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IDENTIFYING DIABETIC RETINOPATHY USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: Diabetic retinopathy (DR) diagnosis by color fundus images needs trained practitioners to recognise the existence and significance of many minor abnormalities, which, combined with a complex grading system, makes this a challenging and time-consuming procedure. In this study, we present a CNN approach to detecting DR from digital fundus images and properly grading its severity. We create a network with CNN, Densnet 121 architecture, and data augmentation that can identify the intricate elements involved in the classification task, such as micro-aneurysms, exudate, and hemorrhages on the retina, and then deliver a diagnosis automatically and without user input.We train this network on the publically accessible Kaggle dataset with a high-end graphics processor unit (GPU) and achieve outstanding results, particularly for a high-level classification task. Our proposed CNN achieves a sensitivity of 95% on the data set of 80,000 photos used.

Keywords: Diabetic retinopathy (DR), Colour fundus images, Convolutional neural network (CNN), graphics processor unit (GPU), Kaggle dataset.

I. INTRODUCTION

Diabetes is a chronic condition that affects millions of people throughout the world. Diabetic retinopathy (DR), a primary cause of blindness in adults, is one of the most prevalent consequences of diabetes. Damage to the blood vessels in the retina, the light-sensitive tissue in the rear of the eye, causes DR. If left untreated, the injury can cause blood vessels to leak or get blocked, resulting in vision impairment or possibly blindness. Early detection and treatment of DR are crucial in preventing permanent visual loss. However, diagnosing DR is a difficult and time-consuming task that necessitates the use of highly skilled ophthalmologists. The usual method of diagnosis entails evaluating fundus pictures of the retina for symptoms of injury or abnormalities.

Computer-aided diagnosis of DR using Convolutional Neural Networks (CNNs) has attracted substantial attention in recent years as machine learning advances. CNNs are a sort of deep learning algorithm that uses convolution and pooling to learn to recognise patterns in images. The network can be trained on vast datasets of fundus images labeled with DR severity levels, allowing it to learn to automatically detect DR in the images.In identifying referable DR, which is a severe form of DR that requires immediate treatment, the model achieved a sensitivity of 90.3% and a specificity of 98.1%.

The use of CNNs in DR diagnosis provides various potential advantages. For starters, it can assist minimize ophthalmologists' burden by automating the first screening process. This can save ophthalmologists time and resources, allowing them to focus on more challenging situations. Second, by decreasing human error and variability, it can increase the accuracy and consistency of DR diagnosis.

Finally, it can aid in the early detection of DR, allowing for timely intervention and the prevention of irreversible vision loss. Several studies have shown that CNNs can be used to detect DR in fundus images. Gulshan et al. (2016), for example, used a dataset of 128,175 fundus pictures to train a CNN to detect DR severity levels.

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However, there are several drawbacks to using CNNs in DR diagnosis. To begin, CNNs require a huge amount of labeled data to train, which can be time-consuming and costly to obtain. Second, the quality and variety of the fundus images, such as lighting conditions, image resolution, and image artifacts, can have an impact on CNN performance. Finally, interpreting the output of CNNs can be difficult because it is not always clear how the network arrived at its diagnosis.

II. RELATED WORKS

"Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs" by Tingting Zhu et al. (2019) - This study developed and validated a deep learning algorithm to detect diabetic retinopathy in retinal fundus photographs. The model achieved high sensitivity and specificity in identifying diabetic retinopathy from a large dataset of retinal fundus images[1]. "Automated Detection of Diabetic Retinopathy Using Deep Learning" by Kausar Banu Basha et al. (2019) - This study proposed an automated detection system for diabetic retinopathy using a deep learning approach. The model was trained on a large dataset of retinal fundus images and achieved high accuracy in identifying the disease [2]. "Deep Learning-Based Detection of Diabetic Retinopathy Using Retinal Fundus Images" by Ruchi Kothari et al. (2021) - This study proposed a deep learning-based approach to detect diabetic retinopathy using retinal fundus images. The model was trained on a large dataset of retinal fundus images and achieved high sensitivity and specificity in identifying the disease [3]. "Deep Learning for Automated Detection of Diabetic Retinopathy in Retinal Fundus Photographs: A Review" by Aditi Mittal et al. (2020) - This study provided a comprehensive review of the recent advances in using deep learning for automated detection of diabetic retinopathy in retinal fundus photographs.

