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Efficient diabetic retinopathy detection using deep learning approaches and Raspberry Pi 4

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ABSTRACT

Diabetic retinopathy (DR) is a leading cause of vision loss, predominantly affecting individuals aged 25-74 with diabetes mellitus. Timely medical intervention can protect against irreversible blindness in over 90% of cases, emphasizing effectively identifying and treating DR. In the scope of deep learning (DL), the possibility of using them in DR screening has garnered a lot of interest. Specifically, we adopted the densely connected convolutional networks (DenseNet) model because to its capacity to acquire complex features and learn from diverse datasets. Developing the computational model on retinal images labelled with varying phases of DR are obtained from databases such as Messidor and Kaggle. To enhance accessibility and user-friendliness, we integrated the DenseNet model into a Raspberry Pi 4, a compact, affordable and widely accessible computing platform. The proposed approach resulted in an impressive classification accuracy of 88%, demonstrating its proficiency in distinguishing between different phases of DR progression. The study aims to assist in the early detection and diagnosis of the disease, providing a potential resource that could help medical practitioners and ophthalmologists to evaluate the extent of DR in a timely manner.

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1. INTRODUCTION

Diabetic retinopathy (DR) is a prevalent and severe health condition arising from diabetes mellitus. It impacts the retina by damaging blood vessels, resulting in issues like microaneurysms, hemorrhages, soft, and hard exudates [1]. Loss of vision usually results from central retinal swelling, leading to impaired vision. Additionally, the growth of retinal abnormal blood vessel, potentially causing bleeding and retinal scarring, ultimately resulting in blindness. Swelling in the retina's central region can disrupt visual function and cause vision loss. Retinal haemorrhage or scarring from the growth of abnormal blood vessels is another common cause of blindness [2]. DR stands as a significant and prevalent concern in the realm of public health. This ocular complication of diabetes mellitus poses a substantial threat to vision, affecting millions of individuals worldwide. DR manifests many levels, every level with unique characteristics and implications for patient care. The five stages of DR ranging from mild nonproliferative diabetic retinopathy (NPDR) to severe proliferative diabetic retinopathy (PDR) represent a continuum of disease progression [3], where early detection and precise staging hold the key to effective treatment and vision preservation. In addition to diabetes, high blood pressure and high cholesterol both enhance the likelihood that you may develop DR. Taking care of your heart and lowering your cholesterol levels will help protect your eyesight [4], [5]. The automatic detection and staging of DR have long been a subject of intense research and development. Traditional methodologies relied on manual assessments by ophthalmologists, a time-consuming and resource-intensive process. Nevertheless, convolutional neural networks (CNNs) and other deep learning (DL) innovations, have revolutionized the field. These cutting-edge techniques utilize the potential of machine learning to analyze retinal images, offering the promise of efficient, accurate, and scalable DR diagnosis [6]-[9]. The purpose behind this project set out to uncover thorough investigation the automatic detection and staging of DR using state-of-the-art DL and CNN techniques. By delving into the existing literature [10]-[12], we navigate the dynamic environment of DR diagnosis, highlights on the transformative potential of artificial intelligence (AI-driven) solutions. By including the features of both the entropy of grayscale images and the unsharp masking for the green channel extraction, the DL approaches used to fundus images from "Kaggle Diabetic Retinopathy" [13] dataset, are implemented using a bichannel CNN architecture, thereby boosting the performance measures [14]. AI techniques have applications beyond ophthalmology in many other medical fields [15], [16]. Persons who have difficulty with urinary tract issues can now be monitored using a system designed by Kim *et al.* [17] to assist with risk assessment and management in a related study, Eun *et al.* [18] suggests ResNet-50 as the CNN architecture for detecting urolithiasis, or kidney stones, in ureters.

