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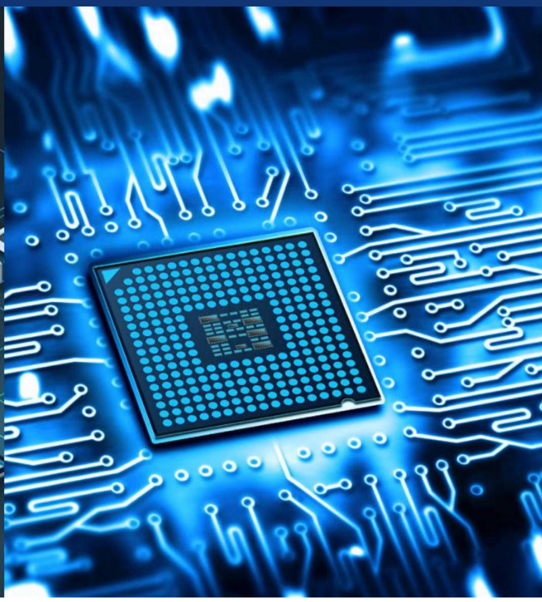

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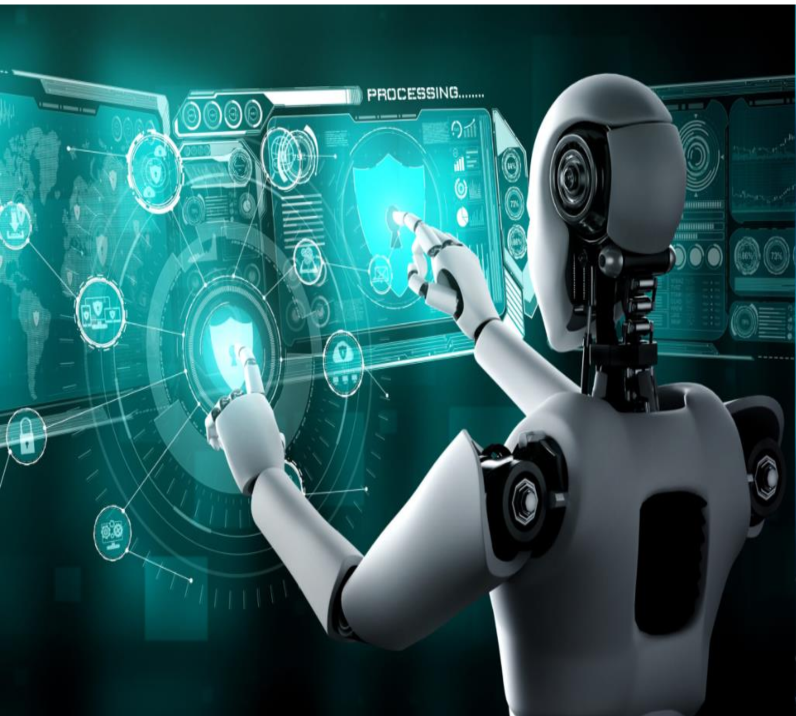

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Diabetic Retinal Screening

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ABSTRACT: Diabetic Retinopathy (DR) is a serious eye condition that is the result of long-standing diabetes, and if not diagnosed early, it may result in loss of vision. Manual screening by expert ophthalmologists for conventional DR diagnosis takes time. In order to automate the process, in this paper we have suggested a hybrid deep learning and reinforcement learning model for Diabetic Retinopathy detection and classification from high-resolution retinal fundus images. A Convolutional Neural Network (CNN) is the main classifier, which identifies key retinal features and classifies images into various DR severity levels. A Reinforcement Learning (RL) agent is also employed with OpenAI Gym, which learns from classification rewards to enhance decision-making. The system is trained on the APTOS 2019 Blindness Detection dataset, which includes 3,662 high-resolution retinal fundus images. The dataset is preprocessed by applying OpenCV methods of image resizing, Gaussian filtering, and normalization. TensorFlow is used to construct the CNN model and it is trained by using a supervised learning method. The RL agent communicates with the CNN by choosing classification actions and getting rewards on the basis of accuracy, thereby improving the performance of the model. In addition, a Raspberry Pi-based retinal imaging device was implemented by employing a Raspberry Pi Camera Module, a 20D Aspheric Lens, and a White-Light Source to obtain retinal images, which are further processed and classified in real time on an HDMI screen. The suggested system aims to improve the accuracy and effectiveness of DR detection, minimizing the workload of healthcare professionals and allowing quicker, automatic screening.