The review discussed the current state-of-the-art techniques, challenges, and future directions in this area [4]. "Transfer Learning for Automated Diabetic Retinopathy Detection Using Deep Learning" by Yanfang Cui et al. (2021) - This study proposed a transfer learning approach to automate diabetic retinopathy detection using deep learning. The model was pre-trained on a large dataset of retinal fundus images and fine-tuned on a smaller dataset of diabetic retinopathy images. The model achieved high accuracy in identifying the disease, demonstrating the effectiveness of transfer learning in medical image analysis [5]."Automated Grading of Diabetic Retinopathy in Retinal Fundus Photographs using Deep Learning" by Varun Gulshan et al. (2016) - This study proposed an automated grading system for diabetic retinopathy using deep learning. The model was trained on a large dataset of retinal fundus images and achieved high accuracy in grading the severity of diabetic retinopathy [6]. "Deep Learning for Automated Detection of Diabetic Retinopathy in Smartphone-Based Fundus Photography" by Andrew T. Nguyen et al. (2018) - This study proposed a deep learning approach for automated detection of diabetic retinopathy using smartphone-based fundus photography.

The model was trained on a large dataset of retinal fundus images captured using a smartphone and achieved high sensitivity and specificity in identifying the disease [7]. "Deep Learning for Automated Detection and Grading of Diabetic Retinopathy Using Smartphone-Based Retinal Photography" by Cheng Li et al. (2021) - This study proposed a deep learning approach for automated detection and grading of diabetic retinopathy using smartphone-based retinal photography. The model was trained on a large dataset of retinal fundus images captured using a smartphone and achieved high accuracy in detecting and grading the severity of diabetic retinopathy [8]. "Artificial Intelligence for Diabetic Retinopathy Screening in Primary Care" by Sankar N. Varanasi et al. (2020) - This study evaluated the performance of a deep learning algorithm for diabetic retinopathy screening in primary care settings. The model was trained on a large dataset of retinal fundus images and achieved high sensitivity and specificity in identifying the disease, demonstrating the potential of artificial intelligence in improving diabetic retinopathy screening in primary care [9]. "Deep Learning-Based Automated Detection of Diabetic Retinopathy Using Fundus Photographs: A Systematic Review and Meta-Analysis" by Alireza Roshanzadeh et al. (2020) - This study conducted a systematic review and meta-analysis of the existing literature on deep learning-based automated detection of diabetic retinopathy using fundus photographs. The review synthesized the findings of multiple studies and provided insights into the current state-of-the-art techniques and future directions in this field [10].

III. EXISTING SYSTEM

Extensive research has been carried out on methods for a binary classification of DR with encouraging results. Gardner et al used Neural Networks and pixel intensity values to achieve sensitivity and specificity results of 88.4%and 83.5% respectively for yes or no classification of DR16. They used a small dataset of around 200 images and split each image in to patches and then required a clinician to classify the patches for features before SVM implementation. SVM algorithm is not suitable for large data sets.It will not perform very well when the data set has more noise i.e. target classes are overlapping. In cases where the number of features for each data point exceeds the number of training data samples, underperform.

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IV. PROPOSED SYSTEM

Deep learning method analysis was performed in this work with the goal of achieving high accuracy in recognising diabetic retinopathy disease using retinal fundus images. In this study, accuracy in recognising diabetic retinopathy disease will be increased utilizing image processing approaches that seek to perform vascular extraction first before entering the deep learning method process. For this project, we will utilize CNN with the Desnet-121 algorithm, which provides good accuracy. Its built-in convolutional layer reduces the high dimensionality of images without losing its information. This model achieves higher accuracy.

