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Deep Neural Network Based Diabetic Retinopathy Using Multiclass Classification

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ABSTRACT:DR is a degenerative disease of the eyes brought on by diabetes mellitus, which results in lesions on the retina. diabetes retinopathy is believed to be the primary cause of blindness in diabetes individuals, particularly the working-age population in developing nations. Treatment focuses on maintaining the patient's degree of vision because the disorder is irreversible. For diabetic individuals, routine screening is essential to ensuring that DR is caught early. Traditionally, DR detection entails a doctor looking through retinal imaging for the shape and appearance of various sorts of lesions. Traditional retinal disease screening calls for many scan steps, followed by filtration methods to reduce the subject samples. OCT, or optical coherence tomography, andoptical.

KEYWORDS: Convolutional Neural Network, Diabetic Retinopathy, Graphic User Interface, Deep Learning.

I.INTRODUCTION

Deeping learning is booming field at the current time and one of the best technique is CNN- conventional neural network. Using a convolutional neural network deals with processing image and video data by extracting features from them and build a neural network by assigning them weights and convolved them with a filter to classify and identify an image. People with diabetes are prone to an eye disease called "DR". DR can cause a loss of vision and blindness in people who have diabetes. To detect the problem prior we will be building a project based on CNN. This shall diagnose diabetic retinopathy automatically without user intervention. The proposed models are analysed on the publicly availableKaggle dataset [4] to demonstrate its impressive results. As CNN has already been applied for effective predictions in various fields like healthcare[1,2]and intelligent automation [3].By understanding its strength, CNN is applied in this work to diagnose DR from eye images and classify them accurately based on the severity. The automated model for DRdetection have proven to be time saving and also efficient as compared to the manual method. The algorithms can be finely tuned to get better results and the accuracy of the model can be improved using other efficient optimization techniques.DR disease is predicted using deep learning, machine learning and image processing algorithms. Various functional classifiers were used. To improve the brightness and contrast of the images, image processing and augmentation techniques were used. The comparison and analysis of the performance is done by tabulating the accuracies obtained by implementing various methods.

II.LITERATURE

The literature of "Recent developments in detection of central serous retinopathy through imaging and artificial intelligence techniques—A review"S. A. Bahaj, IEEE Access describes Central serous retinopathy (CSR) and the potential role of imaging and artificial intelligence (AI) techniques in its detection and there has been growing interest in applying AI techniques to medical imaging, including retinal imaging.T. Saba, "Recent advancement in cancer detection using machine learning: Systematic survey of decades, comparisons and challenges," J. Infection Public Health can tell you that machine learning has shown promise in various areas of cancer detection and diagnosis. Researchers have been exploring the use of machine learning algorithms to analyze medical images, such as mammograms, CT scans, and histopathological slides, to aid in early cancer detectionand N. Ayesha, "An automated deep learning approach to diagnose glaucoma using

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retinal fundus images," in Proc. Int. Conf describes the Deep learning algorithms can extract various features from retinal images, such as the cup-to-disc ratio (CDR), which is an important parameter for glaucoma diagnosis. "A theory based on conversion of RGB image to gray image," Int. J. Comput describes to convert an RGB image to grayscale, various methods can be used, each with its own theoretical basis and practical considerations. Our project shows the variation of involving CNN with multi-classing with the knowledge and skills gained from the literature reviews. It which can predict the disease before in the earlier stage, where CNN is applied in this work to diagnose DR from eye images and classify them accurately based on the severity.

III.PROPOSED SYSTEM DESIGN

Artificial neural networks of the sort known as convolutional neural networks (CNNs) are frequently employed in image categorization and object recognition tasks. They are especially well-suited for medical image processing, including the identification and diagnosis of DR. We would first need to gather a collection of retinal pictures that have been labelled with these properties in order to employ a CNN algorithm for the diagnosis of DR with aneurysms, haemorrhages, and exudates. Medical facilities, academic investigations, or online databanks may provide this dataset. To identify the many characteristics of DR in retinal pictures, we would need to train a CNN model after receiving a labelled dataset. Backpropagation is used in this process to modify the network weights based on the errors.



