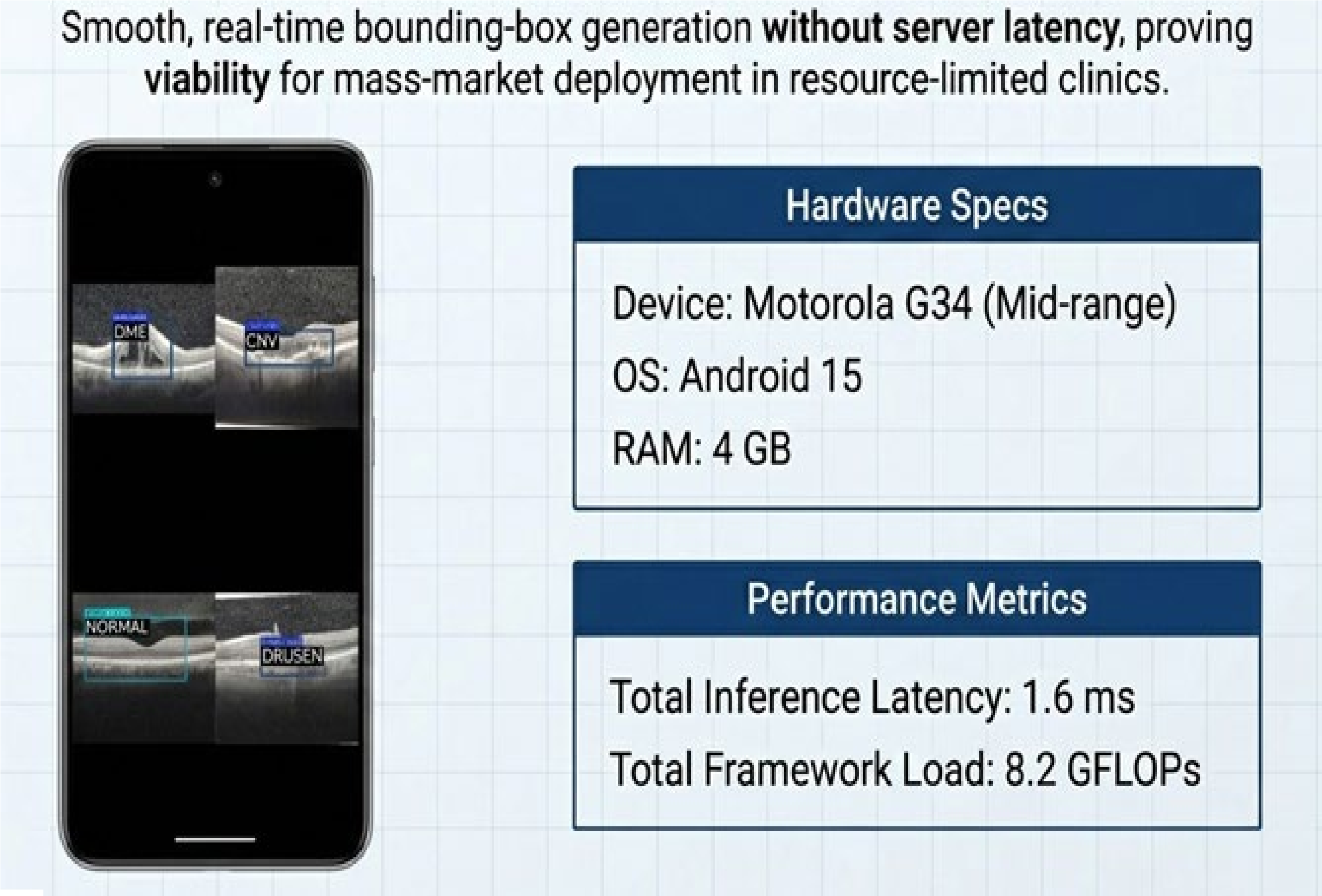


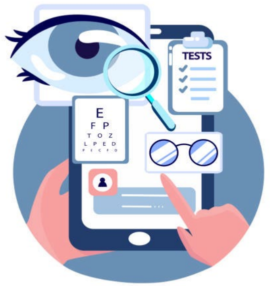
Fig. 5. Confusion matrix for the Ex-YOLO backbone on test dataset

