DIAGNOSIS OF VARIOUS STAGES OF DIABETIC RETINOPATHY USING A DEEP LEARNING BASED APPROACH FROM SMART PHONE BASED FUDUS IMAGES

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ABSTRACT

Abstract- *Smartphone-based fundus imaging has emerged as a promising solution for accessible and cost-effective retinal disease screening. This paper explores the integration of deep learning algorithms with smartphone-based fundus imaging to enhance diagnostic accuracy for retinal disorders such as diabetic retinopathy, glaucoma, and age-related macular degeneration. The proposed approach leverages convolutional neural networks (CNNs) to analyze fundus images and provide automated diagnosis. This study discusses the methodology, challenges, and future directions for smartphone-based deep learning applications in ophthalmology.*

Keyword: - *Smart Phone, Fundus, Imaging, Diabetic Retinopathy.*

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1. INTRODUCTION

Retinal diseases are a leading cause of blindness worldwide [1], with early detection playing a crucial role in preventing vision loss. Traditional fundus imaging techniques rely on expensive and bulky equipment, limiting accessibility, especially in rural and underserved areas.

Retinal diseases account for approximately **2.2 billion cases** of vision impairment worldwide, with **at least 1 billion cases** being preventable or treatable (WHO, 2022). Traditional fundus imaging techniques, such as fundus cameras and optical coherence tomography (OCT), provide high-quality retinal images but are often expensive and inaccessible in remote areas. Smartphone-based fundus imaging, combined with deep learning algorithms, offers a cost-effective and scalable alternative for mass screening and early diagnosis.

2. INTRODUCTION

2.1 Fundus Imaging

Hospitals rely on advanced retinal imaging technologies to diagnose and monitor various ocular diseases, including diabetic retinopathy, glaucoma, and age-related macular degeneration (AMD). These technologies allow for early detection, disease progression monitoring, and treatment planning by providing high-resolution images of retinal structures. Among the most commonly used techniques is fundus photography, which captures color retinal images using a specialized fundus camera equipped with a low-power microscope and a bright flash to illuminate the retina. These cameras can be mydriatic, requiring pupil dilation for better image clarity, or non-mydriatic, which eliminates the need for dilation, enhancing patient comfort. Ultra-widefield fundus cameras extend the imaging field up to 200°, enabling broader retinal assessment. Fundus photography is crucial in diabetic retinopathy screening, hypertensive retinopathy diagnosis, and AI-assisted retinal analysis, with devices such as Zeiss Visucam 224, Topcon TRC-NW400, and Nidek AFC-330 being widely used in hospitals.

2.2 Optical Coherence Tomography

Optical Coherence Tomography (OCT), a non-invasive technique that provides micron-level cross-sectional imaging of the retina. OCT works on the principle of low-coherence interferometry, using near-infrared light to measure reflections from different retinal layers, generating highly detailed images. This technology is instrumental in detecting macular edema, retinal detachment, and glaucoma, as it helps in measuring retinal nerve fiber layer thickness and monitoring structural changes over time. Widely used systems such as Zeiss Cirrus HD-OCT, Heidelberg Spectralis OCT, and Optovue RTVue XR OCT have revolutionized ophthalmic diagnostics by offering real-time, high-resolution retinal layer visualization.

2.3 Optical Coherence Tomography Angiography

Optical Coherence Tomography Angiography (OCTA), which extends OCT functionality by enabling non-invasive visualization of retinal blood vessels and capillaries. Unlike traditional dye-based angiography, OCTA detects motion contrast from red blood cells, constructing vascular maps without the need for dye injections. This method is particularly beneficial in diagnosing diabetic retinopathy, AMD, and retinal vascular occlusions, with Zeiss AngioPlex OCTA, Optovue AngioVue, and Heidelberg Spectralis OCTA being commonly used in hospitals. Adaptive Optics (AO) Imaging has introduced cellular-level visualization of retinal structures by correcting optical aberrations in real-time. AO imaging provides exceptionally high-resolution images of individual photoreceptors, nerve fibers, and capillaries, making it valuable for research and specialized clinical applications. Devices like Imagine Eyes rtx1 AO Fundus Camera and Boston Micromachines AO systems are predominantly used in advanced ophthalmic studies.