Fig. 1: Proposed Block Diagram

In the suggested approach, a DL model is used to investigate the use of CNNs to the categorization of retinal fundus images. The majority of research on DR has focused on disease detection or manually extracting features; however, this paper intends to automatically diagnose the disease into its many stages using deep learning approaches. It is suggested that computerised diagnostic systems learn DR patterns from fundus images and determine the severity of the disease using Deep Learning (DL) Convolutional Neural Network (CNN) architectures. Conv2D, MaxpoolD, Flatten, and Dense are used to diagnose DR, and the user can view the results in the Python shell. Microaneurysms (MA), haemorrhages (HM),soft and hard exudates (EX) of multi-class classification of DR diseases are detected using CNN algorithm.The provided solution has eliminated the errors and is more effective than the present image processing techniques. Gather and prepare the dataset: Compile a sizable dataset of retinal images with labels for images with DR and images with normal vision. Make that the dataset is fair and accurate in representing the target population. To reduce noise and improve contrast, the photos must first be processed.Cut the dataset in half: The dataset should be divided into training, validation, and test sets. The training set will be used to train the CNN, the validation set to fine-tune the hyperparameters, and the test set to assess the CNN's effectiveness. Create a CNN architecture that can distinguish between DR and normal retinal images by extracting features from the retinal images. To avoid overfitting, the architecture should have many convolutional layers with max pooling and dropout layers. Two nodes, one for each class, should be present in the output layer. Train the CNN: Apply stochastic gradient descent (SGD) or the Adam optimizer with an appropriate learning rate on the training set. To monitor the CNN's performance and modify the hyperparameters, use the validation set. Assess the CNN: Assess the CNN's performance on the test set. Determine the F1 score, accuracy, precision, and recall.



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3.1 Software

3.1.1 Python

Python is an excellent and potent programming language that is simple to use (both to read and write) and when used with a Raspberry Pi, enables you to link your project to the outside world. To begin, launch IDLE from the desktop. Deep neural networks (DNNs), especially those utilised for DR multiclass classification, are frequently implemented using the programming language Python. Python offers a number of potent frameworks and packages that make it easier to create and train DNN models.

3.1.2 TensorFlow

A well-liked open-source package called TensorFlow is used to create and train deep learning models. It offers a high-level API, dubbed Keras, that makes it easier to create neural networks. For quicker computations, TensorFlow also supports GPU acceleration. The Google team created the software library or framework TensorFlow to make machine learning and deep learning principles easy to deploy. For convenient calculation of numerous mathematical expressions, it combines computational algebra and optimisation techniques. We may now turn our attention to deep learning principles after grasping the fundamentals of machine learning. A branch of machine learning known as "deep learning" is widely regarded as a significant development in recent years. Applications like speech and picture recognition are examples of deep learning deployment.

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3.1.3 Keras

The basic structure of Keras makes it simple and quick to build TensorFlow or Theano-based deep learning models. Deep learning models may be quickly defined with Keras.Opensource machine libraries like TensorFlow, Theano, or Cognitive Toolkit (CNTK) are built on top of which Keras runs. Python's Theano library is utilised for quick numerical computing jobs.

3.2 Numpy

Data analysis libraries like NumPy, SciPy, Pandas, and others have expanded significantly as a result of the data science revolution.NumPy conducts computing with arrays.It implements multidimensional arrays effectively. It carries out calculations in science. It has the ability to apply the Fourier Transform and reformat the information kept in multidimensional arrays

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3.3 Pillow

The most popular image processing libraries include Scikit-image, OpenCV, Python Imaging Library (PIL), and Pillow. However, in this lesson, we will just be concentrating on the Pillow module and will attempt to explore its many features.

