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Retinal Image Analysis for Heart Disease and Diabetes using Deep Learning

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Abstract—Cardiovascular diseases (CVDs) continue to be the primary cause of death globally, underscoring the need for efficient methods of early detection and risk assessment. The retina provides a distinctive, non-invasive view of the body's vascular system, and recent progress in deep learning has enabled the extraction of health indicators from retinal imagery. This project develops a deeplearning-based system that analyzes retinal fundus images to support screening for diabetic retinopathy and selected systemic health risks, including cardiovascular risk. The system uses a convolutional neural network (CNN) based on Inception-v3 and performs image-quality assessment, preprocessing, EM/GMM segmentation and feature extraction before classification. It classifies diabetic retinopathy into five stages and can optionally combine retinal information with clinical parameters such as age, blood pressure, BMI and glucose levels for preliminary risk assessment. Class activation maps (CAMs) highlight the retinal regions that influence each prediction. The system is implemented as a web-based application using Python and Flask and provides image upload, prediction, visualization, history and report-generation features. It is intended as a fast, non-invasive screening-support and research tool that can assist healthcare professionals, and it does not replace professional medical diagnosis.

Index Terms—Retinal Fundus Images, Deep Learning, Diabetic Retinopathy, Cardiovascular Risk, CNN , Medical Image Analysis, Artificial Intelligence, Non – Invasive Screening.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are disorders of the heart and blood vessels, including heart attacks, strokes, high blood pressure and heart failure. Changes in the size and shape of retinal blood vessels can indicate such diseases, and machine-learning (ML) models can be trained on retinal images to estimate an individual's risk from subtle image characteristics

This work relates to computer-aided diagnosis, risk stratification, explainable AI (XAI), image preprocessing, multimodal health Conventional cardiovascular risk assessment depends on clinical evaluation and specialised tests such as blood-pressure measurement, lipid profiling, electrocardiography (ECG) and, occasionally, advanced imaging. However, these approaches can be slow and expensive, and are often unavailable in low-resource settings.

The retina is a sensitive part of the human eye that contains a large network of small blood vessels. Since these vessels can reflect changes occurring in the body, retinal fundus images can provide useful information about certain systemic diseases.

The goal of this project is to use machine-learning methods, mainly convolutional neural networks (CNNs), to analyze retinal fundus images for diabetic retinopathy and to support the assessment of cardiovascular and diabetes-related risk.

In other words, the aim is to build a system that can screen for these conditions using only the information contained in eye images. Such an approach could offer a quick, non-invasive and affordable way to support doctors, promote early detection and make health-risk assessment more accessible.

Recent advancements in deep learning have created new opportunities for automated analysis of retinal fundus images. In particular, CNNs can automatically extract important features such as blood vessel patterns, vessel width, retinal texture and structural variations. These features help identify abnormalities that may be associated with diabetic retinopathy and cardiovascular risk factors.

Transfer learning can further improve the performance of the proposed system by using pretrained deep learning architectures. This approach reduces training time and improves feature extraction, especially when the available medical image dataset is limited. Image preprocessing techniques such as resizing, normalization, noise removal and contrast enhancement can improve image quality and support accurate classification.

Overall, this research explores the potential of artificial intelligence in preventive healthcare by using retinal fundus images as a non-invasive source of information. The proposed system is intended to support early screening and clinical decision-making rather than replace professional medical diagnosis. The system can be particularly beneficial in rural and resource-limited healthcare environments where access to specialised diagnostic facilities may be restricted.

II. Literature Review

A. Cardiovascular Markers and Diseases from Retinal Images

Li et al. presented a systematic scoping review of studies that apply deep learning to retinal fundus images to predict cardiovascular risk markers and diseases [1]. The review reports growing interest in this approach, with some studies showing improved prediction, and identifies the combination of image-based predictions with conventional clinical risk factors as a promising direction.

B. Central Serous Retinopathy Detection

Hassan et al. applied pre-trained deep networks (DarkNet and DenseNet) to augmented fundus and OCT images for detecting central serous retinopathy [2]. Their work shows that deep models can learn retinal patterns directly from images and that image preparation is useful, supporting automated screening where specialist access is limited.

