

RETINOSCAN

A portable fundus imaging device with integrated machine learning for automated Diabetic Retinopathy detection

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DIABETIC RETINOPATHY

- Diabetic retinopathy (DR) is a progressive disease of the retinal capillaries caused by prolonged high blood sugar in diabetic patients
- Damaged capillaries in the retina lead to vision impairment and, in severe cases, blindness.
- DR can be classified into five stages: No DR, Mild DR, Moderate DR, Severe DR and Proliferate DR.
- DR has no visible external symptoms in its early stages. Internally, however, fundus changes occur. The fundus refers to the interior surface of the eye, including the retina, optic disc, and blood vessels, which are examined to detect DR.

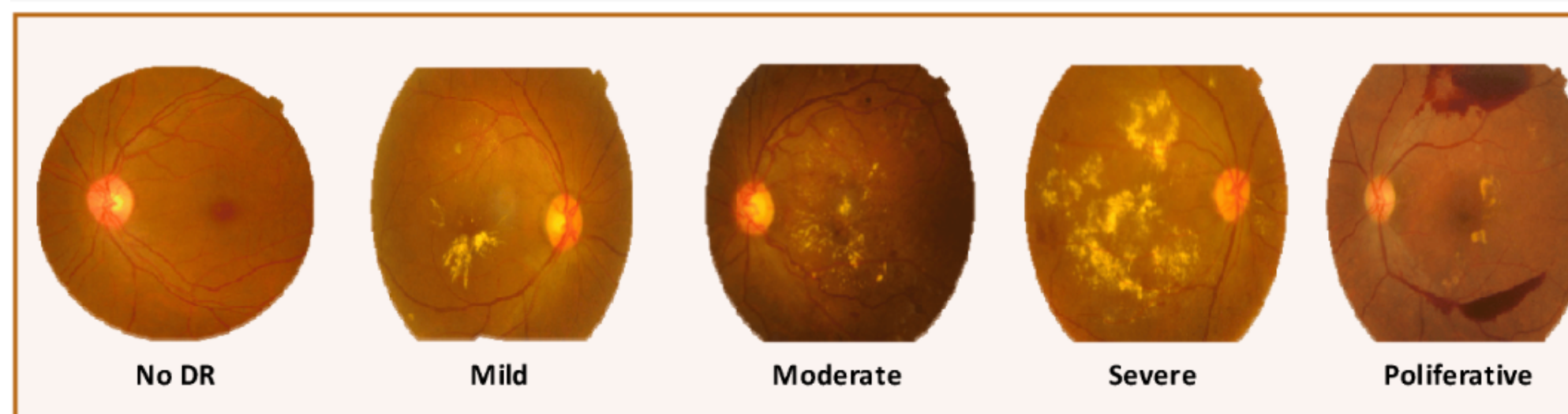


Fig 1: DR Severity Levels

GLOBAL PREVALENCE

- Globally, over 537 million adults live with diabetes.
- Approximately **1 in 5 people** with diabetes have some degree of DR, with some variations across populations.
- Globally, **1 in 10** people with diabetes will develop a vision-threatening form of the disease
- In 2020, an estimated 103 million adults had DR, and over 47 million had vision-threatening retinopathy.