KEYWORDS: Diabetic Retinopathy (DR), Deep Learning, Convolutional Neural Network (CNN), Reinforcement Learning (RL), OpenAI Gym, DR Severity Levels.

I. INTRODUCTION

Diabetic Retinopathy (DR) is a diabetes complication that occurs in the blood vessels of the retina, which can cause blindness if not treated. As the prevalence of diabetes continues to rise globally, DR has emerged as a significant public health issue. Early diagnosis and prompt treatment can greatly minimize the risk of vision loss. But the traditional method of DR diagnosis is by manual review of retinal images by experienced ophthalmologists, which is both time and expense-intensive. This process is also plagued by inconsistencies in human interpretation, resulting in possible misdiagnosis. The fast-paced development of artificial intelligence (AI) and deep learning has made it possible to create automated systems that can interpret medical images with high precision. Deep learning algorithms, especially Convolutional Neural Networks (CNNs), have demonstrated encouraging performance in medical image classification by identifying complex patterns in large datasets. There are still challenges in model optimization, real-time deployment, and accessibility in remote locations. To overcome these challenges, this study suggests an AI-based method for DR detection based on the integration of CNN and Reinforcement Learning (RL). The CNN model learns relevant features from fundus retina images, while the RL agent achieves optimal classification accuracy through learning from rewards. Moreover, we proposed and developed an affordable retinal imaging system on Raspberry Pi that takes and processes retinal photographs in real time and shows results of classification on an HDMI monitor. Through coupling deep learning and hardware innovation, this work aims to offer an affordable and efficient solution for DR screening, especially in resource-scarce situations.

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II. LITERATURE SURVEY

Various research studies have explored the application of deep learning to automate diabetic retinopathy (DR) detection using large-scale datasets to train accurate classification models. Gulshan et al. [1] demonstrated that a deep learning model trained on retinal images could make ophthalmologist-level accurate DR diagnoses. Their work highlighted the significance of high-quality datasets and model optimization in making reliable predictions.

Similarly, Pratt et al. [2] utilized a convolutional neural network (CNN)-based approach for DR classification and reported significant improvements in sensitivity and specificity compared to traditional machine learning methods. The study emphasized the potential of CNNs to outperform hand-crafted feature extraction techniques when dealing with complex medical images.

Transfer learning methods have gained popularity in recent years to enhance the performance of deep learning models in medical image analysis. Researchers have employed pre-trained models such as ResNet [3], InceptionV3 [4], and VGG16 [5] to leverage existing knowledge from large datasets like ImageNet. These models achieved high accuracy in DR classification tasks, especially when fine-tuned with domain-specific retinal datasets. However, the drawback is their computational complexity, making them unsuitable for deployment on low-power embedded systems like Raspberry Pi [6].

In response to such limitations, lightweight architectures like MobileNet [7] and EfficientNet [8] have been proposed to balance performance and efficiency. These models are more appropriate for deployment in real-time portable diagnostic systems due to their lower memory and power consumption.

Reinforcement Learning (RL) has also emerged as a promising tool in medical AI applications. It has been successfully applied in medical diagnosis [9], robotic surgery [10], and drug discovery [11]. RL methods can optimize decision-making by learning from rewards and penalties, enhancing the adaptability and accuracy of the models. For DR detection, RL can be employed to fine-tune classification models by rewarding accurate predictions and penalizing misclassifications, thus boosting overall system performance [12].

Although earlier research primarily concentrated on software solutions, only a few studies have explored the possibility of combining deep learning models with special-purpose hardware for real-time DR screening. For example, researchers have proposed portable, cost-effective retinal imaging systems for field use [13], but few integrate AI-based image classification directly on the hardware. The current research fills this gap by designing a Raspberry Pi-based retinal imaging system that captures high-resolution retinal images and performs real-time classification through an AI pipeline.

By integrating a lightweight CNN with RL and an affordable hardware configuration, the proposed system presents a viable solution for automatic DR screening in various healthcare institutions, particularly in remote and resource-constrained settings. This approach paves the way for democratizing access to advanced diagnostic tools and contributing to early detection and prevention of vision-threatening diabetic retinopathy.

III. DATASET AND METHODS

Dataset

The dataset employed in this research is the APTOS 2019 Blindness Detection dataset, which consists of high-resolution retinal fundus images employed to identify Diabetic Retinopathy (DR). The dataset contains Gaussian-filtered retina scan images resized to 224×224 pixels to ease compatibility with different deep learning models.