Many of the researchers failed to take the five DR stages into account when they split DR images and do the diagnosis only into two categories: no DR and DR in most of the existing works [19], [20]. Clinical specialists in DR rated the AI model that Bajwa *et al*. [2] used to categorize test images as either DR-positive or DR-negative with an accuracy of 93.72%, sensitivity of 97.30%, and specificity of 92.90%. To treat the retina with the appropriate process and prevent deterioration and blindness, it is vital to know the specific stage of DR, and the DR phases help with that. Monteiro [21] introduced a blended grading predictor employing ten distinct DL models. Through a 5-fold cross-validation approach, individual models were trained and their predictions were combined to generate a final score. This strategy aims in reducing the generalization error inherent in a single DL model, presenting a promising technique for leveraging information from multiple models.

This review in addition to integrating the recent advancements but also identifies gaps and challenges that demand further investigation. With this work, we intend to assist in the ongoing attempt for more effective detection and treatment of DR in its early stages, ultimately preserving the precious gift of sight for countless individuals. The following is the outline of the paper: in the second section, the materials and procedures which support the suggested model are discussed. Section 3 depicts the results and the discussions of the suggested work followed by the conclusion in section 4.

2. METHODS

Developing a DL algorithm that can reliably identify DR in its early stages is the primary aim of the study that is presented. By streamlining the clinical diagnosis and identification of DR, can be accessible for clinicians to make decisions quicker.

2.1. Datasets and data preparation

Utilising of multiple datasets has led to advancements in DR detection. These datasets include well-known ones such as DRIVE, Messidor, Kaggle diabetic retinopathy detection (Kaggle-DRD), e-Ophtha, APTOS 2019 blindness detection, IDRiD, and Messidor-2 [22]-[24]. Researchers and developers using ML and DL algorithms have relied on these datasets, which provide a wide range of images representing different degrees of illnessintensity. The database are incredibly helpful for training and assessing models, which allows for advancements in accurate and reliable detection methods. Therefore, to guarantee that their models obtain consistent information, researchers frequently conduct common preprocessing activities including cropping, resizing, and normalisation. Our research adds to the expanding field of research on DR identification using the densely connected convolutional networks (DenseNet) model, with a focus on the Kaggle and Messidor datasets. For DR classification, we can use Kaggle, a large public dataset with over 35,000 high-resolution fundus images that capture DR detection on the retinal cells. These images include artefacts, blurring, focusing, and exposure difficulties, across a range of devices used at different primary care facilities. Our goal in introducing this diversity is to make it more realistic. Also, these databases ground truth labels aren't completely noise-free, which adds to their authenticity. In line with the ICDRDSS, which is an international standard for assessing the severity of DR [25], expert graders assessed the images. With its large size and real heterogeneity, the dataset has enormous potential for building ophthalmology-specific classification models. Three eye care facilities in France collected 120 images of the retinal fundus between 2005 and 2006 to form the MESSIDOR dataset. There are 1,058 original photos within the following Messidor 2 collection. These datasets do not include pixel-wise lesion segmentation data, but they do provide imaging-based medical diagnosis, particularly about DR severity. Also, unlike the popular ICDRSS procedure, this dataset uses its own method of evaluation [26].

2.2. Pre-processing steps

Pre-processing is a crucial first stage of utilizing DL approaches to DR detection, with the goal of improving data quality and consistency to prepare it for model training [27]. Several common pre-processing steps are typically undertaken are image acquisition, image annotation, image enhancement, image cropping and resizing, data augmentation, and data pre-processing respectively. With our work, we made use of the Messidor and open-source databases for DR identification. These datasets included annotated retinal images indicating various phases of DR. Pre-processing steps involved cropping, resizing, and unsharp masking of image data. Resizing helps improve the speed which involves effectiveness of the model by cutting down on data volume, making especially helpful for big datasets or resource-constrained environments. It ensures consistent and accurate image processing, a requirement for many DL methods. The Messidor dataset was resized to 880×850 pixels, the Messidor 2 dataset to 674×680 pixels and Kaggle to 1,024×1,024 pixels of resolution. Image cropping aims to improve model accuracy and efficiency in order to decrease background noise, remove unnecessary sections and facilitating the model concentrates on crucial features. This step frequently results in improved model performance and decreased false positives or negatives. Unsharp masking, while not commonly used DR detection with DL, can sharpen the image and its clarity. It involves applying a sharpening filter to accentuate edges and fine details, potentially improving image quality. If considered as collectively, these pre-processing procedures facilitate DL model's overall effectiveness and reliability in DR disgnosis. The Figure 1 depicts the process flow of the DR detection, extraction of features and assessments of the performance measures.