3. METHODOLOGY

The proposed system integrates smartphone-based fundus imaging and deep learning techniques to enable cost-effective and accessible retinal screening, particularly for underserved rural areas. The methodology involves three key components: hardware development, software implementation, and output visualization, each contributing to the efficient acquisition, processing, and interpretation of retinal images.

3.1 Hardware Implementation

This project involves the 3D modelling and 3D printing technology for the development of hardware setup of Smart Phone based Fundus Imaging Camera.

3D Design of the Smartphone Mount

To enable consistent and stable fundus imaging using a smartphone, a custom-designed 3D-printed mount was developed. The mount ensures proper alignment between the smartphone camera, lens, and the subject's eye. The design includes adjustable holders for different smartphone sizes and a secure slot for attaching the optical components. CAD software such as SolidWorks or Fusion 360 was used for prototyping, and the final design was fabricated using PLA/ABS materials via FDM 3D printing. The mount also features a modular design for ease of assembly, portability, and ergonomic handling during screening**.**

Lens Selection and Optical Design

The optical system plays a critical role in capturing clear and well-focused retinal images. A 20D condensing lens was selected due to its wide field of view and suitability for indirect ophthalmoscopy. The optical path was designed to align the smartphone's camera lens with the fundus lens, ensuring proper magnification and focus depth. Ray tracing simulations and optical modeling (using tools like Zemax or OpticStudio) were considered to validate the alignment and light transmission efficiency. LED-based diffuse illumination was integrated around the optical path to ensure adequate retinal illumination without causing discomfort.

Hardware Assembly and Calibration

All components including the lens holder, smartphone mount, and light source were assembled into a compact and lightweight module. Electrical components (e.g., battery-powered LEDs) were connected to provide controlled lighting. Calibration was essential to ensure proper focal distance, alignment of optical axes, and minimization of glare or reflections. A test setup with artificial eyes and sample fundus images was used for iterative calibration. The calibration also included adjusting the smartphone's camera settings (focus, ISO, exposure) to optimize image quality.

Smartphone Image Acquisition Setup

Once the hardware was assembled and calibrated, the image acquisition process was set up. The user aligns the device with the patient's eye while the camera app (integrated with the AI model) guides focusing. Real-time image preview helps in ensuring clarity and centering. Images are captured through the mounted lens and directly fed into the mobile application for processing. To reduce motion blur and ensure consistency, a live feedback system with autofocus and image stabilization support was integrated into the mobile app. The acquired images are stored locally or uploaded to a cloud database for further training and diagnostic purposes.

3.2 Software Implementation

Exploring the Dataset

A publicly available diabetic retinopathy dataset (such as the APTOS 2019 or Kaggle's EyePACS dataset) was used, which includes thousands of labeled retinal fundus images categorized into different stages of diabetic retinopathy (e.g., No DR, Mild, Moderate, Severe, Proliferative). The dataset was analyzed for class imbalance, image resolution, and quality before preprocessing and model training.

Using Image Data Generator for Augmentation

To improve model generalization and reduce overfitting, ImageDataGenerator was used for real-time data augmentation.

4. IMAGE PROCESSING STEPS

- **Re-scaling**: Normalizing pixel values to the range [0, 1] using rescale=1./255.
- **Shear Transformation**: Applied to simulate eye movement or different angles of view.
- **Zooming**: Introduced zoom range to simulate camera-based variances.
- **Horizontal Flip**: Enabled to artificially expand dataset by mirroring images.
- **Reshaping**: All images were resized to a consistent input shape (e.g., 224x224 or 299x299) depending on the model architecture used.

Building Model

To achieve high accuracy in diabetic retinopathy classification, several state-of-the-art convolutional neural network (CNN) architectures were explored and evaluated. **ResNet50**, a deep residual network with 50 layers, was fine-tuned using transfer learning with pre-trained ImageNet weights, allowing it to effectively learn subtle retinal features. **InceptionV3**, known for its multi-scale processing capability through inception modules, was utilized for its efficiency in capturing fine-grained patterns such as microaneurysms. To enhance performance further, a **hybrid model** was developed by combining the feature outputs of both ResNet50 and InceptionV3, followed by fully connected layers for classification. This fusion improved feature representation and model robustness. **DenseNet201** was also implemented, leveraging its densely connected layers to promote feature reuse and improve gradient flow, which is particularly beneficial for medical image classification with limited data. Finally, the **Xception** model was employed for its use of depthwise separable convolutions, enabling it to maintain high accuracy while significantly reducing computational complexity—making it suitable for potential deployment on mobile platforms.