3.1.Data Organization

The data is divided into five DR severity levels from the train.csv file. The images are placed in the below-given directories:

- 0 - No_DR (No Diabetic Retinopathy)
- 1 - Mild (Early-stage DR)
- 2 - Moderate (Intermediate-stage DR)
- 3 - Severe (Advanced-stage DR with evident retinal damage)

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4 - Proliferative_DR (Most advanced stage with high risk of blindness)

Apart from that, there is an export.pkl file that is a pre-trained ResNet34 model for 20 epochs trained using the FastAI library. The pre-trained model is available to use as a starting point for transfer learning applications.

3.2. Preprocessing of images

Prior to inputting the images into the deep learning model, the following preprocessing steps are performed:

Resizing: Every image is resized to 224×224 pixels to maintain consistency.
Gaussian Filtering: A Gaussian filter is applied to remove noise while preserving important retinal features. The Gaussian filter is defined as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where σ is the standard deviation controlling the degree of blurring.
Normalization: Pixel values are scaled to the range [0,1] using min-max normalization:

$$I_{\text{normalized}} = \frac{I_{\text{original}} - I_{\text{min}}}{I_{\text{max}} - I_{\text{min}}}$$

This ensures uniform pixel intensity distribution,improving model convergence.

Methods

The hybrid deep learning and reinforcement learning-based DR detection approach discussed in this paper is segmented into the following main stages:

3.3. Deep Learning-Based Classification (CNN Model):

A Convolutional Neural Network (CNN) is used as the base classifier for the extraction of retinal features and separation of images into various DR severity grades. The CNN structure includes:

Convolutional Layers: Derive hierarchical features from the input images.
Max-Pooling Layers: Downsample the feature maps to simplify computational complexity.
Fully Connected Layers: Flatten the extracted features and classify them into one of the five stages of DR.
The softmax activation function is used in the CNN model for multi-class classification:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

where P(yi) is the probability of class i, and z_i is the CNN output for class i.
The model is optimized using the **Adam optimizer**, with **Sparse Categorical Cross-Entropy** as the loss function:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where$y_i$is the actual class label and y^$_i$ is the predicted probability of that class.

3.4. Reinforcement Learning Optimization:

In order to improve classification accuracy, a Reinforcement Learning (RL) agent is added employing OpenAI Gym. The CNN serves as a policy network, and the RL agent chooses classification actions and is rewarded according to the accuracy of the predictions.
The reward function is formulated as:

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$$R = \begin{cases} +1, & \text{if correct classification} \\ -1, & \text{if incorrect classification} \end{cases}$$

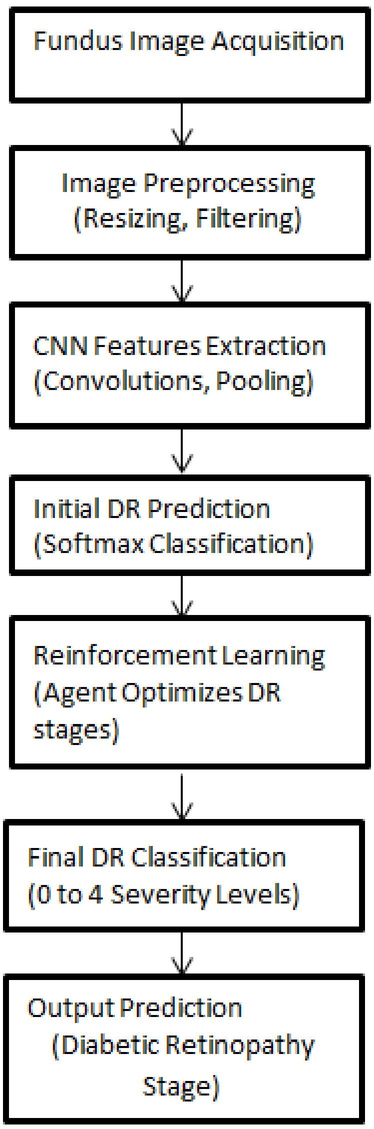
The RL agent updates its **policy** π using the **Q-learning** update rule:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[R + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$$

where:

- Q(s,a)) is the expected reward for taking action a in state s.
- α is the learning rate.
- γ is the discount factor determining future rewards' impact.