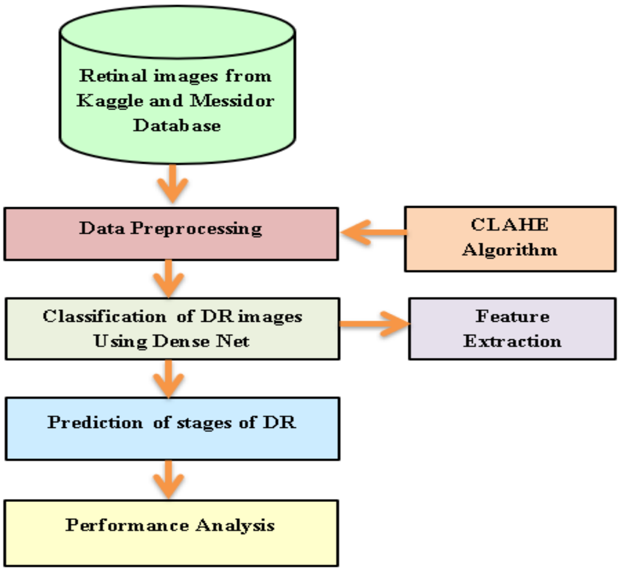


Figure 1. Procedure for DR identification and feature extraction

2.3. Contrast limited adaptive histogram equalization algorithm

For enhancement of images, one method is to use contrast limited adaptive histogram equalization (CLAHE) [28] that aims to enhance clarity. It operates by expanding the image's contrast range, aligning the lightest and darkest pixels with the lowest and highest potential values. In order to accomplish this, CLAHE first partitions the image into smaller areas, known as "tiles", along with histogram equalization applied to every single tile independently. The approach preserves local contrast within each tile while improving the total contrast of the image. In our study, we applied CLAHE to green-featured images to enhance their quality. As illustrated in Figure 2, the fundus pictures had their red, green, and blue channels removed. With the colour data separated, the model can access the finer details in each channel, which could help it better identify important traits and patterns associated with the various phases of DR. Before the data is subjected to additional analysis and model training, this stage helps enhance and refine it.