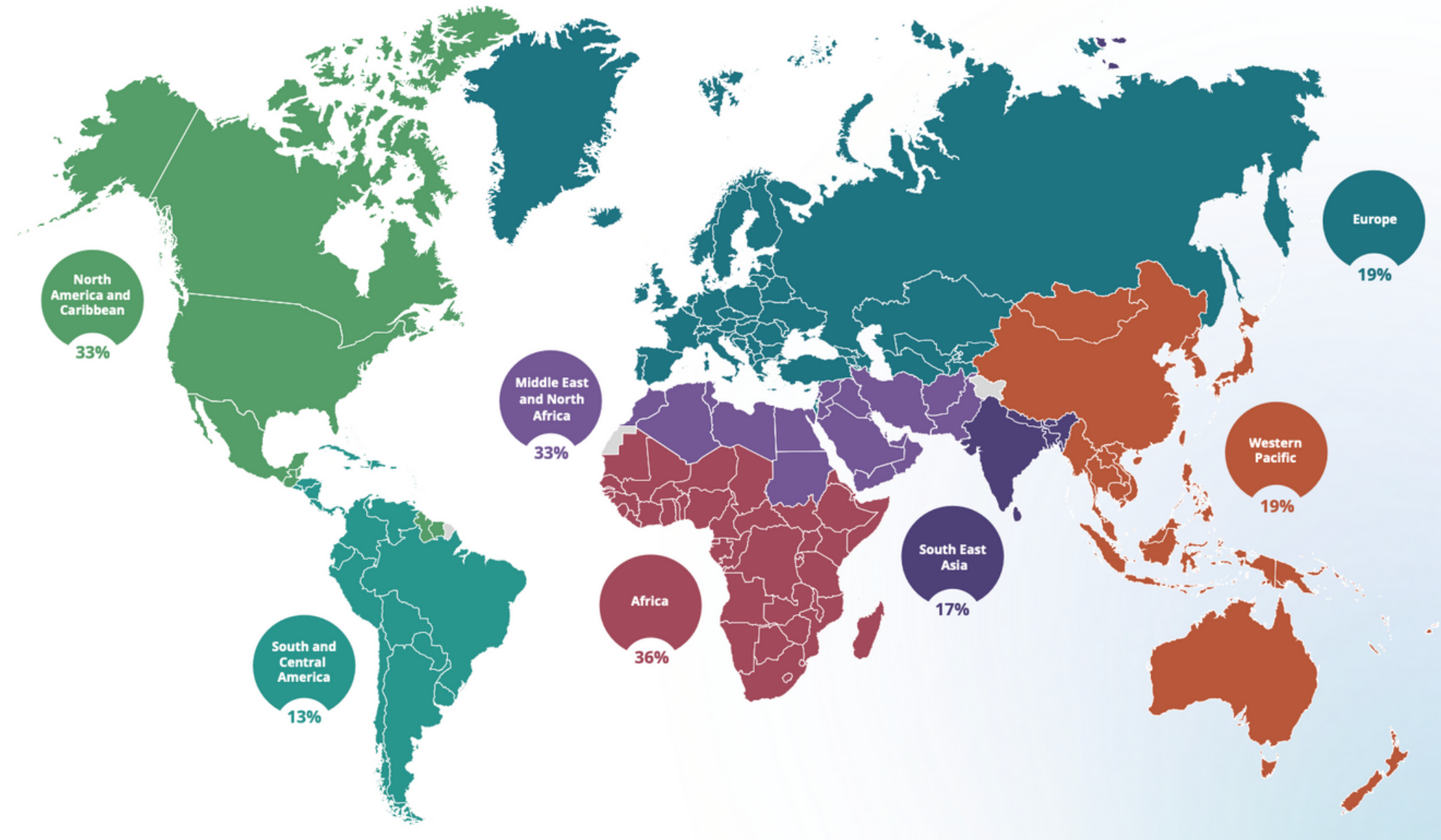


Fig2: Prevalence of diabetic retinopathy in adults with diabetes (20-87 years) in 2020 by IDF Region

PROBLEM STATEMENT

In the early stages, DR is typically **asymptomatic**, with only **internal fundus changes** occurring. By the time external symptoms appear, the disease has often **progressed significantly**, making treatment **less effective**.

Since the early stages of DR seldom lead to vision loss, **regular, cost-effective, and accessible screening** is essential for early detection and timely intervention, which can **prevent up to 95% of blindness**. However, **75% of adults with diabetes** (433 million) live in **low- and middle-income countries**, where access to skilled eye specialists is often limited. Conventional diagnostic methods require **specialised equipment** and **trained personnel**, which may not be available in rural or underserved areas.

This underscores the need for **affordable screening solutions** to bridge the gap in early detection and **prevent vision loss**.

ENGINEERING GOALS

- Develop a Transformer -Based Fundus Image Classification Model
- Implement Robust Image Preprocessing Techniques
- Data Augmentation for Model Generalization
- Convert and Optimize Model for Deployment
- Develop a User-Friendly Interface for Real-Time Diagnosis
- Develop the prototype and incorporate a high-resolution camera with a lens arrangement to achieve precise and high-quality image capture.

