Diabetic Retinopethy Fundus Image Classification and Lesions Localization System Using Deep Learning

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Abstract – Diabetes is a disease that occurs when the body presents an uncontrolled level of glucose that is capable of damaging the retina, leading to permanent damage of the eyes or vision loss. When diabetes affects the eyes, it is known as diabetic retinopathy, which became a global medical problem among elderly people. The fundus oculi technique involves observing the eyeball to diagnose or check the pathology evolution. In this work, we implement a deep convolutional neural network model to process a fundus oculi image to recognize the eyeball structure and determine the presence of diabetic retinopathy and classify it into 5 categories for its early detection. The model's parameters are optimized using the res-net for mapping an image with the corresponding label. The model training and testing are performed with a dataset of medical fundus oculi images and a pathology severity scale present in the eyeball as labels. The severity scale separates the images into five classes, from a healthy eyeball to a proliferative diabetic retinopathy presence. The early detection can determine the contingency of complete and permanent blindness. Thus, requires an efficient screening system.

Keywords - Convolutional Neural Networks, Deep Learning, Diabetic Retinopathy, Non- Proliferative Diabetic Retinopathy (NPDR), Proliferative Diabetic Retinopathy (PDR), Diabetes Mellitus, Res-Net layer

I. INTRODUCTION

Diabetic retinopathy (DR) is a disease that affects the blood vessels present in the retina, which is damaged due to multiple alterations by a set of metabolic disorders The blood vessels present damage in their capillaries due to the loss of pericytes, which are contractile cells that wrap capillary endothelial cells in the body's venules.

Excess glucose molecules cause this damage in the blood, which clump together in the vessels disrupting circulation, a process known as ischemia. These blood vessels' deterioration produces microaneurysms, which is a saccular enlargement of the venous end of a retinal capillary by the lack of blood circulation. This process leads the vessels to lose their impermeability properties, resulting in leaks, such as hemorrhages or lipid sweating.

Diabetic retinopathy can be classified from the earliest to the most advanced stages once examined the retina's fundus condition. The disease presents two main categories: Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). Moreover, NPDR presents three subcategories as mild, moderate, and severe. The damage of this first category is limited and does not go beyond the retina's inner limiting membrane. DR is proliferative when the ischemia damages result in blood vessels growing beyond the retina. In this work, we proposed a DL model to classify retina fundus images and detect the presence of DR in its different stages. The model was optimized using res-net on a Convolutional neural network to differentiate between a healthy eyeball and a proliferated one. So, the aim of the project is to provide a a automated, suitable and sophisticated approach using image processing and pattern recognition so that DR can be detected at early levels easily and damage to retina can be minimized.

II. EXISTING SYSTEM

The paper "A contribution of image processing to the diagnosis of diabetic retinopathy - detection of exudates in color fundus images of the human retina" by [1] T. Walter, J.-C. Klein, P. Massin, and A. Erginay, published in 2021, presents a novel approach for detecting exudates in color fundus images of the human retina,

which is useful in the diagnosis of diabetic retinopathy.

The paper "Diabetic retinopathy detection using twin support vector machines" by [6] M.Singla, S. Soni, P. Saini, A. Chaudhary, and K. K. Shukla, published in the book "Advances in Bioinformatics, Multimedia, and Electronics Circuits and Signals" in 2020, presents a literature survey on the use of support vector machines (SVMs) for diabetic retinopathy (DR) detection. The authors begin by providing an overview of DR and its prevalence, emphasizing the importance of early detection and treatment.

Disadvantages of Existing System:

[1]Lack of emphasis on Data preprocessing.

[2]Limited focus as it uses only Computer Aided Technique.

[4]Existing diagnostic methods have sensitivity to noise and variations in image quality.

The below table I gives a literature summary about the papers being reviewed for this project work.