Real-World Deployment: Edge AI in Action



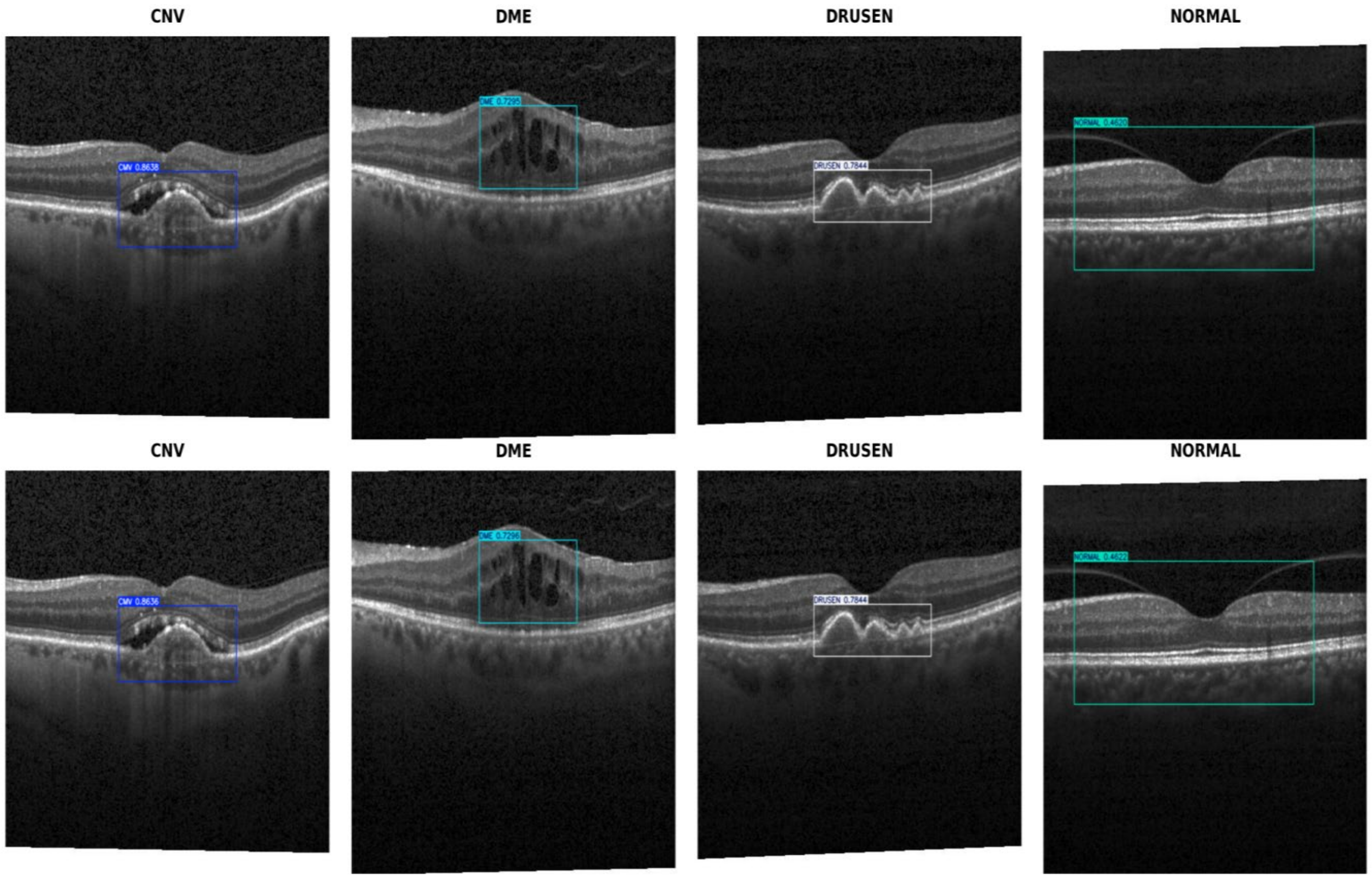


- Converted to TensorFlow Lite
- Float32 & Float16 versions
- Developed using Android Studio & Kotlin
- Tested on Motorola G34