C. Integrating ECG and Fundus Images

Muthukumar et al. combined electrocardiogram (ECG) data with retinal fundus images for early detection and triage of cardiovascular diseases [3]. Their multimodal approach shows that complementary data sources can give a broader picture of patient health than retinal images alone.

D. Cardiovascular Risk Factors from Fundus Photographs

Poplin et al. trained deep networks on retinal fundus photographs to predict cardiovascular risk factors such as age, blood pressure and smoking status [4]. The study shows that retinal images contain cardiovascular information that is not readily quantifiable by manual inspection.

E. Overview of Deep Learning for Retinal Imaging

Barriada and Masip reviewed the datasets, preprocessing techniques, evaluation metrics and deep-learning approaches used in 30 studies on cardiovascular risk assessment from retinal fundus images [5]. The review highlights the role of CNNs in learning image features automatically and the importance of preprocessing.

F. Retinal Images with DXA Data

Al-Absi et al. proposed a multimodal deep-learning method that combines retinal images with DXA scan data to distinguish cardiovascular patients from controls [6]. Their results show the potential of retinal imaging for fast and relatively non-invasive detection of cardiovascular disease.

G. CNN-Based Heart Disease Prediction

Shankar et al. proposed a CNN-based model for heart-disease prediction from patient clinical data [7]. The study shows that CNNs can also support decision-making on healthcare data beyond image-based applications.

II. Proposed System

The proposed system is a deep-learning-based platform for retinal fundus image analysis that supports screening for diabetic retinopathy and selected systemic health risks, including cardiovascular risk. Unlike traditional methods that rely on clinical tests or invasive procedures, it offers a non-invasive, automated and scalable approach by analyzing retinal images, which contain rich information about the small blood vessels linked to heart and vascular conditions [1], [4].

At the core of the approach is a convolutional neural network (CNN), a deep-learning model designed for image data. The system uses the Inception-v3 architecture [8], whose convolutional and pooling layers automatically learn visual features from the retinal image.

RetinaHealth AI is a modular retinal screening-support platform. The workflow begins with retinal-image upload and ends with prediction, visualization, storage and report generation, as shown in Fig. 1.

The major stages are:

Image Upload → Quality Assessment → Preprocessing → EM/GMM Segmentation → Inception-v3 Feature Extraction → Prediction → Points Assignment → CAM Visualization → Result Display → Database Storage → Report Generation

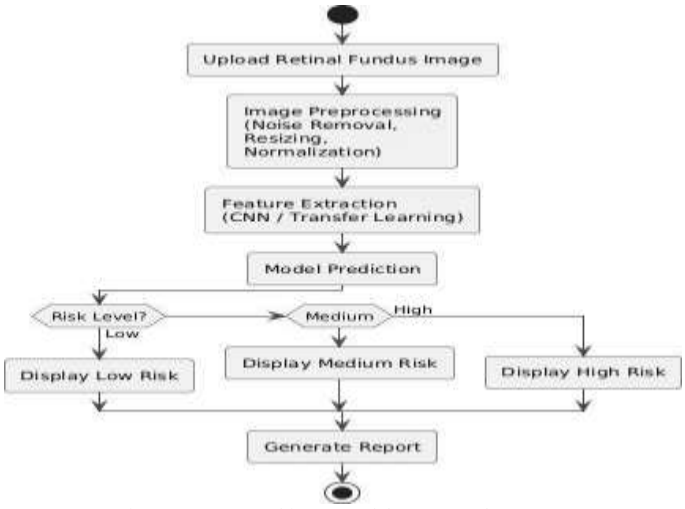


Fig. 1. System architecture of the proposed system

A. Image Upload

The user logs in to the web application and uploads a retinal fundus image, optionally entering clinical parameters such as age, blood pressure, BMI and glucose. This stage receives the file, checks that it is a valid image and passes it to the next stage. Its purpose is to provide a single, controlled entry point so that only well-formed input enters the pipeline.