Table – 1 LITERATURE SUMMARY

Sl. No.	Paper Title	Proposed system	Advantages
1	A contribution of image preprocessing to diagnosis of DR of exadutae in color fundus images of the human retina	Exudate detection using segmentation and CNN	highlight the importance of early detection and treatment to prevent vision loss.
2	Computer Aided Diagnosis of Diabetic Retinopathy	Computer Aided Diagnosis	the importance of feature extraction in CAD systems for DR diagnosis
3	Pulmonary Image Classification Based on Inception-v3 Transfer Learning Model	Transfer learning with Inception-v3.	Highlight the potential of medical imaging techniques, such as computed tomography (CT) and X-ray imaging, for early diagnosis and screening.
4	Application of Higher Order Spectra for the Identification of Diabetes Retinopathy Stages	HOS feature extraction.	HOS-based features outperforms existing methods in terms of accuracy, sensitivity, and specificity

III. PROPOSED SYSTEM

1. Importing Datasets and libraries: The dataset that has been used here are the fundus images that were published by Kaggle as a component of the Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 blindness detection competition. The dataset consists of 3648 high resolution fundus images taken by different models and types of cameras. Images were rated on the scale of 0 to 4 such that ‘0’, ‘1’, ‘2’, ‘3’ and ‘4’ labels refer to five different stages of DR respectively (i.e. no DR, mild NPDR, moderate NPDR, severe NPDR and PDR).

2. Perform Data exploration and visualization: These are crucial in the data analysis process. In data exploration, aim is to gain a better understanding of the dataset by examining its structure, contents and relationships. This exploration helps uncover patterns, trends and potential insights that can guide further analysis. Data visualization involves representing data visually through charts, graphs, plots and other visual elements.

3. Data augmentation and data generation:

Data augmentation is mainly used to enhance the training data for machine learning. Data augmentation involves applying various transformations or modifications to existing images to increase the diversity and quantity of the training data. These transformations can include random rotations, translations, flips, zooms, brightness adjustments, and more. By augmenting the data, the model can learn to be more robust to different variations and improve its generalization capabilities. Data generation refers to the generation of synthetic retinal images that simulate different disease stages or conditions.

4. Building ResNet block based deep learning model:

There are three types of layers that make up the CNN which are the Convolutional layers, Pooling layers and fully connected layers.

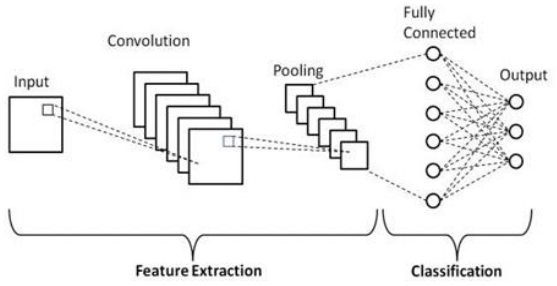

Fig: CNN Architecture

The convolutional layer is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size 256x256. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (256x256).The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image.

5.Compile and train the model: The model architecture that has been defined in the previous stage is compiled by specifying the optimizer, loss function and evaluation metrics. The optimizer used here is Adam. Other optimizers such as ndam or RMSprop can be used as well which determines how the model's weights are updated during training/ The loss function, commonly categorical cross-entropy, measures the discrepancy between predicted and actual labels. Evaluation metrics like accuracy or AUC-ROC assess the model's performance during training. The training data, consisting of labeled retinal images, is fed to the model in batches. The model iteratively learns from the data by adjusting its weights to minimize the loss function. This process is performed over multiple epochs, with each epoch representing a full pass through the training data.

Testing:

Software Testing is the process of evaluating a system and its components with the intent to find whether it satisfies the specified requirements or not. Testing is executing a system in order to identify any gaps, errors, or missing requirements in contrary to actual requirements.

Different Tests:

Various test methods were employed for testing and validation process of the project. Under unit testing individual units were tested for proper and expected working.

Precision Formula:

$$\frac{\text{True Positives}}{\text{True Positives + False Positives}} = \frac{\text{N. of Correctly Predicted Positive Instances}}{\text{N. of Total Positive Predictions you Made}}$$

Precision is a measure of how many of the positive predictions made are correct (true positives).

Recall Formula:

$$\frac{\text{True Positives}}{\text{True Positives + False Negatives}} = \frac{\text{N. of Correctly Predicted Positive Instances}}{\text{N. of Total Positive Instances in the Dataset}}$$

Recall is a measure of how many of the positive cases the classifier correctly predicted, over all the positive cases in the data. It is sometimes referred to as sensitivity.

F1 score Formula:

$$2 * \frac{\text{Precision * Recall}}{\text{Precision + Recall}}$$

F1-score is a measure combining both precision and recall. It is generally described as the harmonic mean of precision and recall. Harmonic mean is just another way to calculate an "average" of values.