METHODOLOGY

1) Data Cleaning and Preprocessing

- Standardize Image Size for Consistency
- Normalize and Enhance Pixel Values
- Address Dataset Imbalance and Quality Issues

2) Data Augmentation

- Apply Random Horizontal Flipping for Orientation Robustness
- Use Random Rotation to Enhance Positional Adaptability
- Implement Random Zooming to Improve Image Scale Variability
- Adjust Image Contrast Dynamically for Illumination Resilience and introduce Shear Transformations for Structural Variability

3) Transformer Model Building

- Implement a Swin Transformer for fundus image classification.
- Apply hierarchical learning with shifted windows to capture local and global patterns.

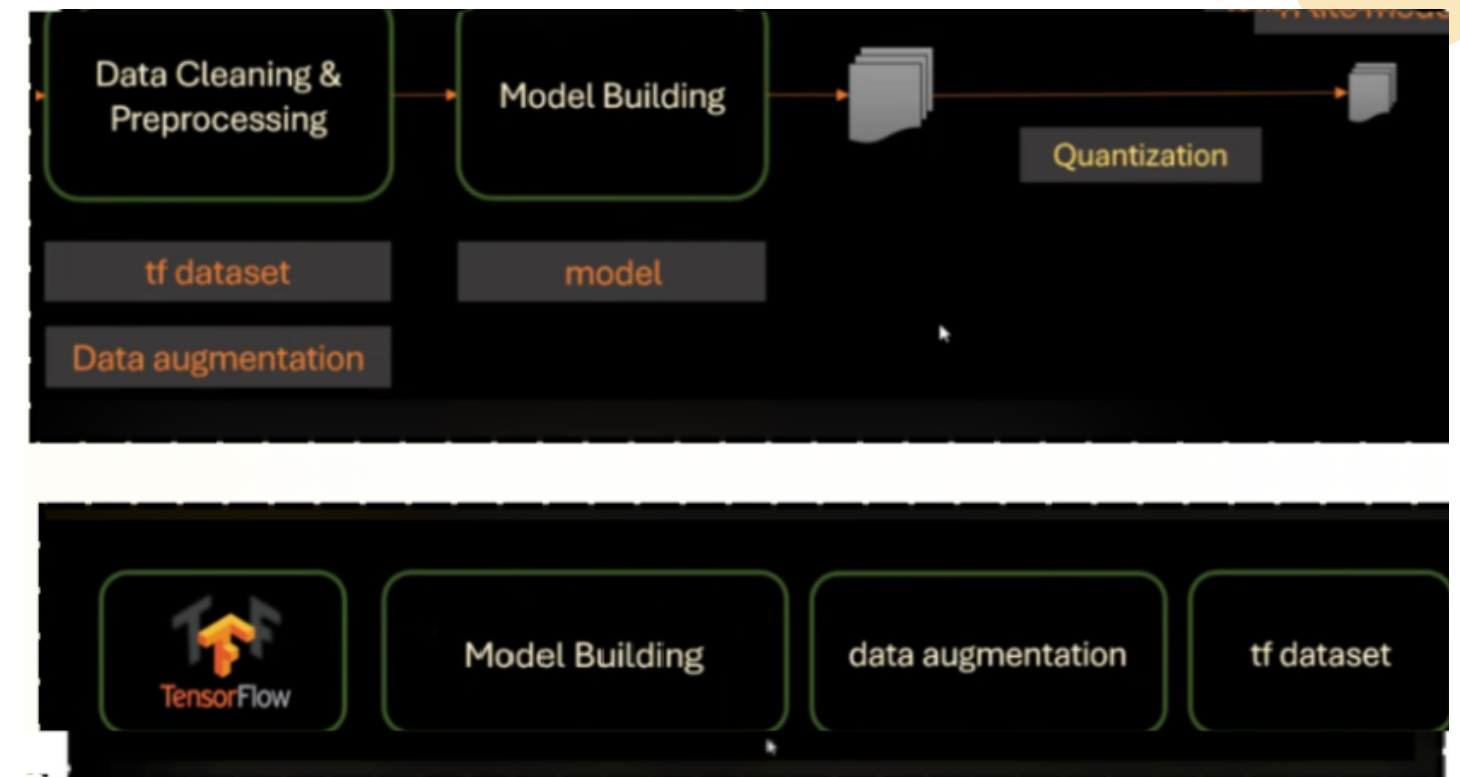


Fig 3:Flowchart

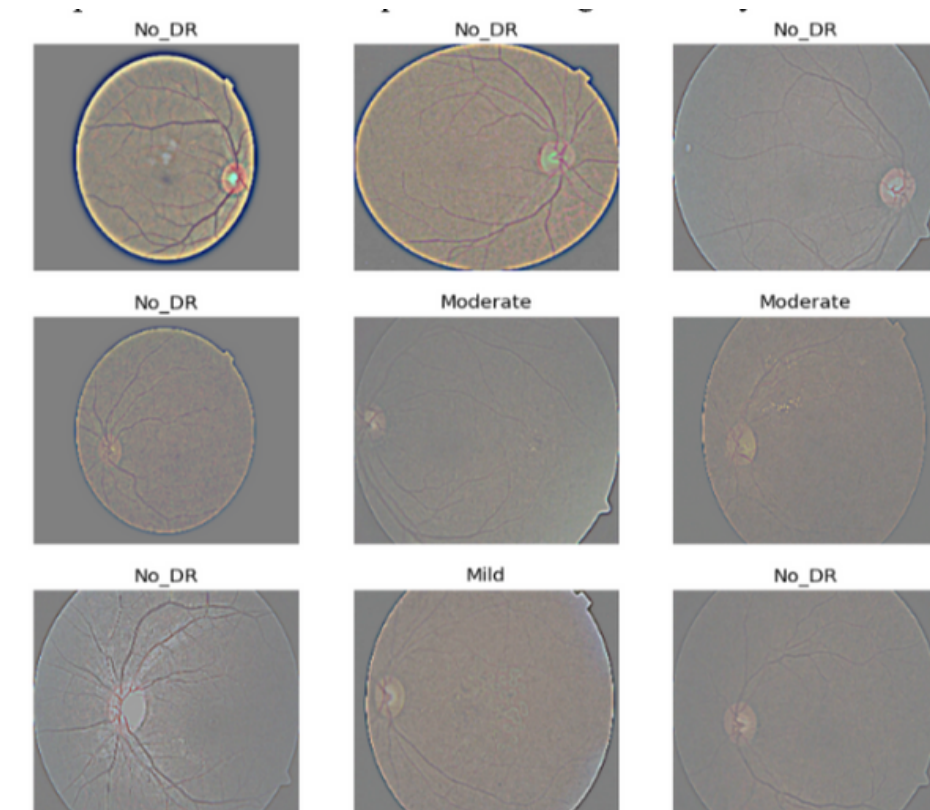


Fig 4: Sample Images from Dataset

METHODOLOGY

4) Quantization

- Convert the Trained Model to TensorFlow Lite for Deployment
- Apply Post Training Quantization for Model Training
- Deploy and Validate the Quantized Model on Devices

5) Gradio Front End and Raspberry Pi Deployment

- Loaded and Initialized TFLite Model For Edge Deployment on Raspberry Pi
- Captured and Preprocessed Images of Fundus Images for Model Input
- Apply Post Training Quantization for Model Optimization
- Perform Real-Time Inference using Gradio-Based Web Interface to Classify Diabetic Retinopathy