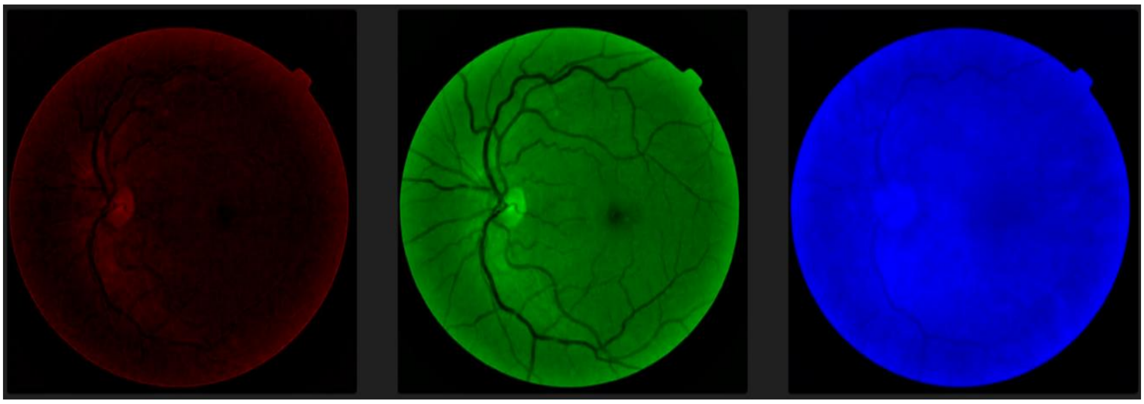


Figure 2. Extraction the fundus images of red, green, and blue channels

Since the Green channel was outperforming the other two, we decided to apply CLAHE on its featured images in order to improve their quality. The pre-processed images following the implementation of CLAHE algorithm can be viewed in Figure 3 which succinctly explains the visual output obtained after applying CLAHE to retinal images within the context of DR analysis. The Figure 3 showcases the enhanced visual representation achieved through the advanced image processing technique of CLAHE.

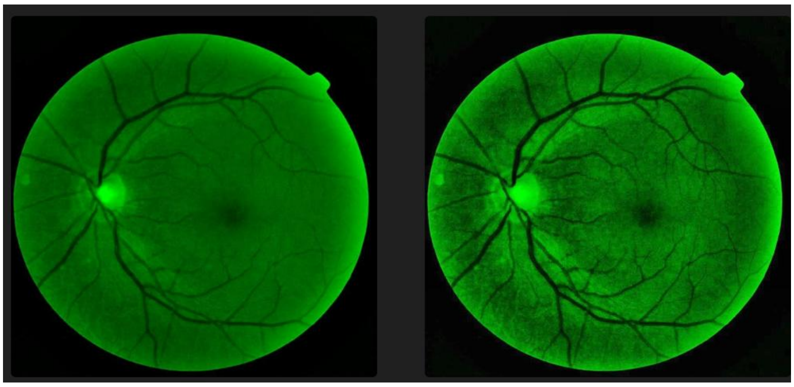


Figure 3. Image preprocessing using the CLAHE method on the green channel

2.4. Proposed algorithm and architecture of the convolutional neural network model

To address issues with deep networks, an architecture for CNNs called DenseNet was developed. By adding dense connections between layers, it improves information flow and solves problems like the vanishing gradient problem. Figure 4 depicts the DenseNet design, which has a dense connectivity structure between layers to encourage feature reuse and gradient flow network-wide.

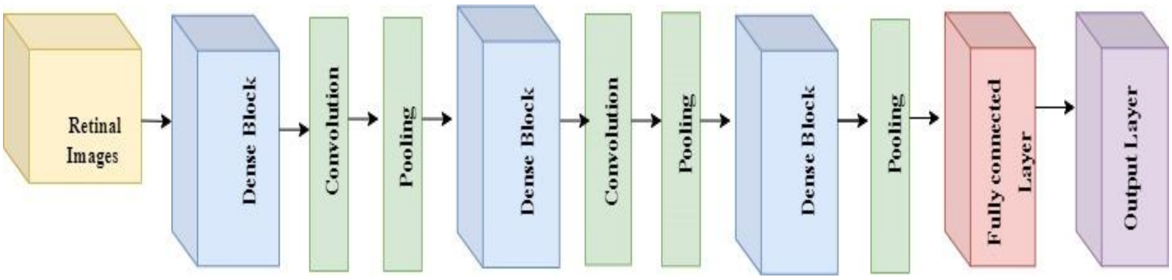


Figure 4. DenseNet architecture

Typically, in traditional CNNs, the feature maps created by one layer are used as input by the next layer [29]. However, DenseNet employs a novel approach to connection establishment, with each layer being feed-forward associated with each following layer. As a consequence, there are many interconnected layers, with each subsequent layer receiving its output as an input. During backpropagation, this method guarantees that all layers directly get gradients from all subsequent layers. This function encourages better gradient flow throughout the system and helps with the vanishing gradient problem.

A number of dense blocks, each with a number of layers, make up DenseNet. Each layer in a dense block forms a subnetwork that is highly connected to all the other levels in that block. By improving the network's information flow and allowing for efficient feature reuse, these dense links may increase representational capacity of the network as a whole.