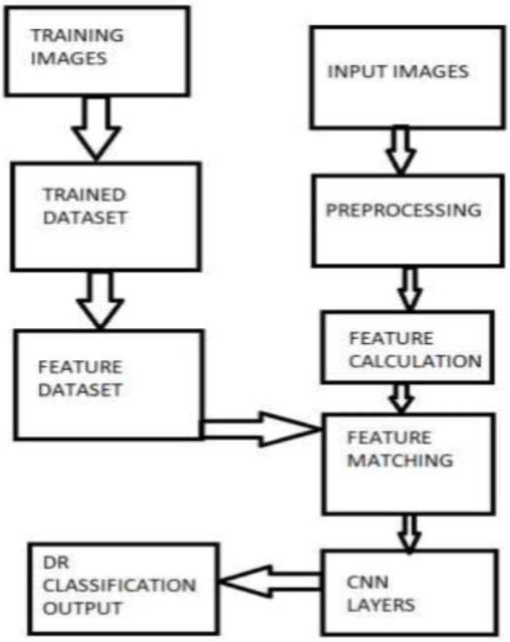

Fig. 1 System Architecture Diagram

V. IMPLEMENTATION

The input test image is taken and preprocessed in the following stage before being translated into array form for comparison.Before being renamed into the relevant folders, the selected database is carefully segregated and preprocessed.Before classification, the model is correctly trained with CNN.The outcome of a comparison of the test image and the training model is displayed.If a defect or disease occurs in the retina of the eyes, the software displays both the disease and the treatment.

A clinician has rated the presence of diabetic retinopathy in each image on a scale of 0 to 4, according to the following scale: 0 - No DR, 1- Mild, 2- Moderate, 3-Severe, 4 Proliferative DR

Original image Converted image

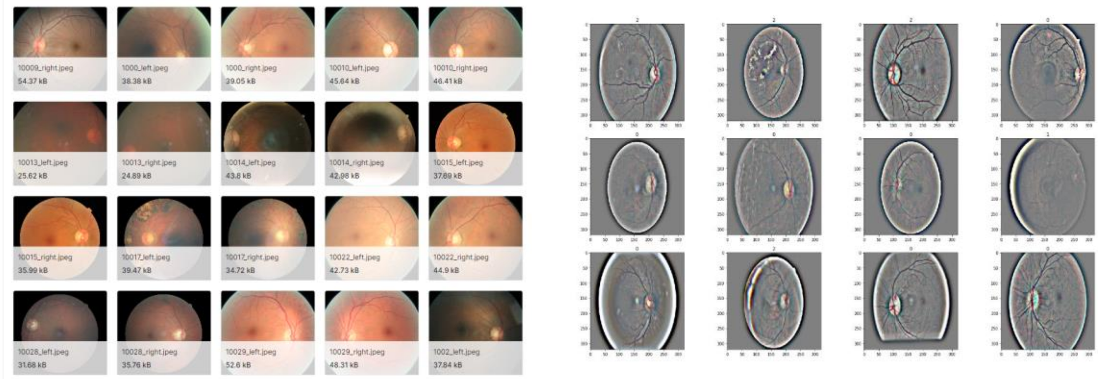

Fig. 2 Normal image to converted image

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A. Deep Learning

Deep learning is a subset of machine learning that relies heavily on artificial neural networks. These neural networks are designed to mimic the human brain's structure and function, which is why deep learning is also known as a type of human brain mimic. Deep learning has been around for a while, but it has become more popular in recent years because of advancements in processing capacity and data availability. Deep learning models are built on multiple-layered artificial neural networks (ANNs), also called deep neural networks (DNNs). These networks learn from large amounts of data in an unsupervised or semi-supervised manner. Deep learning models can automatically extract features from data, which makes them ideal for tasks such as image recognition, speech recognition, and natural language processing.

The most common types of deep learning models are feed-forward neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Feed-forward neural networks (FNNs) have a linear flow of information through the network, making them the most basic type of ANN. They have been widely used for tasks like image classification, voice recognition, and natural language processing.