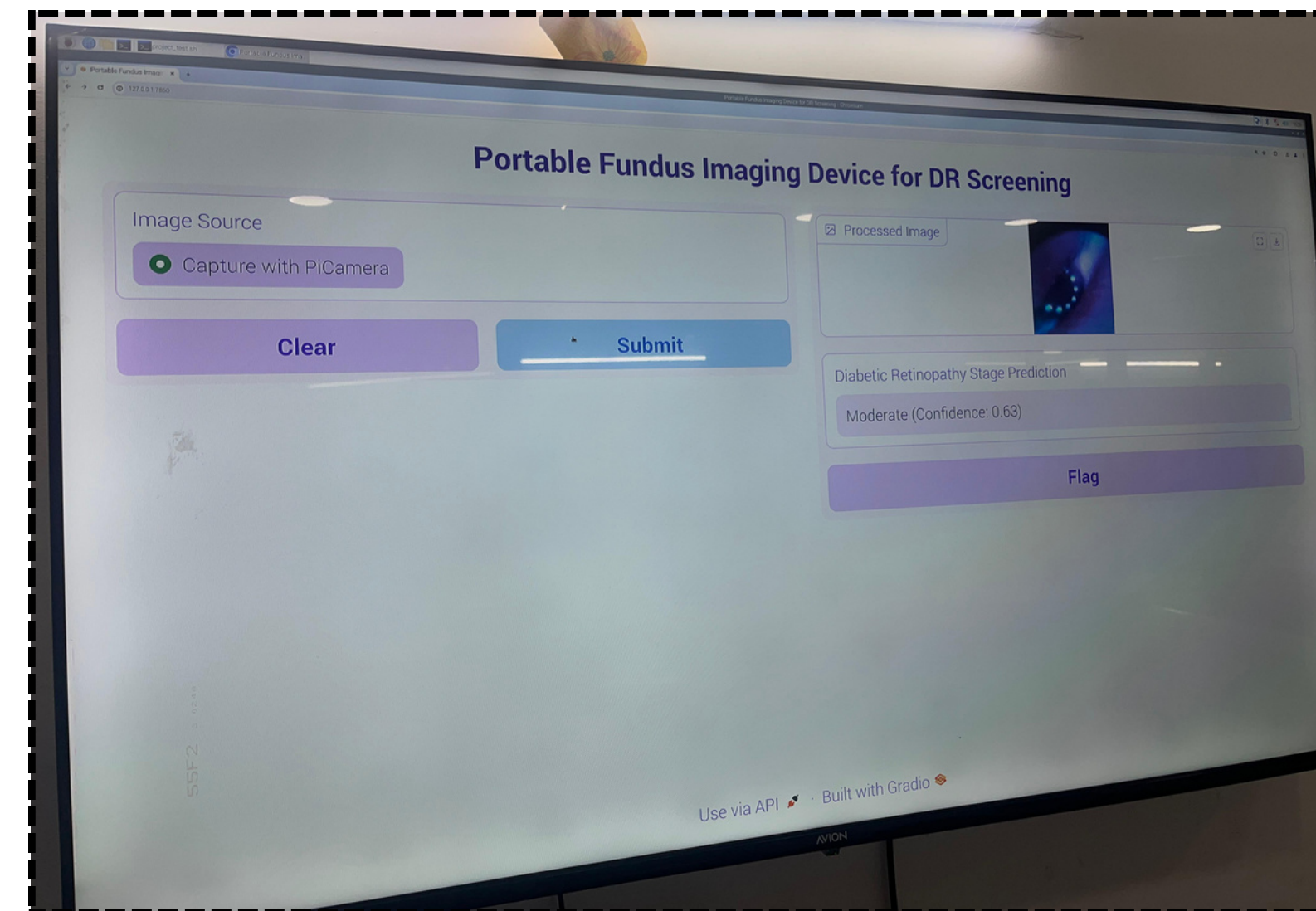


Fig 5: Interactive Gradio Interface

METHODOLOGY

6) Developing the prototype

- A custom prototype was designed and fabricated using ASA material, chosen for its lightweight and durable properties, making it suitable for medical imaging applications.
- To ensure the capture of clear and detailed images, a high-resolution camera was seamlessly integrated into the design.
- Additionally, a carefully optimized lens arrangement was implemented to enhance focus and image sharpness, ensuring accurate visual data acquisition essential for reliable analysis and diagnostics