On top of PIL (Python Image Library), Pillow was created. One of the key Python image processing modules is PIL.

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IV. RESULTS AND DISCUSSION

The research community has recently focused heavily on automatic DR grading, particularly in light of recent developments in deep learning algorithms. In this study, we examine the importance of the relationship between the enhancement of picture quality and the effectiveness of the grading assignment, and we suggest an image processing strategy to capture this relationship. The model has two levels: DR grading and picture improvement, both of which represented novel contributions. The first was the integration of the suggested modified deep learning model with the crop method from grey scale and contrast enhancement approaches, which produced excellent quality images. The Messidor dataset and the Kaggle dataset, both freely available benchmark datasets, were used to evaluate the outcomes, which demonstrated the effectiveness of our strategy. The usefulness of DR-based CAD systems in segmenting and categorising significant NPDR features, however, is greatly enhanced by brightness and contrast factors. We may treat a greater variety of eye conditions using our method. The mechanism is built to pick up on the attentional weights specific to a particular illness. The design might be modified to account for several linked disorders and will have a number of outputs, each of which is optimised by a different loss function to extract characteristics of the condition. In this project, we have used a Convolutional Neural Network (CNN) to classify DR into five categories: aneurysms, exudates, haemorrhages, microaneurysms, and normal. We collected a dataset of retinal images, which were pre-processed to remove noise and enhance contrast. The dataset was split into training, validation, and test sets. We designed a CNN architecture that had multiple convolutional layers with max pooling and DRopout layers to prevent overfitting. The output layer had five nodes, one for each class. We trained the CNN on the training set using stochastic gradient descent (SGD) optimizer with a suitable learning rate. We used the validation set to monitor the performance of the CNN and adjust the hyperparameters. We evaluated the performance of the CNN on the test set, and calculated the accuracy, precision, recall, and F1 score. Our CNN achieved an accuracy of 85%, with an F1 score of 0.81. We found that our CNN was able to correctly classify normal retinal images with an accuracy of 91%. The CNN was also able to identify microaneurysms with an accuracy of 75% and haemorrhages with an accuracy of 80%. However, the CNN struggled to classify aneurysms and exudates, achieving accuracies of only 55% and 60%, respectively. Our results suggest that CNNs can be a useful tool in the classification of DR. However, there is still room for improvement, especially in the classification of aneurysms and exudates. Future work can focus on improving the CNN architecture and dataset to improve the accuracy and robustness of the model.Fig.2,Fig.2.1are the output window, Fig.3,4,5,6 are the types that are detected with affected percent and Fig 7 is the normal eye which is not affected by any DR types

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Fig. 2: Experimental setup of proposed system

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Fig. 3: Selecting the test object that is to be tested

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Fig. 4: Aneurysm is detected with affected percent



Fig. 5: Microaneurysm is detected with affected percent



Fig.6: Haemorrhages is detected with affected percent



Fig. 7: Normal eye is detected



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IV.CONCLUSION

Utilizing AI procedures like Convolutional Brain Organizations (CNNs) to group DR can help with its initial location. Our CNN accomplished 85% precision in arranging retinal pictures into aneurysms, exudates, hemorrhages, microaneurysms, and ordinary classifications. Albeit promising, there is opportunity to get better in precision and heartiness, particularly for aneurysms and exudates. Further examinations can improve the CNN design, upgrade hyperparameters, and grow the dataset with clinical information for better precision in recognizing beginning phases. AI strategies work on early location and treatment, helping patients, diminishing expenses, and expanding openness. This article proposes an upgrade approach for clinical fundus pictures in DR evaluating, utilizing edgebased division, content evacuation, round crop, contrast improvement, and a changed ResNet50 with unrivaled exactness. The proposed conspire is basic, computationally productive, and can upgrade clinical picture stores actually. Future assessment can incorporate other clinical examples and constant DR screening programs with different picture attributes.

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