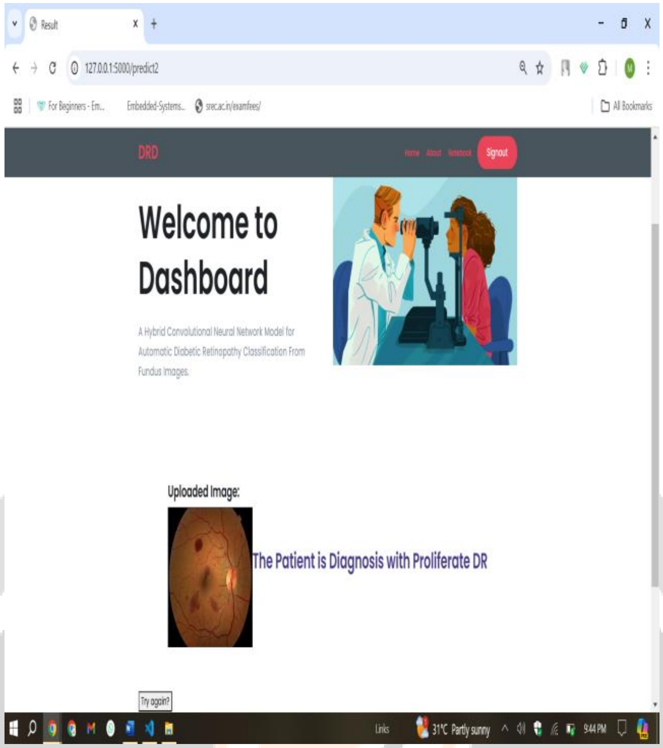


Fig -1: Web Application

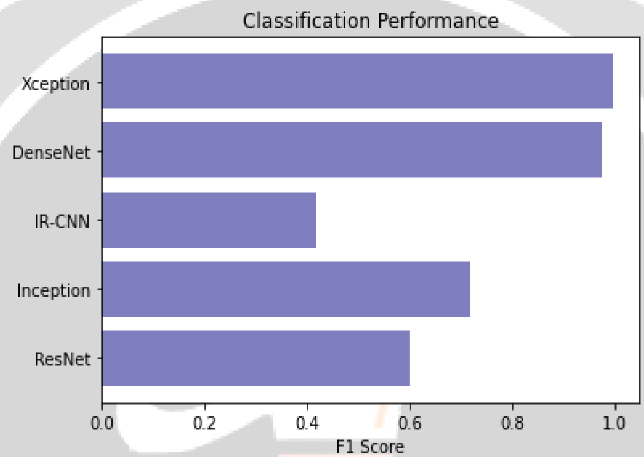
5. SMART PHONE BASED FUNDUS CAMERA

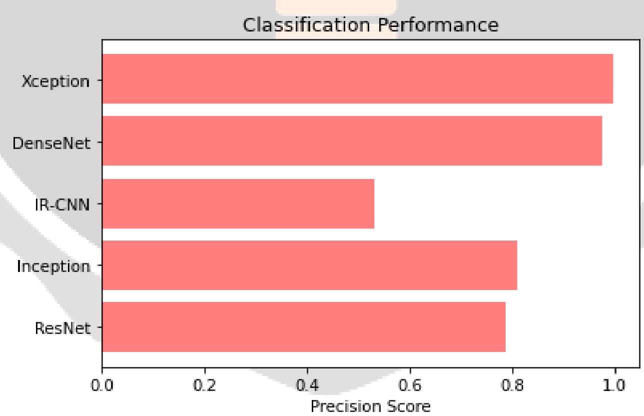
This project presents a novel and cost-effective solution for diabetic retinopathy screening through a smartphone-based fundus camera integrated with deep learning. The system combines a custom-designed 3D-printed optical mount with a condensing lens and LED illumination to transform a standard smartphone into a portable retinal imaging device. Captured fundus images are analyzed using a trained convolutional neural network model embedded within a mobile-friendly web application. The model was trained using augmented datasets and fine-tuned with transfer learning techniques, leveraging architectures like ResNet50, InceptionV3, DenseNet201, and Xception. The final model was deployed using the Flask framework, offering a lightweight interface where users can register via SQLite, upload images, and receive real-time predictions after preprocessing. The system automatically classifies the image into diabetic retinopathy stages and displays the result, supporting early intervention. What sets this project apart is its accessibility and portability, particularly for use in low-resource settings where conventional fundus cameras are either too expensive or logistically impractical. The combination of smartphone imaging and on-device deep learning allows for screening in rural areas, primary healthcare centers, and outreach camps, where early detection can drastically reduce the risk of vision loss. Additionally, the lightweight, battery-operated design, coupled with an intuitive user interface, makes it feasible for non-specialist health workers to operate. This innovation bridges the gap between technology and community healthcare, enabling scalable and proactive diabetic eye care. The system's novelty lies in its integration of affordable hardware, AI-driven analysis, and real-time web deployment—offering an end-to-end solution that is compact, efficient, and impactful.