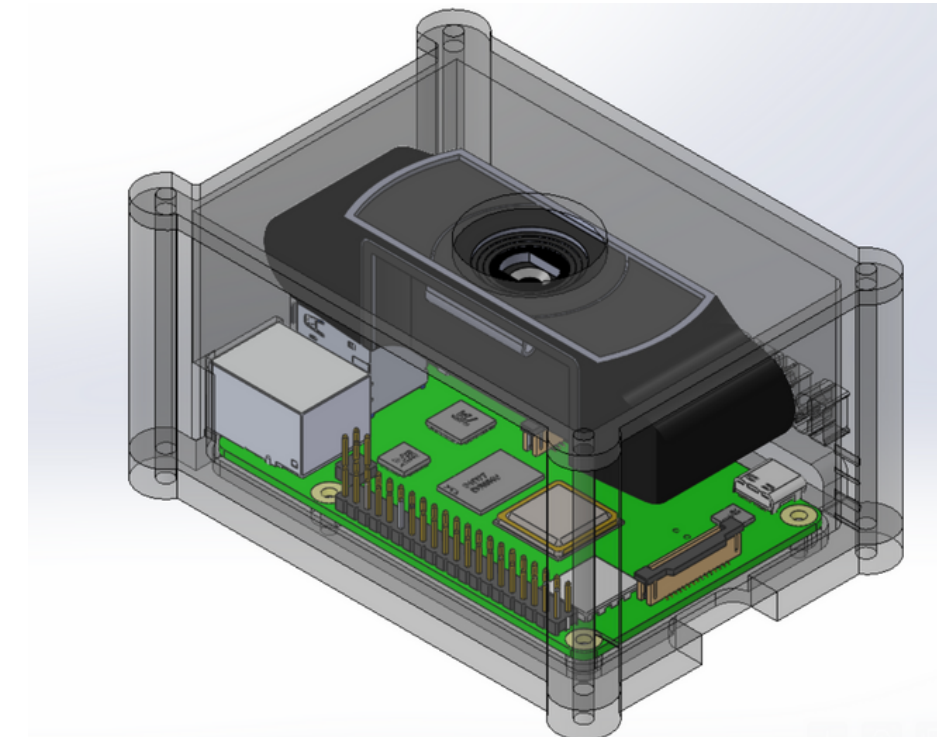


Fig 6: 3D Design of the casing and camera housing



Fig 7: Novel Prototype

RESULT

The model achieved an accuracy of approximately 90%, demonstrating its effectiveness in classifying fundus images for Diabetic Retinopathy detection.

To ensure a comprehensive evaluation, additional performance metrics such as F1 Score, Precision, and Recall were analyzed.