2.5. Training the DenseNet model

Stochastic gradient descent (SGD) and adaptive optimizers like Adam are used to train DenseNet, which focuses on optimization and backpropagation. When solving a classification problem, for example, cross-entropy loss would be the appropriate choice of loss function.

a. Dense connectivity

Let "H_l " denote the output layer "l", and the input to layer "l", is the concatenation of the feature maps from all preceding layers represented as (1):

$$H_l = [\, H_0 \,, H_1, \ldots\ldots, H_{l-1} \,] \tag{1}$$

b. Composite function in dense blocks

The output of each layer with a dense block is computed as (2):

$$H_l = f_l \; ([H_0 \,, H_1, \ldots \ldots, H_{l-1} \,] \,) \tag{2}$$

c. Transition layer

The output of the transition layer is calculated as (3):

$$H_l = \; BN \; (W_l \, * H_{l-1}) \tag{3}$$

where "*" represents convolution, BN represents the batch normalization, and W_l represents the 1×1 convolutional layer.

d. Global average pooling

The global average pooling operation is applied as (4):

$$y_k \; = \frac{1}{H \, x \, W} \sum_{i=1}^{H} \sum_{j=1}^{W} \, H^{\,k}_{\,ij} \tag{4}$$

where "H" and "W" are height and width of the feature maps, and $H^{\,k}_{\,ij}$ is the k-th channel of the feature map at position (i, j).

3. RESULTS AND DISCUSSION

To train the DenseNet model for the DR, a labelled dataset is essential. This dataset must contain retinal images accurately labelled with corresponding DR severity levels. Initially, the dataset undergoes preprocessing to ensure its suitability for training. This typically involves resizing images to a consistent resolution, normalizing pixel values, and potentially augmenting the data to enhance diversity and the model's generalization. Augmentation techniques like rotation, flipping, and zooming are applied to create various image variations. Configuring the DenseNet model architecture follows. This entails specifying the number of layers, growth rate, and other hyperparameters defining the network's structure. Selecting hyperparameters often involves experimentation and fine-tuning for optimal performance. During the training process, the labeled dataset is composed into mini-batches, each fed into the DenseNet model. Model output is compared to ground truth labels using a suitable loss function, with categorical cross-entropy being a common choice for DR classification as depicted in Figure 5.

This loss quantifies dissimilarity between predicted and true label distributions. During training, the DenseNet model iteratively updates parameters by backpropagating gradients through the network and adjusting weights determined by the chosen optimization algorithm This continues on for a number of epochs, with a pass occurring at the end of each epoch through the entire training dataset. In most cases [30], [31], tracking the model's performance dictates the number of epochs on a separate validation set, stopping when performance reaches a satisfactory level or starts to deteriorate.

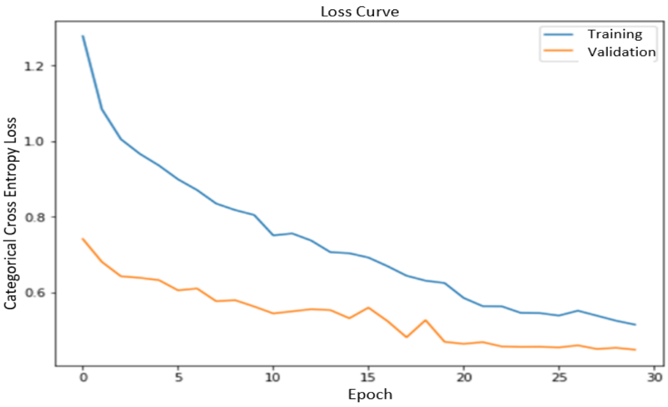
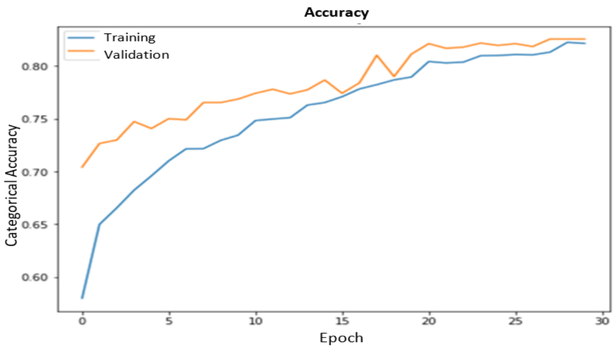
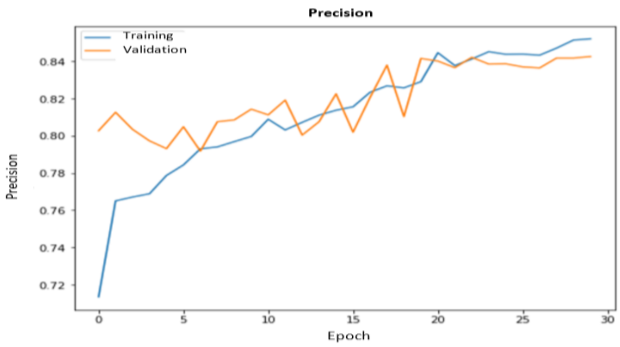