Results

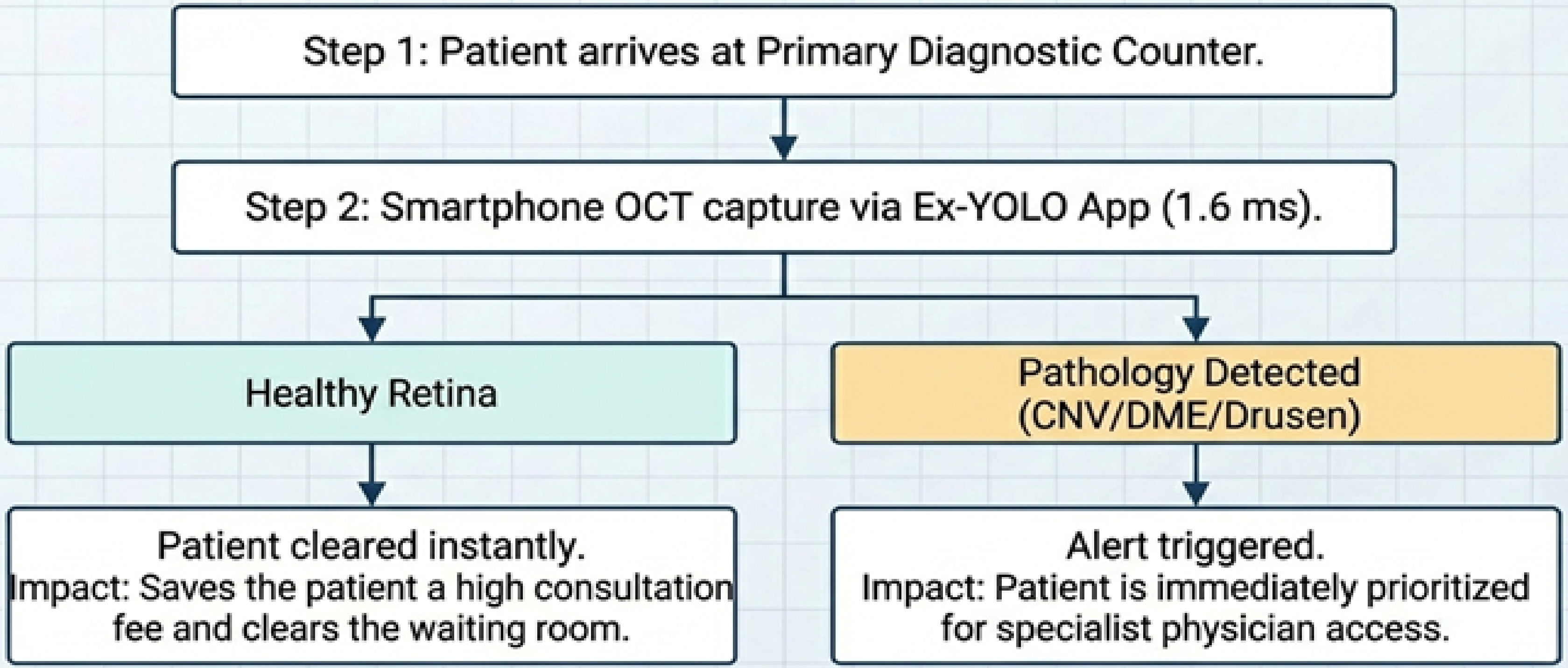
Detected Sample Output Images



- Precision: 0.742
- Recall: 0.700
- mAP50: 0.745
- Inference time: 2.6 ms

The New Point-of-Care Workflow

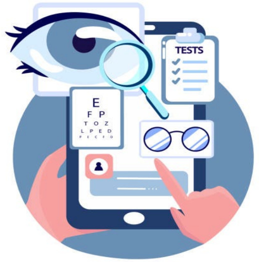
Automated primary screening creates immense clinical bandwidth by filtering out healthy scans at the edge.