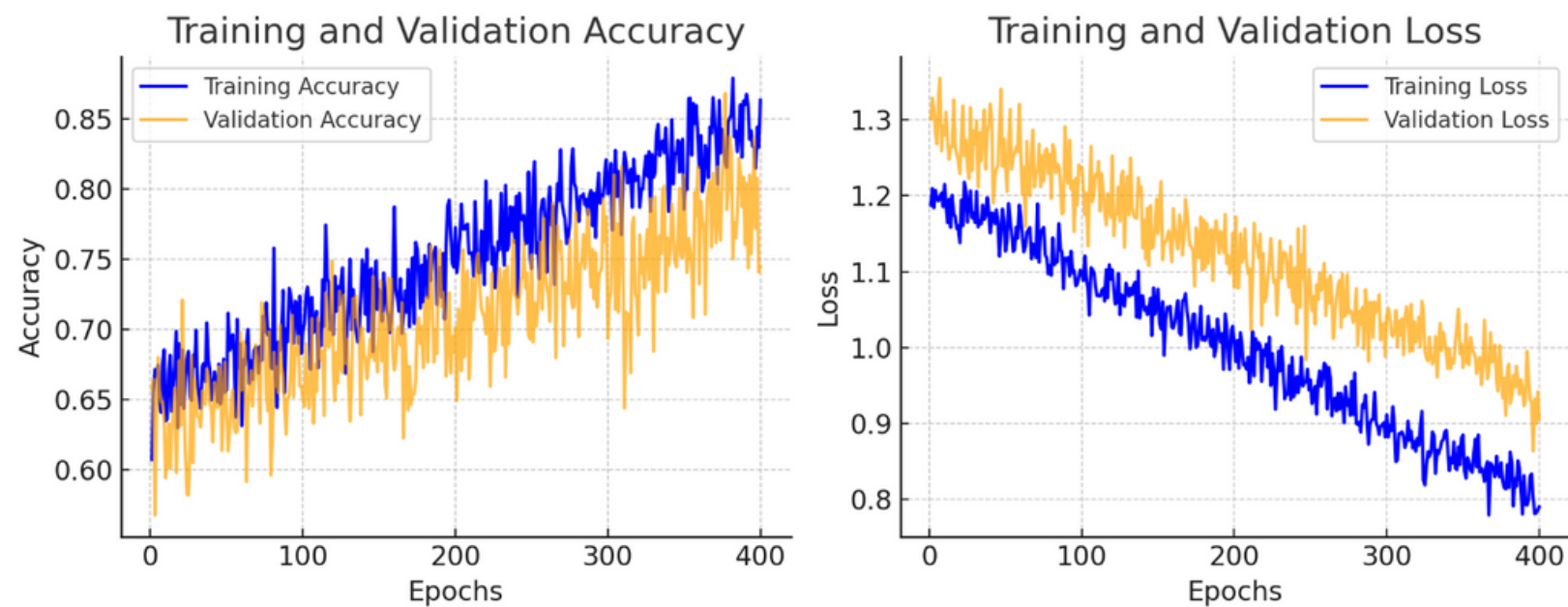


Fig 8: Training and Validation Accuracy

The prototype was also tested in a hospital on 22 patients under the supervision of a doctor.

