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AI-DRIVEN DIAGNOSTIC TOOL FOR EYE DISEASES: ENHANCING EARLY DETECTION IN REMOTE AREAS THROUGH PORTABLE RETINAL IMAGING

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ABSTRACT

Recent developments in artificial intelligence (AI) and machine learning (ML) have revolutionized medical diagnostics, offering opportunities for the improvement of healthcare delivery, particularly in remote and underserved communities. This paper introduces PAIRE (Portable Artificial Intelligence based Retinal Imaging), a diagnostic tool designed to analyze frontal-view retinal images captured by accessible devices such as smartphones. PAIRE focuses on early detection of common eye diseases such as Age related Macular Degeneration and Ocular Hypertension, facilitating timely medical intervention in rural communities that lack specialized eye care. Convolutional Neural Networks (CNNs), Feed Forward Neural Networks (FNNs) and transfer learning are used combined with many other techniques. The model is trained on diverse retinal image datasets to ensure robust performance. The tool is evaluated on its accuracy and practicality in real world settings.

Keywords: Medical Imaging, Machine Learning, Convolutional Neural Networks, Ophthalmology, Bioengineering

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I. INTRODUCTION

1.1. Background and Motivation

Machine learning models have demonstrated significant success in utilizing computer vision techniques to diagnose various eye diseases. Studies have utilized supervised machine learning classifiers to differentiate healthy eyes from those with glaucoma based on visual field and optical imaging measurements [1]. Additionally, computer-aided diagnostics systems have been developed to automatically detect eye diseases like hypertensive retinopathy using machine learning and deep learning techniques [2]. The analysis of fundus images (retinal images taken with a fundus camera) has primarily been an instrumental tool in diagnosing retinal diseases. The lack of accessibility to quality healthcare in developing countries was the primary motivation for this study. Various factors such as large populations, lack of hygiene, and the insufficiency of medical centers in many regions of developing countries makes it difficult to get timely medical attention [3]. Additionally, financial constraints pose a major problem, as many individuals in developing countries have to bear healthcare costs out-of-pocket. In fact, out-of-pocket healthcare expenditures in low-income and middle-income countries account for 39.9% of total health expenditures, leading to 9.4% of households spending over 10% of their income on health and 2.1% spending over 25%, with no significant correlation between health insurance coverage and the incidence of catastrophic health expenditures [4]. Geographic barriers also play a significant role, with long travel distances and inadequate transportation options making it difficult for rural populations to reach healthcare facilities [5].

1.2. Research Objectives

The primary aim of this study is to alleviate some of the barriers to timely medical intervention talked about in 1.1. The goal is to develop an application with an easy to use interface and one that is accessible. The tool aims to assist individuals with potential eye diseases by facilitating easier preliminary medical guidance and screening, and then guiding them to seek professional care as necessary.

II. LITERATURE REVIEW

Artificial intelligence (AI) and machine learning (ML) techniques have shown great potential in detecting and classifying various eye diseases from medical imaging data. Several AI/ML models have been developed for automated detection and classification of eye diseases from different imaging modalities like fundus photographs, optical coherence tomography (OCT), and OCT angiography (OCT-A). Some commonly used techniques include deep learning models like Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), as well as classic machine learning methods like Support Vector Machines (SVMs) and Random Forests [6]. Deep learning models have generally outperformed classic ML techniques, achieving high accuracy, sensitivity, and specificity for various eye diseases like Diabetic Retinopathy, Age-related Macular Degeneration, Glaucoma, and Retinal Detachment [7].

Many developing countries face a high burden of eye diseases due to factors like lack of access to healthcare, pollution, and lifestyle changes. For instance, in Bangladesh, 1.5% of adults are blind, and 21.6% have low vision [8]. South Asian countries have a high prevalence of cataract, glaucoma, and other eye conditions. AI/ML systems can help automate screening and provide decision support, improving access to eye care in underserved areas. However, challenges remain in data availability, model applicability, and real-world deployment, especially in settings that lack resources [9].

