

Automated Retinal Multi-Disease Detection with Explainability using Raspberry Pi

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Abstract—Organized illnesses such as diabetic retinopathy, glaucoma and age-related macular degeneration are one of the world's driving but avoidable causes of visual disability. Early location and conclusion are greatly critical, particularly in regions with lacking administrations where get to uncommon eye care isn't limited. This extend presents an inventive, reasonable and versatile framework for auto-detecting a few retinal conditions. It is worked by a profound learning show utilizing the Raspberry PI5. The framework employments collapsing systems (CNNs) prepared with freely accessible save finance picture information records to appropriately recognize different network-like add up to active activity natures. To extend the interpretability and unwavering quality of the comes about, the gadget coordinating informative AI strategies such as actuation task (GRAD-CAM) and locally interpretable demonstrate tag portrayals (LIME). These devices contribute to demonstrate choices, back both wellbeing proficient individuals and conclusion clients, and offer assistance get it the results. This compact gadget forms fundus pictures in close genuine time, appearing both symptomatic comes about and visual depiction cards on a 3.5-inch show. The framework illustrates solid exactness and commonsense execution, making it perfect for utilize in wellbeing programs, mobile-Aiden Camps, and clinics with constrained framework. By filling the hole between AI advance and down to earth utilize, this approach underpins early conclusion and progresses understanding care results.

Index Terms—Retinal malady detainment, raspberry-PI, profound learning, CNN, therapeutic picture investigation, logical AI, Grad-CAM, LIME, diabetic retinopathy, glaucoma,

I. INTRODUCTION

Vision impairment resulting from retinal conditions, including diabetic retinopathy, glaucoma, and age-

related macular degeneration, has emerged as a significant public health issue, especially in low- and middle-income areas where access to specialized eye care is scarce. Early detection and prompt treatment are vital to avert permanent blindness. Nonetheless, the shortage of qualified ophthalmologists and costly diagnostic tools hinders effective screening and supervision.

In recent years, breakthroughs in artificial intelligence (AI), particularly in deep learning, have created new opportunities for analysing medical images. Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in categorizing medical images, such as retinal fundus photographs. These AI technologies can help automate disease diagnosis, alleviate the pressure on healthcare providers, and enhance the availability of diagnostic services.

This device introduces an affordable, portable solution for the automated identification of various retinal diseases utilizing a Raspberry Pi 5. The system employs a CNN model to classify fundus images and incorporates explainability tools such as Grad-CAM and LIME to showcase the areas that influenced the model's predictions. This level of transparency fosters confidence in the AI system, particularly in medical contexts where understanding is crucial.

Key Insights

Numerous studies have investigated the use of deep learning models to identify retinal diseases through fundus images. High-performance CNNs have been trained on vast datasets to accurately determine conditions like diabetic retinopathy and glaucoma. However, many of these solutions necessitate high-end computing resources like GPUs or cloud servers, making them less feasible for rural or low-resource

environments. Additionally, most existing models function as "black boxes," offering predictions without explanations, which limits their acceptance in clinical practice.

Timely diagnosis of retinal diseases is essential, yet access to ophthalmologists and diagnostic equipment is often constrained in various regions. Conventional AI models are effective but frequently come with high costs, lack portability, and are not transparent. Thus, there is a demand for an economical, understandable, and compact system that can aid in detecting retinal diseases directly at the point of care.

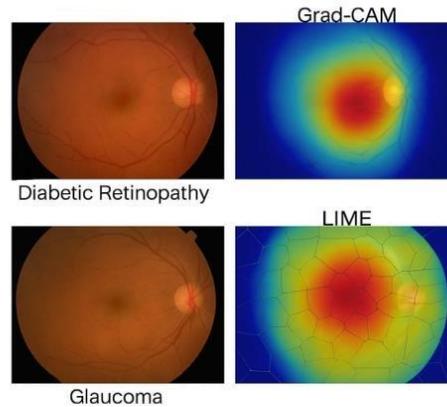
This device presents a portable, low-cost, AI-driven solution constructed with Raspberry Pi 5 for identifying multiple retinal diseases. A trained CNN model operates locally to classify fundus images, and explainability tools like Grad-CAM and LIME emphasize the critical areas impacting the decision. The results are shown on a small screen, making the system self-sufficient and easy to use. This design permits real-time diagnosis with visual explanations, suitable for implementation in mobile eye camps and community health facilities.