Support is the number of actual occurrences of the class in the specified dataset. It can be said as the number of samples of the true response that lies in each class of target values.

Accuracy is the base metric used for model evaluation describing the number of correct predictions over all predictions.

Accuracy Formula:

$$\frac{\text{True Positives + True Negatives}}{\text{True Positives + True Negatives + False Positives + False Negatives}} = \frac{\text{N. of Correct Predictions}}{\text{N. of all Predictions}} = \frac{\text{N. of Correct Predictions}}{\text{Size of Dataset}}$$

Based on all the above stated parameters, the below table 1 has been generated which shows the calculated values of precision, recall, f1-score and support.

	precision	recall	f1-score	support
Mild	0.77	0.56	0.65	72
Moderate	0.72	0.81	0.76	204
No_DR	0.93	0.99	0.96	349
Proliferate_DR	0.63	0.56	0.59	68
Severe	0.74	0.42	0.54	40
accuracy			0.82	733

Table 1 shows the calculated values of above formulas:

According to the above calculated parameters, the confusion matrix is generated for the deep convolutional neural network model

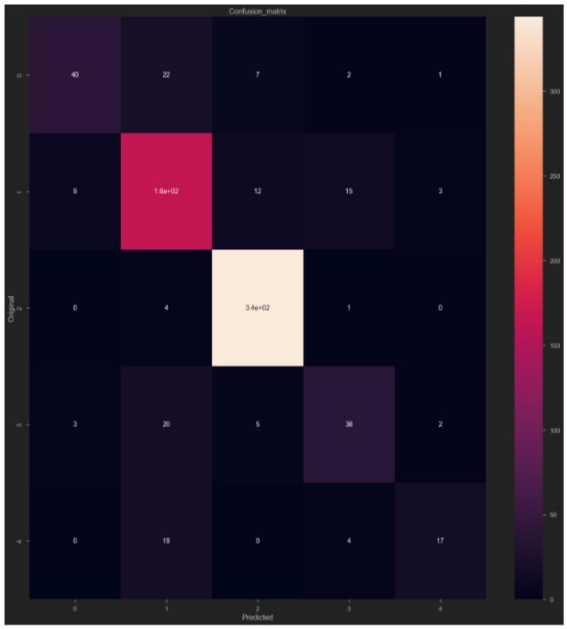

Fig:Confusion Matrix

This is the confusion matrix that is generated for the deep convolutional neural network model.

V. SYSTEM ARCHITECTURE

The fig. 1 shows the architecture design used in the Diabetic Retinopathy Screening project, “Diabetic Retinopathy Screening using a Two-Stage Deep Convolutional Neural Network trained on an extremely unbalanced dataset” that consists of a two-stage deep convolutional neural network(CNN) tailored to address the challenges posed by an extremely unbalanced dataset.

The first stage of the architecture is the initial screening CNN, which serves as the primary classifier to determine whether retinal images are healthy or potentially affected by diabetic retinopathy. This stage aims to reduce computational load by quickly filtering out a majority of negative cases. The initial screening CNN is designed using convolutional layers, pooling layers, and fully connected layers.

The second stage of the architecture is the fine-grained classification CNN, responsible for further analyzing potential cases of diabetic retinopathy identified in the initial screening stage. This stage focuses on capturing more detailed features and distinguishing between different stages of the disease.

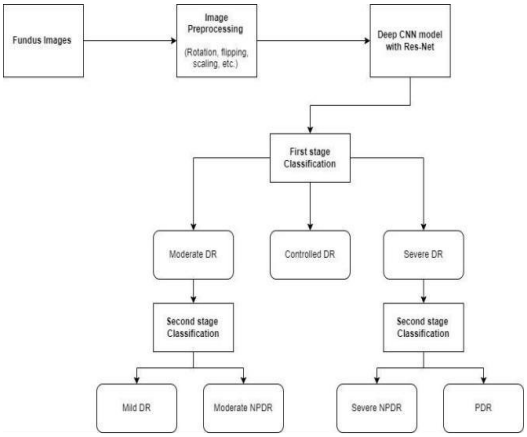

Fig:1 System Architecture

VI. RESULTS AND DISCUSSION

The system was created using Windows 10 as well as a 64-bit processor with 8 GB of RAM. The model implemented with the help of Python and many additional libraries like NumPy, OpenCV.