6. RESULTS AND CONCLUSION

To evaluate the performance of the proposed deep learning models for diabetic retinopathy classification, several state-of-the-art CNN architectures were tested and compared across four key performance metrics: Accuracy, Recall, Precision, and F1 Score. The results are summarized in the figure below. Among all models, Xception demonstrated the highest performance across all metrics, achieving the best scores in accuracy, recall, precision, and F1 score. This superior performance can be attributed to its use of depthwise separable convolutions, which efficiently capture complex patterns in fundus images while maintaining computational efficiency. DenseNet201 closely followed Xception, benefiting from its dense connectivity structure that facilitates gradient flow and feature reuse—making it highly effective in medical image classification.

The hybrid model (IR-CNN), which combines the strengths of Inception and ResNet architectures, showed moderate performance, indicating potential for improvement in feature fusion or training optimization. InceptionV3 alone performed better than ResNet50, particularly in recall and F1 score, highlighting its ability to detect multi-scale features relevant to early-stage diabetic retinopathy. ResNet50, although a powerful model, showed relatively lower performance in this domain, likely due to its deeper architecture and residual connections being less optimized for fine-grained medical features without further tuning. The Xception model's dominance across all four metrics emphasizes its suitability for real-time medical image analysis on mobile platforms, where accuracy and efficiency are both critical. These results validate the robustness and effectiveness of the proposed smartphone-based fundus imaging system integrated with deep learning, making it a promising solution for early diabetic retinopathy screening, especially in low-resource or remote healthcare environments.