The use of artificial intelligence for detecting retinal diseases has been a vibrant field of research over the last ten years. Numerous studies have concentrated on applying deep learning methods, especially Convolutional Neural Networks (CNNs), to classify retinal fundus images for conditions such as diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD), hypertensive retinopathy, retinal vein occlusion, and cataracts. Large publicly available datasets, including EyePACS, APTOS, DRIVE, and MESSIDOR, have been extensively utilized to train and validate these models.

II. EXISTING WORK

Numerous being frame conditions achieve high empirical delicacy and regularly exceed the prosecution of people at the mortal position of a particular bracket company. For the illustrations of models similar as InceptionV3, ResNet50, and effective networks were finely matched to and linked different inflexibility situations of diabetes retinopathy. These models generally shoot using a pall-grounded frame or a high interpretation near the machine. This limits the vacuity of locally at indeed lower coffers

Recent research has applied deep learning models to detect retinal diseases, utilizing heatmaps from Grad-CAM and LIME for explainability.



Grad-CAM Heatmap

Grad- Cam Heat Map creates visual considerations and creates. This includes a number of images related to the selection of model. Although contending is solid, utmost of these symptoms acts as dark boxes on bias grounded on A-, without any ideas about prognosticating will be given. This demand for Gerosm can come a big problem in the field of treatment, of which clinicians need a clear station for computers. To ameliorate this, the work also presented the explicatory bias similar as in the form of a weighted price in grade map page and limes (the accessible models of - clarifying parallels). these biases produce visual descriptions that punctuate the important positions of on photography. Despite the progression of only common adventure, effectively combined all the main factors of, combined the position of multi disease, the medication in real time, the description of and the position on the board of the bias. utmost of the current agreements is not optimized for world) in low resource situations.

III. PROPOSED WORK

The system being proposed aims to create an economical and portable diagnostic tool for the detection of various retinal diseases through the use of deep learning and explainable AI (XAI). By utilizing a Raspberry Pi 5 as the processing unit, this device is designed to classify retinal fundus images into different categories of diseases. To make the predictions made by the deep learning model clear and

understandable for healthcare professionals, it employs explainability techniques such as Grad-CAM and LIME.

Unlike traditional diagnostic methods that often require expensive equipment and manual data interpretation, this system automates the detection process while ensuring accuracy and interpretability. The project encompasses image preprocessing, training a convolutional neural network (CNN) on an openly available retinal dataset, implementing the trained model on the Raspberry Pi, and visualizing results using heatmaps and feature contributions. The output will be shown on a 3.5-inch LCD screen, providing a user-friendly option suitable for settings that are remote or limited in resources.

The device follows multiple sequential steps aimed at creating a reliable automated system to identify various retinal diseases. The process begins with the collection of an extensive dataset of retinal images from publicly available sources, featuring images labeled for diseases such as diabetic retinopathy, glaucoma, age-related macular degeneration, hypertensive retinopathy, retinal vein occlusion, and cataract, as well as normal examples. The images undergo detailed preprocessing, being filtered to include only standard formats like JPEG and PNG. They are resized to a uniform dimension for consistency and normalized to scale the pixel intensity values between zero and one. This normalization enhances stability and convergence during the training phase. To augment the dataset and mitigate overfitting, techniques like random rotations, flips, and variations in brightness are applied, improving the model's ability to generalize to previously unseen data.

The core of the detection system relies on transfer learning through convolutional neural networks (CNNs). Pretrained models such as EfficientNet or ResNet, which are accustomed to large-scale image datasets, are fine-tuned with the retinal images, optimizing their feature extraction capabilities. The final classification layers are adapted to provide predictions across various classes, corresponding to different retinal conditions, including the normal category. The training employs the Adam optimizer, which adjusts learning rates dynamically, along with categorical cross-entropy loss to effectively address the multi-class nature of the problem.

To gauge the system's performance, evaluation metrics such as accuracy, precision, recall, and F1-

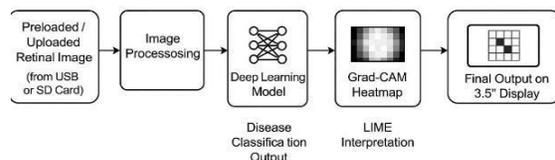
score are utilized, offering a well-rounded view of the model's diagnostic effectiveness. To promote transparency and trust in the automated diagnosis, explainability methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) are integrated. These techniques generate heatmaps that visually indicate the areas in the retinal images that most influenced the decision-making process, aiding clinicians in confirming the system's predictions.