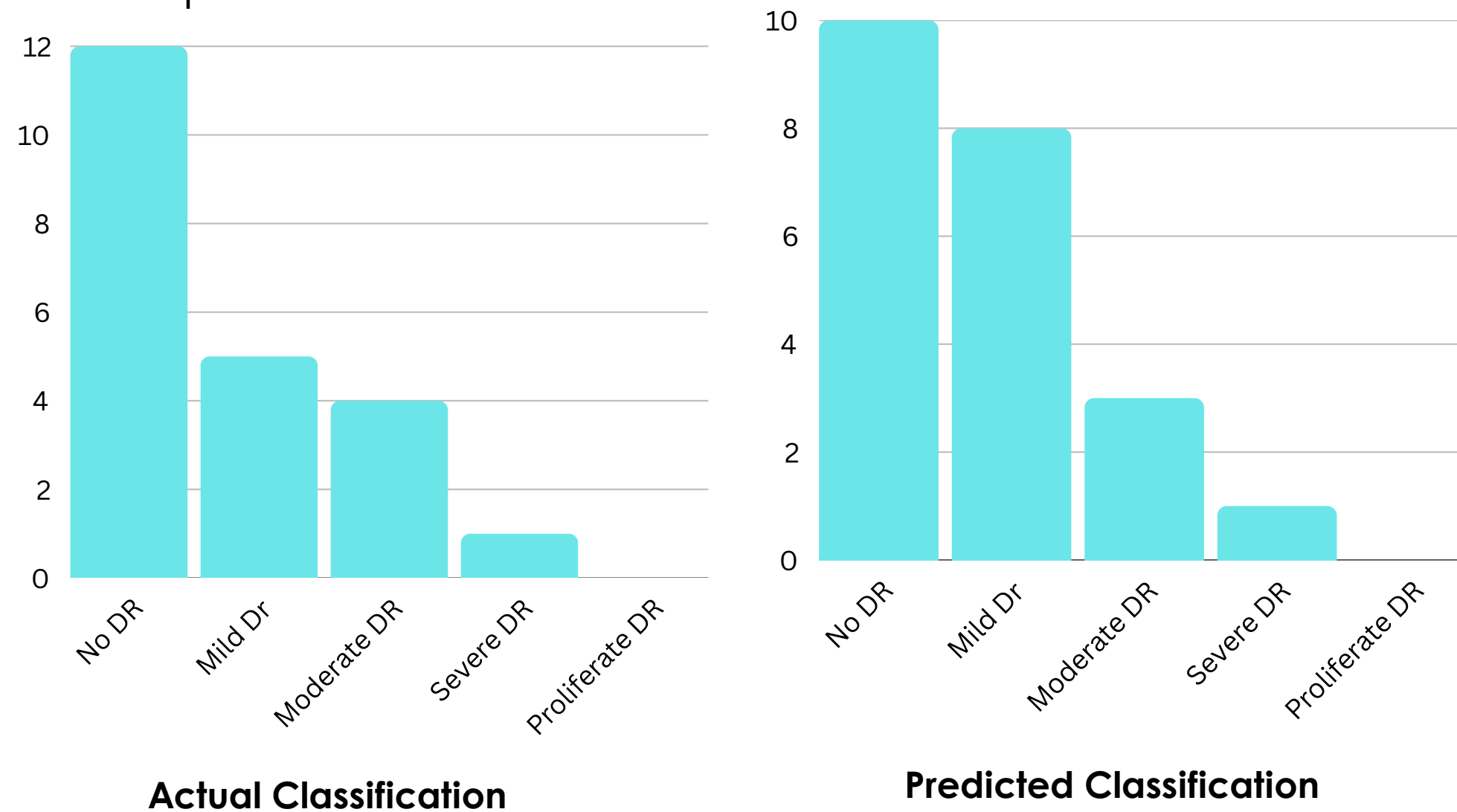


Fig 9: Bar Graph comparing Actual and Predicted Classification

10 out of 12 patients having No DR were correctly classified. All 5 Mild DR patients were correctly classified. 3 out of 4 Moderate DR patients and 1 Severe DR patient were accurately classified.

INFERENCE

The Swin Transformer demonstrates superior feature extraction and classification accuracy thus showing the effectiveness of attention-based architectures in medical imaging. The results validate the model's ability to generalize across diverse datasets, reinforcing its clinical relevance.

Challenges and Solutions

Dataset Imbalance: Uneven distribution of DR severity levels was mitigated through advanced augmentation techniques.

Image Quality Variations: Contrast normalization and noise reduction improved image clarity for better feature extraction.

Real-Time Optimization: Model quantization reduced computational load, enabling deployment on portable and low-power devices.

Prototype Advancements

Better Generalization: Data augmentation improves adaptability across diverse datasets.

Portable & Cost-Effective: Optimized for lightweight deployment, ensuring accessibility in resource-limited settings.

Real-Time & User-Friendly: Gradio-based interface enables quick, automated DR diagnosis without specialized training.

CONCLUSION

The prototype met expectations by improving DR classification accuracy, generalizing well across datasets, and enabling real-time deployment. The integration of quantization and a user-friendly interface enhanced its accessibility and efficiency.

Applications of the Work

- Telemedicine & Remote Screening: Enables DR detection in rural and underserved areas without specialized personnel.
- Hospital & Clinic Integration: Assists ophthalmologists in faster, more accurate diagnosis.
- Preventive Healthcare Programs: Supports early detection initiatives to reduce blindness rates globally.

Future Additions

- Glaucoma & Other Retinal Disease Detection: Expanding the model to detect conditions like glaucoma and age-related macular degeneration.
- Multimodal Analysis: Integrating additional retinal biomarkers for improved diagnostic accuracy.

REFERENCES

1. <https://idf.org/news/idf-iapb-dr-policy-brief/>
2. Yannuzzi, Lawrence A., et al. "Ophthalmic fundus imaging: today and beyond." American journal of ophthalmology 137.3 (2004): 511-524.
3. Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, Baining Guo; Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 2021, pp. 10012-10022
4. Ze Liu, Han Hu, Yutong Lin, Zhuliang Yao, Zhenda Xie, Yixuan Wei, Jia Ning, Yue Cao, Zheng Zhang, Li Dong, Furu Wei, Baining Guo; Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 12009- 12019
5. Ting, Daniel Shu Wei, et al. "Artificial intelligence and deep learning in ophthalmology" British Journal of Ophthalmology 103.2 (2019): 167-175.
6. Usman Akram, M., Khalid, S., Tariq, A., Khan, S. A., & Azam, F. (2014). Detection and classification of retinal lesions for grading of diabetic retinopathy. Computers in Biology and Medicine, 45, 161–171.
7. Xiao, C., Choi, E., & Sun, J. (2018). Opportunities and challenges in developing deep learning models using electronic health records data: a systematic review. Journal of the American Medical Informatics Association.
8. Witkin, A., & Salz, D. (2015). Imaging in diabetic retinopathy. Middle East African Journal of Ophthalmology, 22(2), 145. doi:10.4103/0974-9233.151887
9. Das, D., Biswas, S.K. & Bandyopadhyay, S. A critical review on diagnosis of diabetic retinopathy using machine learning and deep learning. Multimed Tools Appl 81, 25613–25655 (2022).