Figure 5. Categorical cross entropy loss

Categorical accuracy is another performance measure which is a quantitative measure of how many samples in a dataset have been correctly categorized. When working with various classes, decides the overall accuracy of classification. A better-performing model will have higher category accuracy. Precision is another metric that quantifies the proportion of true positive predictions (correctly predicted positive samples) out of the total predicted positive samples. It measures the model's ability to avoid false positives. Precision is calculated as true positives divided by the sum of true positives and false positives . This is depicted in Figure 6 as the Categorical performance measures of accuracy and precision. The Figure 6(a) represents the categorical accuracy. The performance measure in terms of precision for the proposed model is shown in Figure 6(b).



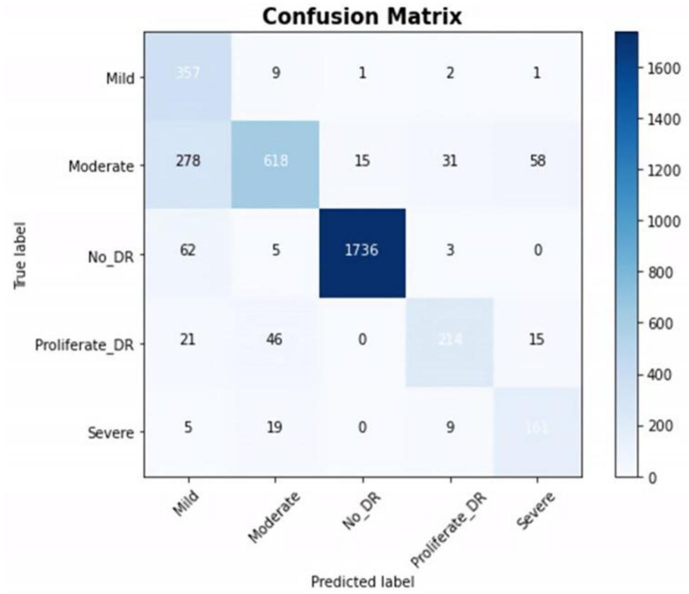
(a)



(b)

Figure 6. Categorical performance measures of the proposed model: (a) accuracy and (b) precision

A potential method for assessing how well a classification model is performing is by examining at its confusion matrix. The information illustrates the total number of accurate predictions for each class, including negative as well as positive results. Figure 7 represents the confusion matrix and the performance measures of the proposed approach using DenseNet algorithm. The Figure 7(a) depicts the confusion matrix for the Kaggle and Messidor datasets. The performance measures of the algorithm are represented in Figure 7(b) in terms of accuracy, precision, recall, and F1 score.