Clinical Precision in the Palm of Your Hand

By engineering Squeeze-and-Excitation mechanisms into an ultra-efficient YOLOv8 architecture, Ex-YOLO successfully migrates expert-level retinal diagnostics from the server room to the primary care counter.

0.68	3.5 GFLOP	100%
Baseline Recall (Market-Leading)	Classifier Cost (Ultra-Lightweight)	Offline Capability (True Edge AI)



Conclusions

- Lightweight and efficient Ex-YOLO proposed
- Improved feature attention using SE blocks
- High accuracy with low computational cost
- Suitable for Edge-AI healthcare applications

References

[1] K. Roy, S. S. Chaudhuri, P. Roy, S. Chatterjee, and S. Banerjee, “Transfer learning coupled convolution neural networks in detecting retinal diseases using OCT images,” in *Intelligent Computing: Image Processing Based Applications, J. Mandal and S. Banerjee, Eds.*Singapore: Springer, 2020, vol. 1157, pp. xx–xx, doi:10.1007/978-981-15-4288-6_10.

[2] M. S. Junayed, M. B. Islam, A. Sadeghzadeh, and S. Rahman, “CataractNet: An automated cataract detection system using deep learning for fundus images,” *IEEE Access, vol. 9, pp. 128799–128808,* 2021.

[3] I. Leandro, B. Lorenzo, M. Aleksandar, M. Dario, G. Rosa, A. Agostino, and T. Daniele, “OCT-based deep-learning models for the identification of retinal key signs,” *Scientific Reports, vol. 13, no. 1, p. 14628,* 2023.

[4] F. J. M. Shamrat, R. Shakil, B. Akter, M. Z. Ahmed, K. Ahmed, F. M. Bui, and M. A. Moni, “An advanced deep neural network for fundus image analysis andenhancing diabetic retinopathy detection,” *Healthcare Analytics, vol. 5, p. 100303, 2024.*

[5] G. Gencer and K. Gencer, “Advanced retinal disease detection from OCT images using a hybrid squeeze and excitation enhanced model,” *PLoS ONE, vol. 20, no. 2,* e0318657, 2025.

[6] D. A. Geetha, T. H. Lakshmi, K.V. Sagar, M. Chaitanya, S. Kantamaneni, V. V. R. Battula, and S. K. Jali, “Detection and classification of diabetic retinopathy using YOLO-V8 deep learning methodology,” *Journal of Theoretical and Applied Information Technology,* vol. 102, no. 7, pp. 7580–7588, 2024.

[7] A. S. Abdi and A. M. Abdulazeez, “A comprehensive review of deep learning in OCT image segmentation and classification,” [Journal/Conference], year not specified.

References

[8] K. Du, A. R. Nair, S. Shah, A. Gadari, S. C.Vupparaboina, S. C. Bollepalli, S. Sutharahan, J.-A. Sahel, S. Jana, J. Chhablani, and K. K. Vupparaboina,"Detection of disease features on retinal OCT scans using RETFound," *Bioengineering, vol. 11, no. 12,* p. 1186, 2024.

[9] A.-I. Ardelean, E. R. Ardelean, and A. Marginean, "Can YOLO detect retinal pathologies? A step towards automated OCT analysis," *Diagnostics, vol. 15, no. 14,* p. 1823, 20252222

[10] W. J. Jaimes,W. J. Arenas, H. J.Navarro, and M. Altuve, "Detection of retinal diseases from OCT images using a VGG16 and transfer learning," *Discover Applied Sciences, vol. 7, no. 3, p. 160, 2025.*

[11] https://www.kaggle.com/datasets/paultimothymooney/ kermany2018

22

Thank you!