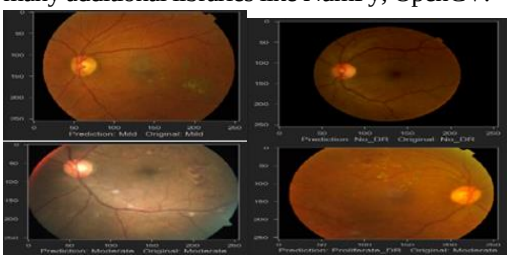

Fig 2 Comparative results predicted by the Deep CNN model

After executing the project on the testing dataset, we display the result classification in a comparative way. Fig 2 shows the prediction made by our deep CNN model with the original classification of the fundus images.

```
from torch.utils.data import Dataset, DataLoader
from PIL import Image
import matplotlib.pyplot as plt
im[port pandas as pd
import torch
import os
import numpy as np
from sklearn.metrices import roc_auc_score
from sklearn.model_selection import
stratifiedShuffleSplit
```

Importing necessary libraries

This phase involves the importing of the necessary modules that are required to run the proposed system model.

```
def res_block (x, filter,stage):
fig, axs = plt. Subplots (5, 5, figsize= (20,20))
#Convolutional_block
count = 0
X_copy = X
f1 ,f2 ,f3 = filter
for I in os.listdir('./train'):
# Main Path
#get the list of images in a given class
X= Conv2D(f1, (1,1),strides = (1,1),
train_class = os.listdir(os.path.join('train',1))
name ='res_'+str(stage)+'_conv_a' ,
# plot 5 images per class
kernel_initializer= glorot_uniform(seed  = 0))(x)
for j in range(5):
x = MaxPool2D((2,2))(X)
img=os.path.join('train',i,train_class[j])
X = BatchNormalization(axis =3,
img=PIL.Image.open(Img)
name='bn_'+str(stage)+'_conv_a)(x)
axs[count][j].title.set_text(i)
X = Activation('relu')(x)
axs[count][j].inshow(img)
Count +=1
fig.tight_layout()
```

Building the ResNet model

This is about the building the ResNet model which is further used for object dedection and image segmentation.

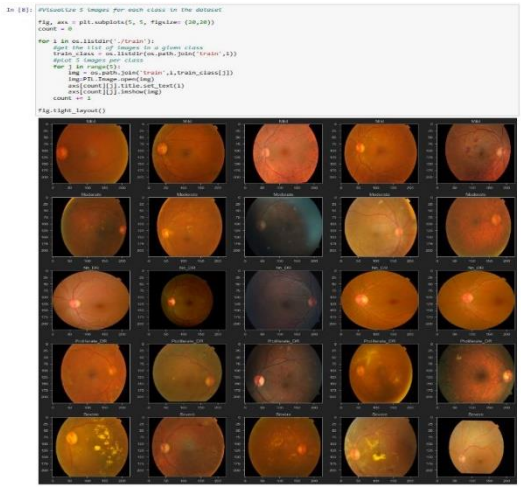

Fig:3Visualization of the fundus images present in the datasets.

The above Fig 3 tells about data augmentation is mainly used to enhance the training data for machine learning. Data augmentation involves applying various transformations or modifications to existing images to increase the diversity and quantity of the training data Visualizing 5 images for each class in the dataset.

VII. CONCLUSION

Diabetic Retinopathy is a type of eye disease caused by Diabetes [2]. Diabetic retinopathy causes two types of conditions known as Neovascular glaucoma [3] and Diabetic macular edema. In the case of Neovascular glaucoma, Diabetic Retinopathy can lead to complete eye blindness. Early detection of DR may prevent or postpone vision deterioration, but it is difficult since the disorder often manifests with few symptoms until it is too late to treat. One important point to note is that the proposed model achieved an impressive accuracy of 82.2%, which outperforms many existing methods for detecting diabetic retinopathy.

For screening and detecting, the conventional manual methods of detecting diabetic retinopathy were insufficient to handle the imbalanced dataset. To overcome the problems of accuracy and efficiency in the detection of retinopathy, the two stage classification has been done with the help of deep Convolutional Neural Network

which classifies the imbalance dataset firstly into controlled DR, moderate DR and severe DR.

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