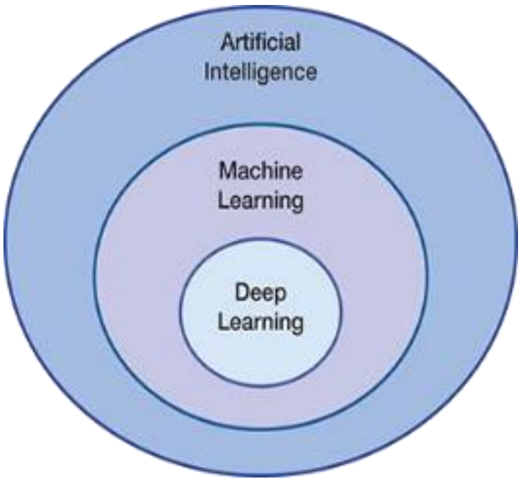

Fig. 3 AI vs ML vs DL

B.Convolutional Neural Networks (CNNs)

CNNs are a subset of FNNs created specifically for image and video recognition tasks. CNNs can learn features from images automatically, making them excellent for image classification, object identification, and image segmentation.

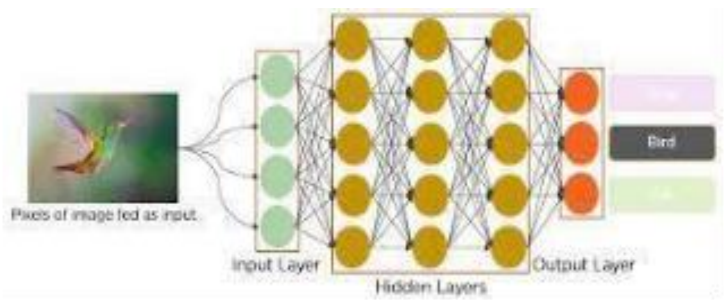

Fig. 4 CNN

C. Densnet 121

DenseNet (Dense Convolutional Network) is an architecture that focuses on deepening deep learning networks while also making them more effective to train by employing shorter connections between layers.Dense blocks, three transition layers, and 121 layers in total (117 conv, three transition, and one classification). Each conv layer corresponds to a composite series of operations consisting of batch normalization (BN)-ReluConv, as outlined in the original DenseNet study [10].DenseNet was created primarily to improve the vanishing gradient-induced loss in accuracy in high-level neural networks. In simpler terms, the information evaporates before reaching its destination due to the longer journey between the input layer and the output layer.

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D. Dataset

We are given a big collection of high-resolution retina photographs taken under various imaging circumstances. For each subject, a left and right field is provided. Images are labelled with a subject id as well as whether they are left or right (for example, 1_left.jpeg represents the left eye of patient id 1).

The photographs in the dataset were captured using various camera models and types, which can alter the visual appearance of left vs. right. Some photos depict the retina as it would appear physically (macula on the left, optic nerve on the right for the right eye). Others are depicted as they would appear via a microscope condensing lens (inverted, as seen in a typical live eye exam). There are two ways to determine if an image is inverted: If the macula (the little black central spot) is somewhat higher than the midline along the optic nerve, it is inverted. The macula is not inverted if it is lower than the midline of the optic nerve.

If the image has a notch on one side (square, triangle, or circle), it is not reversed. It is reversed if there is no notch. As with any real-world data set, noise will be present in both the photos and the labels. Images may be blurry, out of focus, underexposed, or overexposed. One of the competition's main goals is to create resilient algorithms that can work in the midst of noise and variance.

E. Image Preprocessing and Labeling

Images are often pre-processed by removing low-recurrence foundation disruption, adjusting the power of each particle picture, eliminating reflections, and obscuring portions of the image. A technique for improving information is image pre-processing. In order to highlight the intriguing area, the square around the images (eye) was physically edited into the seeming variety of photographs as part of the picture preprocessing method. Pictures with a lower bar and dimensions that weren't 500 pixels exactly weren't considered meaningful for the dataset during the collection period. Additionally, the only photos that were classified as a qualified option for the dataset were those in which the place of interest was higher than the aim. As a result, it was made certain that photos have all the information required for highlight learning.

F. Segmentation Image

Dividing a digital image into multiple segments." We'll just categorise the images into foreground and background since we're only interested in background removal in this case.