B. Image Quality Assessment

Before analysis, the uploaded image is checked for suitability using its dimensions, brightness, contrast, variance and colour characteristics. Images that do not meet the required conditions are not passed to the model. This stage prevents unreliable predictions caused by dark, blurred or otherwise unsuitable images and therefore improves the dependability of the results.

C. Preprocessing and Segmentation

Images that pass the quality check are converted to the required format and resized to 299 × 299 pixels, the input size of Inception-v3. EM/GMM segmentation [10] then groups pixels into regions according to their intensity distribution. This standardizes the input and separates retinal structures from the background before feature extraction.

D. Feature Extraction and Prediction

The Inception-v3 network [8] converts the image into a

2048-dimensional feature vector. Fully connected layers use this vector to generate the prediction: a five-stage diabetic-retinopathy classification and, when optional clinical parameters are supplied, a preliminary estimate of diabetes/glycemic, hypertension and cardiovascular risk (for example, low, moderate or high).

E. Results, Points Assignment and Storage

A CAM heatmap [9] highlights the regions that influenced the prediction. Points are assigned to the prediction result and displayed together with the predicted class and heatmap. The record is then saved in the database for the history feature, and a PDF report can be generated. This stage turns the model output into information a user or clinician can interpret and review later.

III. EXPERIMENTAL RESULTS

The system was run on sample retinal images to check the complete workflow. The web application allowed users to sign up, log in, upload images and view the results, and the prediction-history feature stored results correctly. Figs. 2–8 show the application pages and analysis results. A quantitative performance evaluation on an independent test set is left for future work.