(a)

	precision	recall	f1-score	support
0	0.49	0.96	0.65	370
1	0.89	0.62	0.73	1000
2	0.99	0.96	0.98	1806
3	0.83	0.72	0.77	296
4	0.69	0.83	0.75	194
accuracy			0.84	3666
macro avg	0.78	0.82	0.78	3666
weighted avg	0.88	0.84	0.85	3666

(b)

Figure 7. Proposed results of DenseNet architecture: (a) confusion matrix and (b) performance measures

3.1. Integration with Raspberry Pi 4

Controlling LEDs to indicate DR stage is made possible through the integration of the proposed work with a Raspberry Pi. As part of this integration, the classification system is connected to the Raspberry Pi, which can then receive information from the system and turn on LEDs that correlate to different levels of disease severity. The first step is to get the Raspberry Pi ready with all the necessary software and libraries. Configuring the Pi for development and installing an operating system (such as Raspbian) are part of this process. Since the Raspberry Pi's GPIO pins are what really connect to the LEDs, it's also necessary to install libraries that allow for control of these pins. After that, you should update the Raspberry Pi 4 with the DenseNet model that has been trained. Making a connection between the categorization system and the Pi allows this to happen. After receiving stage predictions, the Raspberry Pi can control the LEDs through GPIO pins. Users can control the status of each DR stage-corresponding LED by setting its corresponding GPIO pin to high (on) or low (off). Figure 8 demonstrates how to efficiently manage the GPIO pins and LED conditions using the tools provided in programming languages like Python.

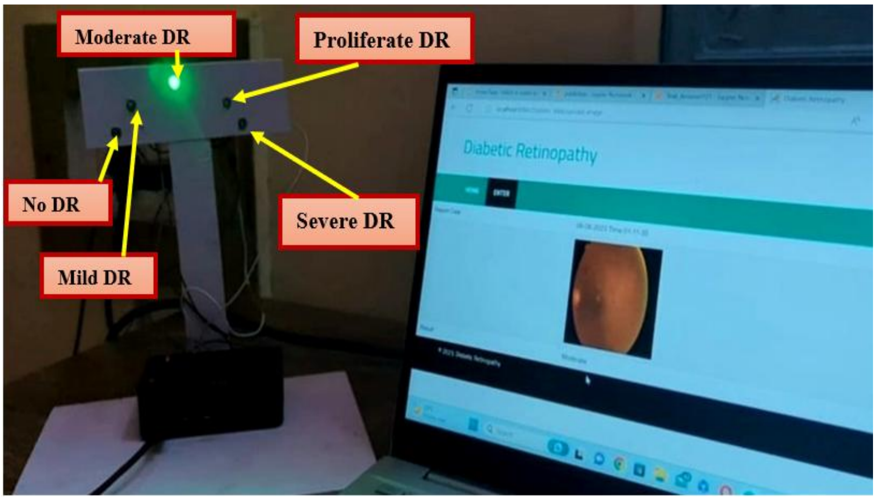


Figure 8. Integration with Raspberry Pi 4

4. CONCLUSION

DL methods exhibit significant potential in diagnosing and detecting early-stage DR compared to traditional methods. DL's performance improves as the volume of available databases increases, offering substantial opportunities for physicians to analyze, screen, and draw insights from retina image datasets.While DL techniques have made notable progress in DR classification, there's room for enhancing performance metrics. This can be achieved by incorporating real-time clinical datasets and integrating hardware modules with DL techniques. Improving DR classification models with cutting-edge approaches and DL should be the goal of ongoing research. With the help of modern technology, patients and healthcare providers can connect remotely, opening up new possibilities such as recording retinal images at home and conducting assessments in real-time using data collected in real-time.

Researchers can gain insight into DR and develop more targeted treatments by combining Raspberry Pi retinal images with patient data such as medical history and genetic information. Predictive models for customised preventive and management suggestions can be developed by broadening the scope of the current research to include other risk factors, such as blood glucose levels and the duration of diabetes. Better patient outcomes and less condition-related vision loss are on the horizon attributed to these enhancements. The goal of this objectives is to help with early disease detection and management by giving ophthalmologists and other healthcare providers an efficient method for quickly and accurately assessing the severity of DR. This has the potential to help improve patient outcomes and prompt interventions to avoid diabetic eye disease.

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