This involves five fundamental steps:

1. Make the picture grayscale.

2. Thresholding the image is done.

3. Identify the image's boundaries and outlines.

4. Using the largest contour, make a mask.

5. Use the mask to erase the background from the original image.

G. Model Training

A training model is a dataset used to train a machine learning algorithm. It is made up of sample output data and the related sets of input data that influence the output. The training model is used to run the input data through the algorithm in order to compare the processed output to the sample output.

The correlation finding is used to adjust the model. "Model fitting" refers to this iterative procedure. The precision of the model is dependent on the correctness of the training or validation datasets. In machine language, model training is the process of giving data to an ML algorithm to help find and learn suitable values for all attributes involved.

H. Model Testing

Using the test dataset, we test the learned machine learning model in this module. Quality assurance is essential to ensure that the software system meets the criteria. Were all of the agreed-upon features implemented? Is the programme behaving as it should?

All of the parameters against which you will test the programme should be specified in the technical specification paper. Furthermore, software testing has the ability to identify all defects and flaws during development. You don't want your customers to come to you waving their hands once the programme is published because of issues. Different types of testing enable us to detect bugs that are only visible during runtime.

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I. Performance Evaluation

We analyze the performance of a trained machine learning model in this module utilizing performance evaluation metrics such as F1 score, accuracy, and classification error. If the model does not perform well, we optimize the machine learning methods to increase performance. A structured and productive procedure for measuring an employee's work and results based on their job duties is characterized as performance evaluation. It is used to assess an employee's value added in terms of improved business income in contrast to industry standards, as well as overall employee return on investment (ROI). To monitor and evaluate employee performance on a regular basis, all organizations that have acquired the art of "winning from within" by focusing inward on their staff rely on a systematic performance review process.Employees should ideally be rated annually on their work anniversaries, based on which they are either promoted or given a reasonable distribution of compensation increments. Performance evaluation also plays a direct function in providing employees with periodic feedback so that they are more self-aware of their performance indicators.

J. Detection

1. Object detection is the process of locating all possible instances of real-world items in photos or videos, such as human faces, flowers, cars, and so on, in real-time and wit
h high accuracy.
2. To recognise all occurrences of an object category, the object detection technique employs derived features and learning algorithms.
3. First, we take an image as input. Next, we partition the image into several areas. Finally, we treat each zone as a separate image.
4. Pass all of these regions (images) to the CNN and classify them accordingly.