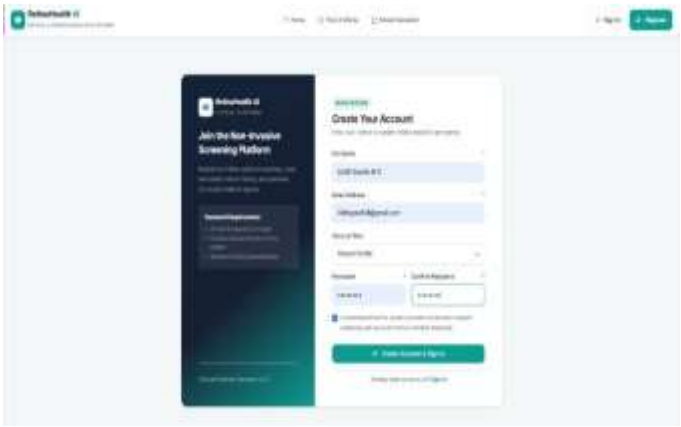


Fig. 2. Registration Page



Fig. 3. Home Page



Fig. 4. Home Page After Sign-In



Fig. 5.Platform Analysis Overview

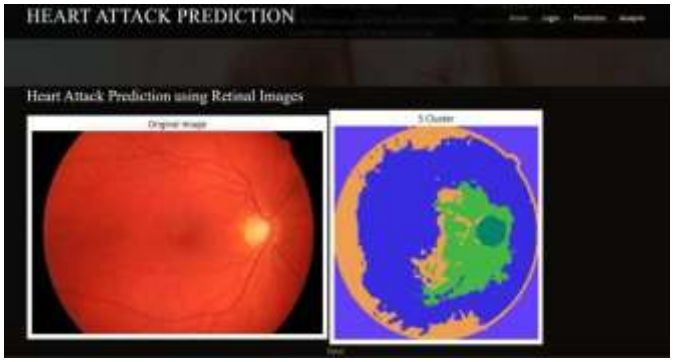


Fig. 6. Cluster Analysis Result

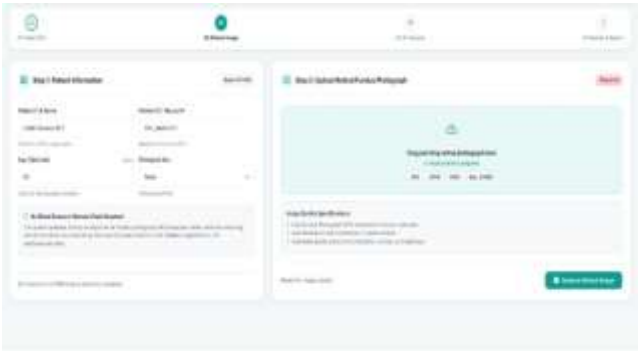


Fig. 7. Patient Information and Image Upload Page

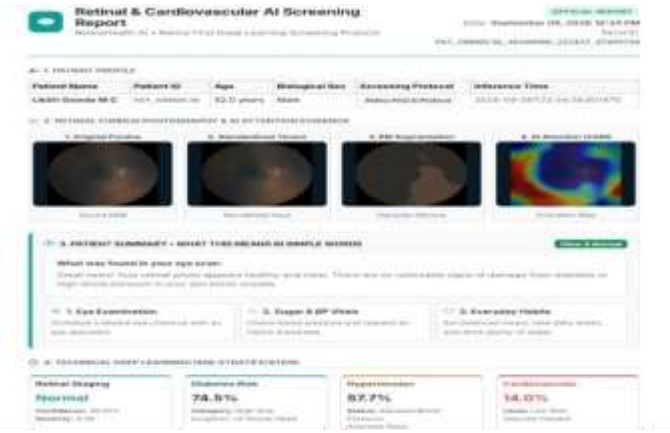


Fig. 8. Screening Report

V. ALGORITHMS USED

A. EM/GMM Segmentation

A Gaussian mixture model represents the pixel intensities of an image as a weighted sum of Gaussian components, each corresponding to a region type. The Expectation-Maximization (EM) algorithm [10] estimates the parameters iteratively: the E-step computes the probability that each pixel belongs to each component, and the M-step updates the component means, variances and weights. The two steps repeat until convergence, and each pixel is assigned to its most probable component. This soft, probabilistic grouping suits retinal images, which are often noisy and have overlapping intensities.

B. Inception-v3 Feature Extraction

Inception-v3 [8] is a CNN built from inception modules that apply convolutions of several sizes in parallel, together with pooling, to capture features at multiple scales. In this system the 299 × 299 retinal image is passed through the network to produce a 2048-dimensional feature vector that compactly represents the visual information in the image.

C. Prediction Generation

Predictions are generated in the following steps. (1) The quality-checked image is resized to 299 × 299 and segmented. (2) Inception-v3 converts it into a 2048-dimensional feature vector. (3) Fully connected layers transform this vector and an output layer produces a score for each class. (4) The class with the highest score is returned as the predicted label, i.e. one of the five diabetic-retinopathy stages, together with its confidence. (5) If clinical parameters were entered, they are combined with the retinal information to give a preliminary risk estimate. (6) A class activation map [9] is computed to show which image regions contributed most to the predicted class. (7) The predicted result, points, heatmap and risk information are displayed, stored in the history and included in the PDF report. The output is a screening aid and not a clinical diagnosis.

VI. FUTURE SCOPE

A. Integration with Real Medical Databases

Connect with hospital information systems (HIS) or electronic health records (EHR) for seamless access to patient data.
Allow specialists to review screening reports remotely through telemedicine platforms

B. Inception -v3 Feature Extraction

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III. CONCLUSION

This paper presented RetinaHealth AI, a deep-learning-based retinal-image screening-support system for diabetic retinopathy and selected systemic health-risk assessment. The system processes retinal fundus photographs through image-quality assessment, preprocessing, EM/GMM segmentation and Inception-v3 feature extraction, and uses the extracted features for five-stage diabetic-retinopathy classification. Optional clinical parameters such as age, blood pressure, BMI and glucose can be combined with retinal information for preliminary diabetes, hypertension and cardiovascular-risk estimation, and CAM heatmaps improve the interpretability of the predictions. A Flask-based web application integrates image processing, prediction, history management, database storage and PDF report generation. The main contribution is the integration of several screening-support functions into a single modular platform rather than a focus on a single prediction task. The system is intended to assist preliminary screening and research and should not be considered a replacement for professional medical diagnosis. Further work with larger datasets, independent validation and clinical evaluation is necessary before real-world deployment.

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