III. METHODOLOGY

3.1. Data Collection

We used a standard Ocular Disease Recognition dataset of 5000 retinal scans [10]. We split up the data set into 4500 images for training and validation datasets and then saved 500 images for the test dataset. We then transformed the data set into multiple images of size 512 by 1024 with 3 channels for color by compressing and adjusting retinal scans of each eye to 512 by 512 and then concatenating those images. The data set also contained some simple biological data about the patient containing information about age and gender. Which was also inputted into the model.

3.2. Model Development

The model is composed of three main components: a main Feed Forward pipeline, a moderate CNN (12), and a ResNet CNN. The moderate CNN is the first part of the image processing. A repetition of batch normalization, convolutional layers and max pooling to get variation in the data and representations. There is also a dropout layer placed in to control over fitting. The structure of the moderate CNN is repeated three times before the residual layers.

Residual layers are the main part of the image processing. They are made with 2-skip residual connections, found to be significantly effective at better convergence [11], skipping over two batch normalization and convolutional layers. After the 2-skip there is a simple one layer CNN with max pooling and normalization. The majority of the parameters for the model are used in the residual layers and it has 3 repetitions of its structure. After the repetition the network gets flattened and fed into the main pipeline through a small FNN (112 dimensional).

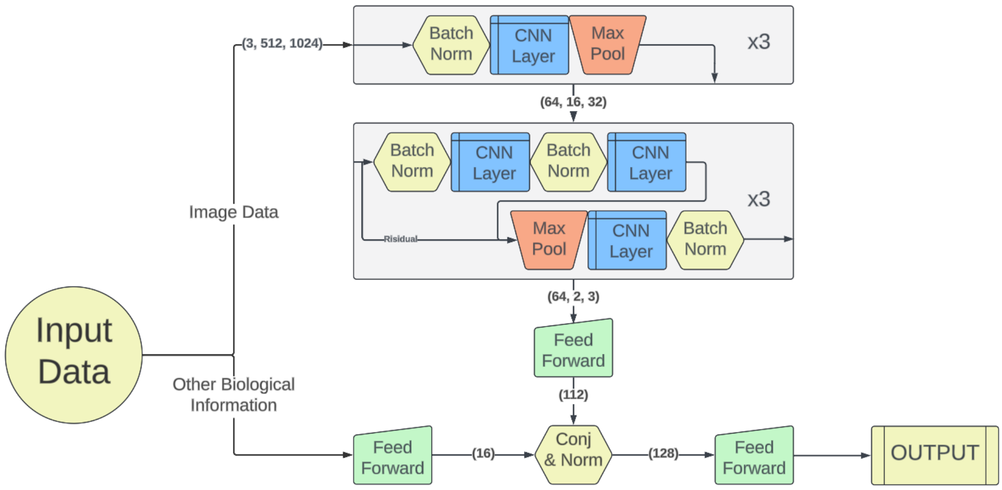

Figure 1: Model Architecture

The main Feed Forward pipeline of the model takes in the other numerical information about the person and then puts that into a FFN (16 dimensional). Then conjugating it with the information from the image processing parts the FFN leads to a 128 dimensional output which gets further fed through the pipeline until there are 4 final outputs. Throughout the entire model Leaky ReLu is the activation function other than the last layer which utilizes a sigmoid function, for the classification of the image, outputting true or false for each of the diseases trained on: Cataract (C), Age related Macular Degeneration (A), Hypertension (H) or Pathological Myopia (M).

3.3. Training

The model was trained for 20 epochs on the data set previously mentioned with training converging after the 5th epoch. Training time was 6 hours on a NVIDIA GeForce GTX 1650.

3.4. Model Evaluation

The model had an overall accuracy of 94.25%. With scores of 92% for Cataract, 93% for Age Related Macular Degeneration, 97% for Hypertension, and 95% for Pathological Myopia, the model demonstrated high accuracy across all conditions. These results suggest a robust, well-trained model with potential valuable clinical applications, especially in preliminary screenings.