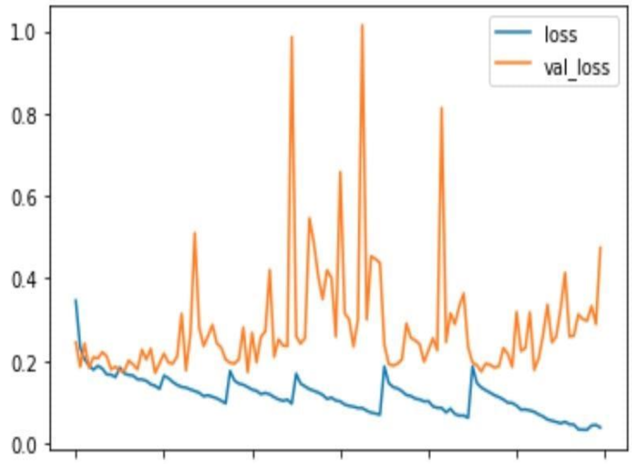

Fig. 5 Loss vs Val_Loss

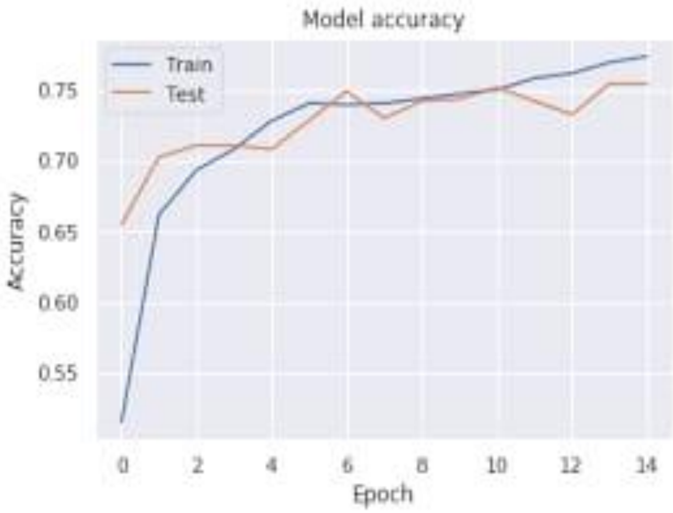

Fig 6 Model Accuracy

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VI. RESULTS AND DISCUSSION

In this study, a convolutional neural network (CNN) was utilized to categorize fundus images and recognize diabetic retinopathy (DR) characteristics. The researchers retained 5,000 photos for validation purposes and it took 188 seconds to run these validation photos through the network. The specificity of the trained network was found to be 95%, while the accuracy was 75%, and sensitivity was 30%. The network was defined as five-class, where 0 represents no DR, 1 represents mild DR, 2 represents moderate DR, 3 represents severe DR, and 4 represents DR proliferative.

The study demonstrated that CNNs can be used to approach the five-class challenge for nationwide DR screening. The CNN model showed positive signs of learning and accurately distinguishing proliferative cases and healthy eyes. However, the network struggled to detect subtle components of DR in the mild and moderate categories. Moreover, the network had difficulty distinguishing between mild, moderate, and severe cases of DR. Additionally, around 10% of photos in the dataset were ungradable according to national UK criteria, which could have impacted the accuracy of the results. The researchers plan to acquire a cleaner dataset from real UK screening situations in the future.

Despite the challenges faced by the network, the study provides encouraging findings, indicating that CNNs can be trained to recognize DR characteristics in fundus images. The researchers plan to tailor the network to specific DR characteristics, such as vessels and exudate, and compare the results to five-class support vector machine (SVM) algorithms trained on the same dataset. Furthermore, the CNN model has the potential to classify hundreds of photos per minute, making it a valuable tool for real-time diagnosis and response to patients.