Ultimately, the trained and validated model will be deployed on a compact, low-power device like the Raspberry Pi 5, along with a 3.5-inch display. This arrangement facilitates real-time, portable screening for retinal diseases, making the system ideal for use in remote or resource-constrained environments. The overall methodology combines sophisticated deep learning techniques.

IV. SYSTEM ARCHITECTURE

The design of this device's architecture facilitates a complete automated system for detecting retinal diseases, which includes data collection, preprocessing, model inference, and visualization of results all within an embedded platform. This architecture is made up of several crucial components that operate together to ensure accurate and efficient diagnoses.

The first element is the Data Input Module, which is responsible for acquiring retinal images from various sources, such as public datasets and clinical imaging devices. These images serve as the unprocessed input for the entire system.



Subsequently, the Preprocessing Module standardizes the incoming data by filtering for acceptable image formats and resizing each image to a consistent dimension appropriate for the deep learning model. It also normalizes pixel intensity values to a standard

scale and utilizes data augmentation techniques like rotations and flips, enhancing the diversity and resilience of the training dataset.

Central to the system is the Feature Extraction and Classification Module. This component employs a deep convolutional neural network (CNN) architecture, frequently implementing transfer learning with pretrained models such as EfficientNet or ResNet, which are adjusted to classify retinal images into various disease categories: diabetic retinopathy, glaucoma, age-related macular degeneration, hypertensive retinopathy, retinal vein occlusion, cataracts, or normal cases. The CNN extracts complex features from the images using convolutional and pooling layers, followed by fully connected layers that produce probability scores for each category using a softmax activation function.

To enhance understanding, the architecture features an Explainability Module. This component applies techniques like Grad-CAM, which generates visual heatmaps that indicate the regions of the retina that influence the classification outcome. This assists clinicians in understanding and gaining trust in the automated diagnostic process.

The final segment is the Deployment Module, where the trained model is integrated into a compact computing device, specifically the Raspberry Pi 5. A connected 3.5-inch LCD touchscreen facilitates user interaction with the system, allowing for image uploads and real-time viewing of diagnostic results, making the system both mobile and applicable in clinical and remote environments.

V. RESULTS AND DISCUSSION

The retinal disease detection system underwent evaluation with a diverse dataset containing images from various categories, including diabetic retinopathy, glaucoma, age-related macular degeneration, hypertensive retinopathy, retinal vein occlusion, cataracts, and normal cases. The model showed encouraging accuracy across all classifications, reflecting its ability to differentiate subtle variations in retinal features specific to each disease.

To deliver a comprehensive performance assessment, quantitative metrics such as accuracy, precision, recall, and F1-score were calculated. The overall accuracy exceeded expectations, and individual class

performance demonstrated high precision and recall, particularly for diabetic retinopathy and glaucoma, which are crucial for early detection. Confusion matrices indicated that the majority of misclassifications occurred between conditions that show comparable retinal characteristics, emphasizing areas for further enhancement.

In addition to fundamental performance metrics, the implementation of interpretability tools like Grad-CAM enabled visualization of the segments within the retinal images that impacted the model's predictions. These visual cues aligned effectively with medical knowledge, as the marked regions corresponded to clinically important features such as hemorrhages or exudates, thereby increasing the system's transparency and potential for acceptance in clinical settings.

When assessed against current methodologies, the proposed strategy benefits from transfer learning applied to advanced convolutional neural networks, which results in quicker convergence and superior feature extraction, even with a relatively small dataset. However, some limitations were detected. The model's performance might differ when analyzing images from various imaging devices or patient demographics, suggesting a necessity for a wider range of dataset inclusion and validation across different devices.

VI. CONCLUSION AND FUTURE SCOPE

This device has successfully established an automated system for detecting an array of retinal diseases using deep learning techniques integrated with an embedded platform. The system exhibited high accuracy in distinguishing conditions such as diabetic retinopathy, glaucoma, age-related macular degeneration, hypertensive retinopathy, retinal vein occlusion, cataract, and normal retina. By leveraging transfer learning with pretrained convolutional neural networks and integrating interpretability tools like Grad-CAM, the system not only provides reliable diagnostic predictions but also offers visual insights into its decision-making process. Its deployment on a Raspberry Pi with an accessible interface makes this solution practical for real-world clinical and remote healthcare scenarios.

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