IV. IMPLEMENTATION ON PORTABLE DEVICES

4.1 Hardware Selection

For an eye disease detection app to be effective in third world countries, two components of hardware selection are crucial: the camera quality and computational power of the smartphone. Ideally, high resolution cameras (at least 12MP) with features like camera stabilization and autofocus are necessary for capturing clear, detailed retinal images. Powerful processors found in flagship models from brands like Samsung, Apple, and Google are better equipped to run computationally intensive ML models required for accurate image analysis [12]. However, running image processing and analysis on the cloud could mean that budget-friendly low to mid range smartphones could also run such an app. These include brands like Xiaomi, Oppo, Vivo, and Realme, which are widely used in developing countries. These would be suitable for preliminary screening and referral purposes, making them a practical choice for deployment on a larger scale, especially in less developed nations [13]. 4.2 Software Development Developing an app for eye disease detection involves several key components, including a user friendly interface, robust backend infrastructure, and effective machine learning models. The app must be designed to run efficiently on both high-end and budget-friendly smartphones, considering the hardware limitations and connectivity issues common in developing countries.

4.2.1. Architecture

The proposed architecture for the eye disease detection app includes the following components: 1. User Interface (UI): A simple, intuitive interface designed for non-specialist users, such as community health workers or patients themselves. It includes features for capturing retinal images, inputting patient data, and receiving diagnostic feedback. 2. Image Capture and Preprocessing: Integration with the smartphone camera to capture high-quality retinal images. Preprocessing steps, such as image normalization and enhancement, are performed locally on the device to improve image quality before analysis. 3. Backend Server: A cloud-based server that hosts the machine learning models. Images captured by the app are uploaded to the server for analysis. 4. Machine Learning Model: Deployed on the backend server, our model can analyze retinal images to detect signs of eye diseases. 5. Results and Recommendations: The diagnostic results are sent back to the app, providing the user with information about the presence of any eye diseases and recommended next steps, such as visiting an eye care specialist.

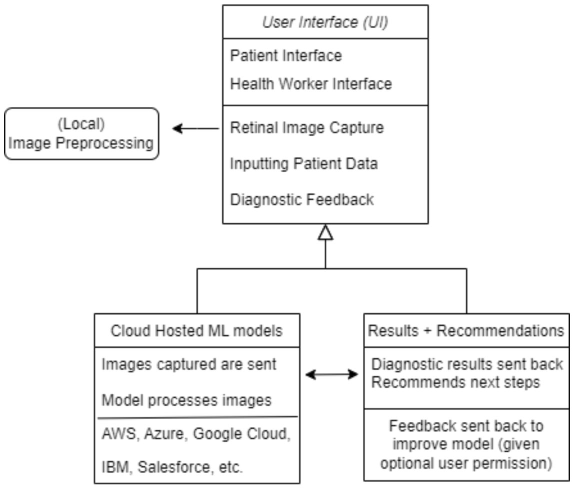

Figure 2: Proposed Architecture for Eye Disease Detection App

4.2.2. User Experience in Developing Countries

To ensure the app is user-friendly and effective in developing countries, several considerations must be addressed. Firstly, the app should support multiple languages and dialects widely used in the target regions. Voice commands and other accessibility features are also vital. Additionally, the app should have a lightweight design and be optimized to run smoothly on low-end devices with limited processing power. The app can also provide users with educational materials about common eye diseases, such as their symptoms, the importance of early detection, and also information like infectability, precautions to take, etc. Community feedback mechanisms can also be implemented to gather user input and improve the app's functionality to tailor to the needs of the local population.

V. CONCLUSION

The need for accessible medical diagnostic tools in rural areas of less developed and developing countries, such as those in South Asia and various parts of Africa, is critical. These regions often face significant barriers to healthcare, including limited availability of essential diagnostics, geographic isolation, and a shortage of trained healthcare professionals. Our research aimed to address these challenges by developing a machine learning model for eye disease diagnosis, which was implemented using TensorFlow. The model achieved an accuracy of 92.60%, demonstrating its potential effectiveness. In addition to the model, we proposed the development of a mobile application or platform to facilitate the use of this diagnostic tool in remote areas. By leveraging digital health technologies, we can bridge the gap in healthcare accessibility and ensure that even the most underserved populations receive the care they need.

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