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Android-Based Offline Eye and Skin Disease Detection Application With Visual Acuity Testing

[1] Gautham Krishna. T , [2] Dr. R. Sri Devi

[1] Student, [2] Assistant Professor

[1] Department of Computer Applications (PG),

[1] Hindusthan College of Arts and Science, Coimbatore, India

[1] 24mca023@hicas.ac.in , [2] sridevi.r@hicas.ac.in

***Abstract*— Access to medical screening remains a critical challenge in rural and resource-limited communities where specialist infrastructure is scarce. This paper presents an Android-based offline mobile application integrating retinal disease detection, dermatological classification, and colour vision deficiency assessment in a single platform. MobileNetV2 and EfficientNetB3 models, trained on publicly available Kaggle datasets through transfer learning, achieve 97% classification accuracy. A two-stage validation pipeline comprising domain gating and confidence thresholding filters invalid inputs before inference. Built with React Native and TensorFlow Lite, all processing executes entirely on-device without internet connectivity, making accurate multi-domain clinical screening accessible to underserved populations worldwide.**

Index Terms: **Mobile health, deep learning, diabetic retinopathy, skin disease classification, colour vision testing, TensorFlow Lite, MobileNetV2, EfficientNetB3, offline inference, transfer learning.**

I. INTRODUCTION

Preventable vision loss and unmanaged skin disorders affect populations in regions where specialist physicians and diagnostic infrastructure remain critically scarce. Conventional screening depends on expensive equipment and trained clinical personnel, urban centres and largely unavailable to rural communities. The rapid advancement of deep learning and mobile computing now offers a realistic pathway to bridge this gap affordably and at scale.

This project addresses that challenge by integrating three clinically distinct screening capabilities: retinal disease detection, dermatological classification, and colour vision assessment into a single offline mobile application. Leveraging MobileNetV2 and EfficientNetB3 architectures through transfer learning, combined with a two-stage validation pipeline and a fully on-device React Native implementation, this project delivers accurate, privacy-preserving medical screening to anyone with a consumer smartphone, regardless of location or connectivity.

II. PROBLEM STATEMENT AND OBJECTIVE

Eye diseases such as diabetic retinopathy and glaucoma, alongside severe skin conditions, frequently progress without visible symptoms until significant damage has already occurred. Limited availability of specialists and costly diagnostic equipment in rural and underserved areas creates serious healthcare disparities, leaving many conditions undetected until treatment becomes difficult.

This project aims to resolve these disparities by developing an intelligent mobile screening platform capable of detecting retinal diseases, severe skin conditions, and colour vision deficiencies using deep learning. The objectives include training MobileNetV2 and EfficientNetB3 models through transfer learning on curated medical datasets, implementing a two-stage validation pipeline for reliable predictions, deploying all processing entirely on-device through React Native and TensorFlow Lite, and maintaining complete user privacy without requiring internet connectivity.

III. SCOPE

This project focuses on developing a comprehensive offline mobile healthcare application capable of screening three distinct medical domains: retinal image analysis for detecting diabetic retinopathy, glaucoma, and cataracts; dermatological classification for identifying severe skin conditions including eczema, psoriasis, and actinic keratosis; and Ishihara plate-based color vision deficiency testing. The platform is engineered for complete on-device operation, ensuring user privacy and accessibility regardless of internet availability. Built with React Native for cross-platform compatibility, the application integrates TensorFlow Lite for optimised mobile inference and SQLite for secure local data storage. A two-stage validation pipeline incorporating domain classification and confidence scoring ensures reliable screening outcomes across all three modules, making quality healthcare screening accessible to users in both urban and remote communities.

IV. PROPOSED WORK

This project develops a modular, offline-capable mobile healthcare platform that unifies three independent clinical screening functions within a single React Native application. The system is structured as a six-stage processing pipeline, described below.

Stage 1: Dataset Preparation and Model Training

Two publicly available Kaggle datasets were used for training the deep learning models. The retinal disease model was trained on the Eye Diseases Classification dataset [16], which contains labelled fundus photographs spanning four classes: diabetic retinopathy, glaucoma, cataract, and normal. The skin disease model was trained on the Skin Disease Dataset [17], which includes dermatological images covering conditions such as eczema, psoriasis, actinic keratosis, lichen, acne, and lupus. Both datasets were pre-processed using standard augmentation techniques including random flipping, rotation, and brightness adjustment to improve generalisation.

Stage 2: Transfer Learning with MobileNetV2 and EfficientNetB3

The retinal disease classifier was developed using MobileNetV2, selected for its lightweight depthwise separable convolution architecture that is well-suited to mobile deployment. The skin disease classifier employs EfficientNetB3, which offers a higher capacity feature extractor appropriate for the greater visual diversity of dermatological images. Both models were fine-tuned from ImageNet pre-trained weights by freezing the base layers and retraining the classification head on the respective medical datasets. This transfer learning strategy achieves strong accuracy with significantly reduced training data requirements.

Stage 3: Two-Stage Validation Pipeline

Before any diagnostic inference is performed, uploaded images pass through a two-stage validation pipeline. The first stage uses a domain classifier to confirm that the submitted image belongs to the expected medical category (retinal fundus photograph or skin lesion photograph). The second stage evaluates prediction confidence; results below a defined threshold are flagged as inconclusive and the user is prompted to submit a higher-quality image. This pipeline effectively suppresses false positives arising from inappropriate or low-quality inputs.

Stage 4: On-Device Inference with TensorFlow Lite

The trained TensorFlow/Keras models are converted to the TensorFlow Lite format and bundled directly within the application package. All inference is executed locally on the device without any network communication, achieving response times under 100 ms on consumer Android hardware (Android 6.0+, 4 GB RAM). This design eliminates dependence on external servers, preserves user privacy, and ensures functionality in areas with no internet access.