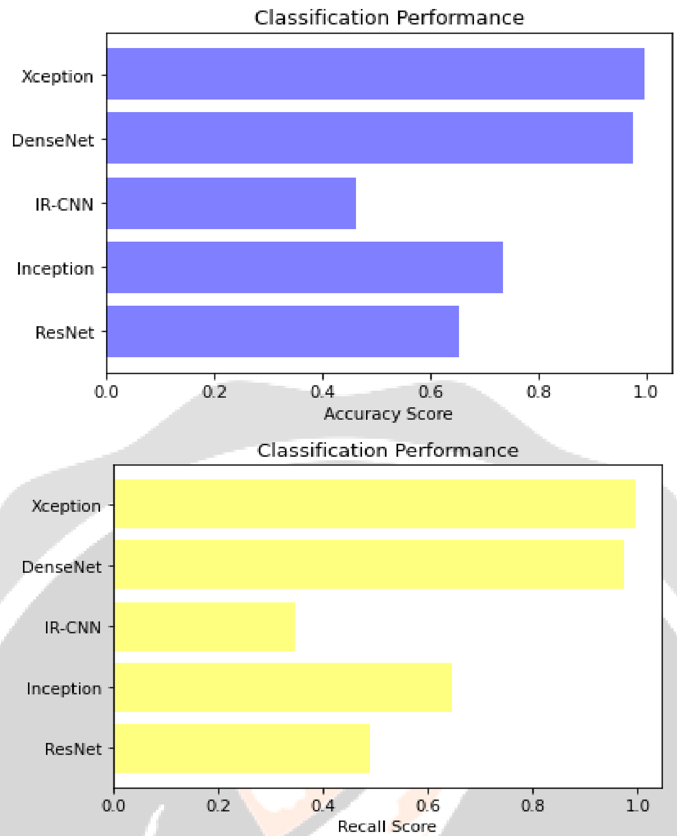


Fig -2: Performance Metrices

7. FUTURE WORK

As a part of future development, the primary focus will be on seamlessly integrating the smartphone-based fundus camera with the trained deep learning model to enable real-time diagnosis of diabetic retinopathy. This integration will allow users—such as healthcare professionals or community health workers—to directly capture retinal images using a smartphone-mounted fundus imaging system and immediately receive predictive results through an embedded application. The captured image will be automatically preprocessed, analyzed by the onboard model, and the diagnostic output will be displayed instantly on the device screen.

To achieve this, further optimization of the model for mobile or edge deployment will be explored, possibly using frameworks like TensorFlow Lite or ONNX for efficient performance on Android or iOS platforms. Additionally, efforts will be made to improve image acquisition consistency through better optical alignment and calibration, ensuring high-quality input for accurate predictions. User-friendly features such as cloud backup, patient history storage, and multilingual support may also be added to enhance usability. This next phase aims to transform the current system into a fully self-contained, portable, and real-time AI-based screening tool, ideal for mass screening and deployment in rural and resource-limited settings.

8. REFERENCES

[1]. "Diabetic Retinopathy Classification with Deep Learning via Fundus Images: A Short Survey," *IEEE Access*, vol. 12, pp. 1-16, 2024, doi: 10.1109/ACCESS.2024.3347012

[2]. "Automated Smartphone Based System for Diagnosis of Diabetic Retinopathy," in *2019 6th International Conference on Computing for Sustainable Global Development (INDIACom)*, Greater Noida, India, 2019, pp. 1-6, doi: 10.1109/INDIACom.2019.8768290.

[3]. "Smart Phone based Fundus Imaging for Diabetic Retinopathy Detection," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 9, no. 33, pp. 1-9, 2023, doi: 10.4108/eetiot.v9i33.2802.

[4]. "Automatic Diabetic Retinopathy Diagnosis Using Adaptive Fine-Tuned Convolutional Neural Network," *IEEE Access*, vol. 9, pp. 40838-40849, 2021, doi: 10.1109/ACCESS.2021.3064707.
[5]. "Diagnosis of Diabetic Retinopathy Using Deep Neural Networks," *IEEE Access*, vol. 7, pp. 119678-119687, 2019, doi: 10.1109/ACCESS.2019.2937422.
[6]. . Roy and S. Chatterjee, "A Review of Deep Learning Methods for Diabetic Retinopathy Detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 5, pp. 1647-1662, May 2021, doi: 10.1109/JBHI.2020.3028975.
[7] M. A. Hossain, M. Hasan, and M. A. Islam, "Lightweight Deep Learning Models for Diabetic Retinopathy Grading in Mobile Health Systems," *IEEE Transactions on Mobile Computing*, vol. 22, no. 7, pp. 3798-3811, July 2023, doi: 10.1109/TMC.2022.3144002.
[8] R. G. Raj and A. S. Kumar, "Teleophthalmology and Deep Learning for Diabetic Retinopathy Detection in Underserved Populations," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 9, pp. 1-9, 2021, doi: 10.1109/JTEHM.2021.3068071.
[9] J. Li *et al.*, "Improving Diabetic Retinopathy Detection Accuracy Using Multi-Scale Convolutional Neural Networks," *IEEE Transactions on Medical Imaging*, vol. 38, no. 11, pp. 2640-2649, Nov. 2019, doi: 10.1109/TMI.2019.2910184.
[10] A. Gulshan *et al.*, "Deep Convolutional Neural Networks for Computer-Aided Detection of Diabetic Retinopathy in Fundus Photographs," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1276-1289, May 2016, doi: 10.1109/TMI.2016.2527025.