IV. SOFTWARE BLOCK DIAGRAM



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V. HARDWARE REQUIREMENTS

5.1. Requirements

The hardware requirements for designing the Raspberry Pi-based retinal imaging system included the following components:

Raspberry Pi 4 Model B: A single board computer with good processing capabilities and connectivity to operate deep learning models.

Raspberry Pi Camera Module (12.3 MP): High-resolution camera module to image detailed retinas with a focus of 102 mm.

20D Aspheric Lens: An optical lens for achieving high-resolution fundus imaging.

White-Light LED Source: Offers proper illumination for taking clear retinal images.

7-Inch HDMI Screen: A display to visualize captured images and classification outcomes in real time.

HDMI Cable: Interconnects Raspberry Pi with the HDMI screen.

32 GB microSD Card: To save the operating system of the Raspberry Pi, deep learning model, and program software.

5.2. Setup of Connections

- Connect the Raspberry Pi 4 Model B to a 7-inch HDMI display via an HDMI cable.
- Insert the microSD card (loaded with Raspberry Pi OS) into the Raspberry Pi.
- Mount the Raspberry Pi Camera Module on the CSI port of the Raspberry Pi.
- Mount the 20D Aspheric Lens on the camera module.
- Connect the White-Light LED Source for the best retinal image illumination.
- Power the Raspberry Pi using a 5V 3A USB-C power supply.

5.3. Photography Setup & Workflow

Mount the Camera & Lens: Mount the 20D Aspheric Lens on the Raspberry Pi Camera Module, aligning it correctly.

Configure Software: Install required software like Raspberry Pi OS and utilize OpenCV for image processing.

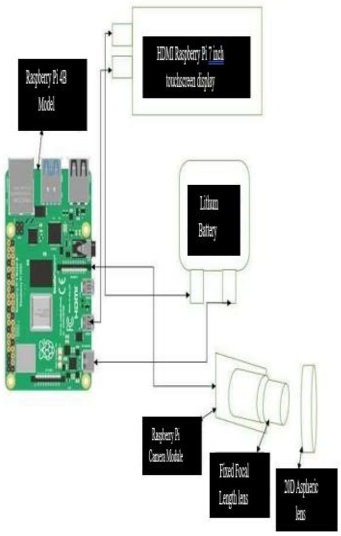
Live Preview: Use the 7-inch HDMI screen for live preview of the camera feed.

Capture & Store Images: The Raspberry Pi takes high-resolution retinal images, saves them on the microSD card, and processes them for analysis.

Automated Detection: The installed deep learning model on the Raspberry Pi examines the captured image, classifies it into a DR severity stage, and shows the result on the HDMI screen in real-time.

Post-Processing: Classified images and results can be saved for subsequent analysis or remote consultation with physicians.

5.4. Hardware Block Diagram



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VI. OUTPUT

VII. FUTURE SCOPE

The system, as proposed, has great promise for future growth. Incorporation of cutting-edge deep learning algorithms such as Vision Transformers (ViTs) and Generative Adversarial Networks (GANs) can vastly improve classification rates. Increasing the dataset with mixed populations will enhance generalization and reduce biases in diagnosis. Deployment on the cloud can allow for real-time remote diagnosis, facilitating early detection and timely intervention. In addition, optimizing the system for edge AI will improve on-device processing, making it more efficient and faster. The device can also be extended to identify other retinal diseases like Glaucoma and Age-Related Macular Degeneration, increasing its clinical application. Moreover, adding a mobile app or telemedicine platform will enhance accessibility, particularly in rural locations. Improving the user interface and automating the screening process will further ease diagnosis. These developments will make the system a complete, affordable solution for retinal disease detection, enhancing global eye care accessibility and efficiency.

VIII. CONCLUSION

This work introduces a new method for automated detection of diabetic retinopathy (DR) via CNN and reinforcement learning implemented on an imaging system based on Raspberry Pi. The system takes high-quality retinal images, processes them in real-time, and classifies DR severity correctly, minimizing reliance on human screening. It is low cost and portable, making it suitable for mass screening in areas that are hard to reach and have limited resources, filling a much-needed void in early DR detection. By automating and optimizing the diagnostic process, this system can go a long way in lightening the workload of ophthalmologists and enhancing patient outcomes. Enhancements in model precision, cloud integration for real-time diagnosis, and widening to multi-disease detection will further augment its clinical utility. With further advances, this technology can transform the screening of retinal disease into a routine method of providing global access to good-quality eye care and aiding the early prevention of blindness.

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