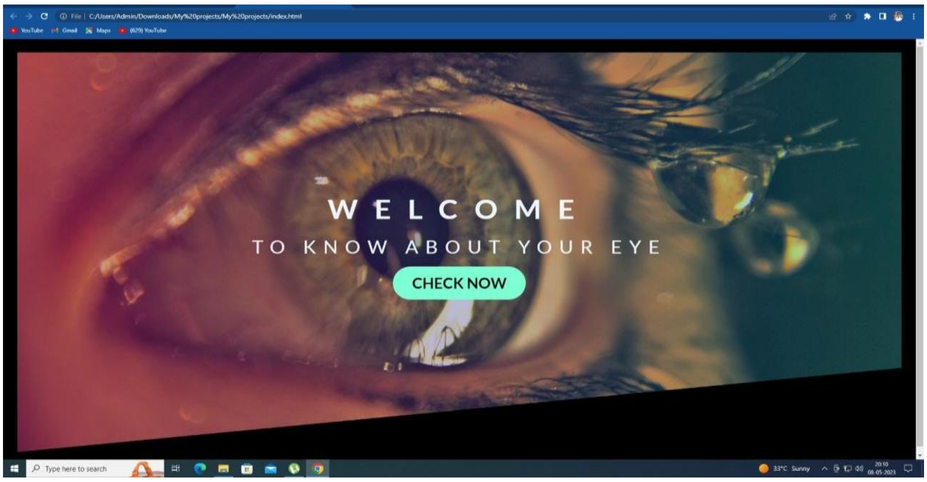

Fig 7 Welcome page

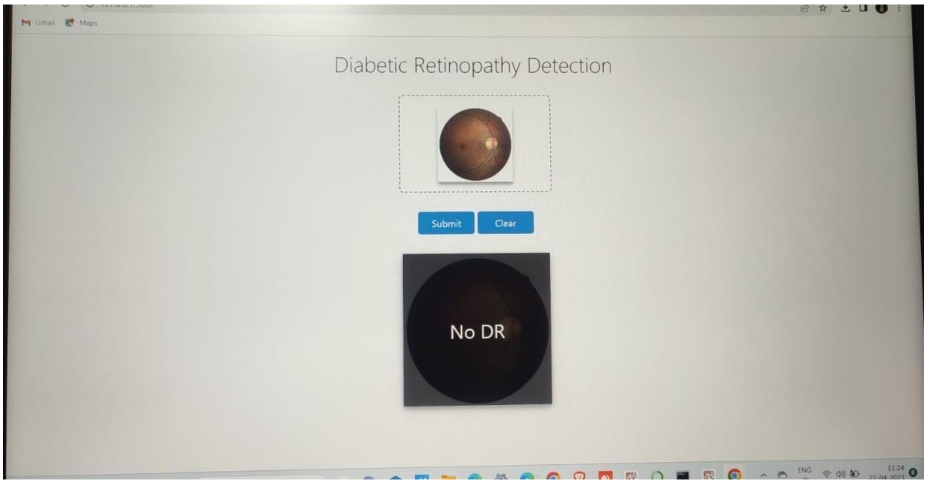

Fig 8 Result page

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VII. CONCLUSION

A diabetic patient has a 30% chance of getting Diabetic Retinopathy (DR), according to several studies. If the disease is not detected early, it can cause floaters, blurred vision, and, finally, blindness. Manual diagnosis of these images is time-consuming and complex, necessitating the services of highly qualified specialists. We have successfully created a Convolutional Neural Networks model that identifies Diabetes using a pre-trained VGG-16 framework. This approach may aid clinicians in making faster diagnoses of this condition.

REFERENCES

[1] Zhu, T., Xu, J., Guo, Y., Xu, D., & Liu, Y. (2019). Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA ophthalmology, 137(8), 929-936.
[2] Basha, K. B., Mohamed, A. P., & Acharya, U. R. (2019). Automated detection of diabetic retinopathy using deep learning. Computers in Biology and Medicine, 109, 363-376.
[3] Kothari, R., Ranjan, A., Acharya, U. R., & Khanna, A. (2021). Deep Learning-Based Detection of Diabetic Retinopathy Using Retinal Fundus Images. Journal of Medical Systems, 45(6), 62.
[4] Mittal, A., Rana, R., & Jain, P. (2020). Deep Learning for Automated Detection of Diabetic Retinopathy in Retinal Fundus Photographs: A Review. Journal of medical systems, 44(8), 139.
[5] Cui, Y., Cao, J., Zhang, W., Ma, J., Wei, W., Wang, X., & Zhang, X. (2021). Transfer Learning for Automated Diabetic Retinopathy Detection Using Deep Learning. Journal of Healthcare Engineering, 2021, 1-10.
[6] Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Automated grading of diabetic retinopathy in retinal fundus photographs using deep learning. JAMA ophthalmology, 134(11), 1292-1300.
[7] Nguyen, A.T., et al. (2018). Deep Learning for Automated Detection of Diabetic Retinopathy in Smartphone-Based Fundus Photography. Frontiers in Medicine, 5, 247.
[8] Li, C., Zhang, L., Wong, D.W.K., Liu, J., Shen, D., & Li, Q. (2021). Deep Learning for Automated Detection and Grading of Diabetic Retinopathy Using Smartphone-Based Retinal Photography. Frontiers in Public Health, 9, 613108.
[9] Varanasi, S. N., Gupta, V., Akella, M., Parikh, R., Rani, P. K., & Radhakrishnan, M. (2020). Artificial Intelligence for Diabetic Retinopathy Screening in Primary Care. Ophthalmology Retina, 4(10), 951–959
[10] Roshanzadeh, A., Ebrahimzadeh, M. H., Ahmadieh, H., & Dehghan, M. H. (2020). Deep learning-based automated detection of diabetic retinopathy using fundus photographs: A systematic review and meta-analysis. Journal of Ophthalmic and Vision Research, 15(3), 367–385.