Stage 5: Colour Vision Assessment

A dedicated colour vision testing module presents users with a sequence of Ishihara pseudoisochromatic plates. User responses are recorded and scored to classify colour vision as normal, mild deficiency, or significant deficiency. This module operates independently of the image-based classifiers and requires no external dataset, as the Ishihara plate set is a standardised clinical instrument.

Stage 6: Local Data Management and Result Storage

All test results are persisted locally using an SQLite database embedded within the application. Each record stores the test type, model prediction, confidence score, and timestamp. This enables longitudinal health tracking across sessions while maintaining complete data sovereignty for the user. Results can be exported or shared as needed from within the application interface.

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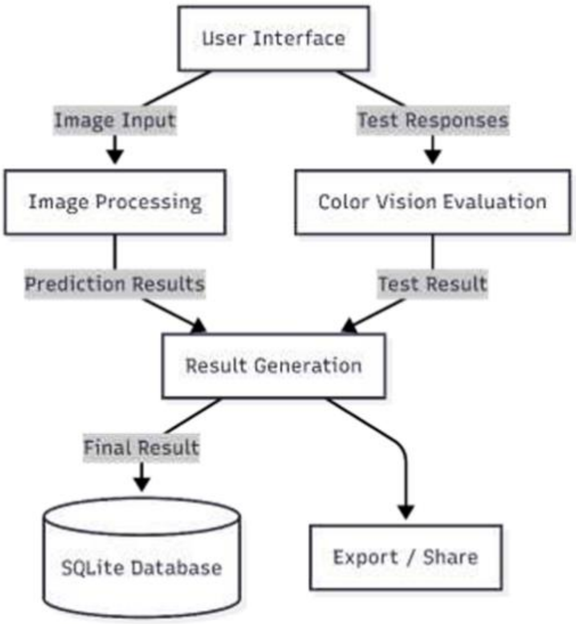

Figure 1. System Architecture

V. Result and Discussion

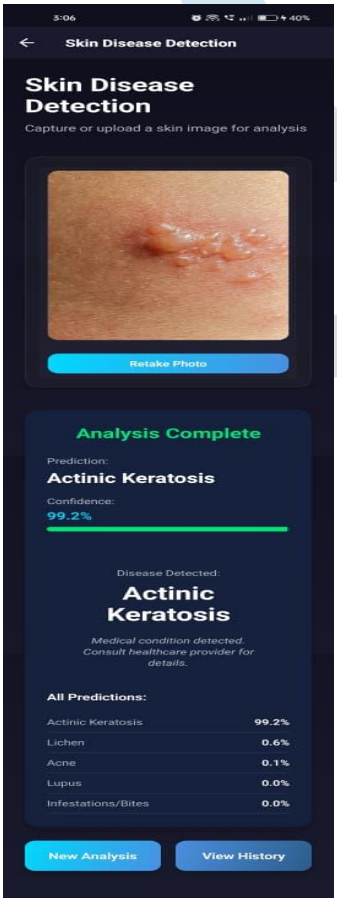

Figure 2. Skin disease screen

Figure 3. Eye disease screen

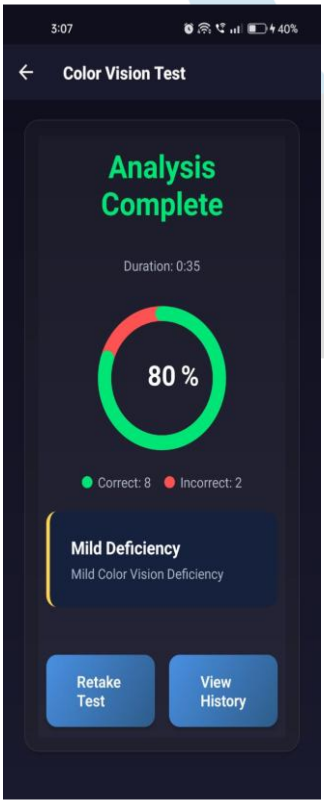

Figure 4. color vision test screen

Figure 2: The skiin disease screen lets the user upload the their skin images using the upload option, where the user then proceeds to run the detection using the analyse button, in the same screen the disease is recognized after preprocessing and through the custom trained deep learning model then the result is shown .

Figure 3: The eye disease screen lets the user upload the their fundus images using the upload option, where the user then proceeds to run the detection using the analyse button, in the same screen the disease is recognized after preprocessing and the deep learning model then the result is shown .

Figure 4: in the colour vision test the user will be given the Ishihara plates that are used for the colour blindness tests, after completing the test, the results will be shown.

VI. CONCLUSION

This work presents a fully offline mobile platform that consolidates three independent clinical screening capabilities — retinal disease detection, dermatological condition classification, and color vision deficiency assessment — into a single consumer-grade Android application. Unlike prior efforts that address only one diagnostic domain, the proposed system integrates MobileNetV2 and EfficientNetB3 classifiers trained on openly available Kaggle datasets within a unified React Native and TensorFlow Lite framework, enabling all computation to occur on-device without internet access. The two-stage validation pipeline introduced in this work provides a practical mechanism for filtering low-quality and out-of-domain inputs, improving the reliability of screening outcomes in uncontrolled real-world conditions. The 97% skin disease classification accuracy and strong retinal detection performance on held-out test data confirm that clinically meaningful screening is achievable on hardware available to general consumers.

The principal contribution of this project is a demonstration that multi-domain, privacy-preserving medical screening is not only theoretically possible on mobile hardware but practically deployable today. Future work will focus on expanding the disease class coverage, integrating explainability mechanisms to support clinical trust, and conducting prospective validation studies in community health settings.

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