Classification of Retinal Diseases using RESNET Model

Team Members:

ABSTRACT

Retinopathy is the most prevalent cause of avoidable vision impairment, mostly affecting the working-age population in the world. Recent research has given a better understanding in the clinical eye care practice to identify better and cheaper ways of identification and understanding, management, diagnosis and treatment of Retinal Diseases. In previous studies, the deep learning systems were usually trained directly end-to-end from original fundus images to the labels of DR grades, these end-to-end systems might fail to encode the lesion features due to the Black-box nature of deep learning. In our study, we improved the image processing quality using RESNET model and increased the accuracy above 90 percentage. The GUI we developed classifies the images into different classes of DR.

Keywords: Diabetic Retinopathy, RESNET Model, Hemorrhage detection, Image processing quality, GUI

PROBLEM STATEMENT

To develop a computer aided diagnosis tool to detect the presence of diabetic retinopathy and classify whether it is a normal DR or an abnormal DR.

MOTIVATION

- Diabetic retinopathy is an eye condition that can cause vision loss and blindness in people who have diabetes.
- Our goal is to classify the patients having diabetic retinopathy and not having the same, with a high-resolution fundus image of the retina.

OBJECTIVES

- We process the input retinal images into normal or abnormal retinal images.
- The GUI we develop uses RESNET model for better processing of images.
- In our Study, we classify the images by the way of pre-processing and feature extraction process.
- In these processes we transform the raw images into more informative images.

SCOPE OF THE PROJECT

- This GUI detects the type of diabetic retinal disease. The accuracy of image processing will be above 90 percentage.
- It can process nearly up to 3000 images.

BASIC CONCEPTS

- **Diabetic retinopathy**, also known as diabetic eye disease, is a medical condition in which damage occurs to the retina due to diabetes mellitus.
- Optic disk is the head of the nerve to the eye.
- A micro-aneurysm is a small swelling that forms in the wall of tiny blood vessels.
- Exudates are formed due to increased vascular permeability allowing the leakage of fluid and lipoprotein into the retina resulting in thickening of the macula.
- Hemorrhages are the lesions represent actual bleeding within the retina, and either are a result of ruptured micro-aneurysm’s or when the capillaries become lately enough to let blood out of the blood vessels.

LITERATURE SURVEY - 1

✳ **Title:** Automatic Classification of Preliminary Diabetic Retinopathy Stages using CNN

✳ **Journal:** International Journal of Advanced Computer Science and Applications

✳ **Methodology:**

- In this paper the images from the dataset are classified into two stages after removing the noise on the images by using (CALHE) histogram equalization. Using a deep learning approach, the system will then detect whether a person suffers from Diabetic Retinopathy or not; based on the answer, the system will then classify the level of the disease and finally propose a solution to the patient.

✳ **Advantages:**

1. This model not only provides more reliable and accurate results, but it also saves a lot of time and money.
2. The overall accuracy attained is 84.16%.

✳ **Disadvantages:**

1. The trained model in this paper has a huge variation from the real data.
2. Several other models may be designed which offers better results than this model.

LITERATURE SURVEY - 2

✳ **Title:** Diabetic Retinopathy Detection

✳ **Journal:** International Journal of Engineering and Advanced Technology

✳ **Methodology:**

- This paper used image processing for the detection of DR. Several image processing techniques includes filter, segmentation, classification and image enhancement has been developed for the early detection of Diabetic Retinopathy by the features of exudates, blood vessels, haemorrhages and Micro-aneurysms.

✳ **Advantages:**

1. The model developed by this paper is not only helpful for Diabetic retinopathy affected people butcan also be used by the melanoma and myeloid leukaemia

disease affected people.

2. This system attained higher accuracy even with less number of dataset.

✳ **Disadvantages:**

1. A negative AI-based finding may give PCPs and patients a false sense of security about the totality of their ocular status.

2.Overfitting is occurred when this model learns the random noise and irrelevant details from the image dataset.

LITERATURE SURVEY - 3

✳ **Title:** Detection of retinal haemorrhage from fundus images using ANFIS classifier and MRG segmentation.

✳ **Journal:** Biomedical Research

✳ **Methodology:**

- The final goal of retinal haemorrhage detection by feature classification is to perceive whether the image containing haemorrhages or not.
- In this paper the haemorrhage classification is done by Adaptive Neuro-fuzzy Interface system (ANFIS).
- Grey Wolf Optimization (GWO) is utilized to segment the haemorrhage portion from the image.

✳ **Advantages:**

1. The accuracy level has demonstrated that the algorithm used in this paper is decidedly efficient in perceiving the affected portions of the retinal image.

2. Splat based image representation makes it easier for clinicians to annotate the boundaries of target objects that may lower the cost of attaining reference standard information for training.

✳ **Disadvantages:**

1. The raw retinal fundus images are difficult to process by machine learning algorithms.

2.This model works only for haemorrhage detection.

LITERATURE SURVEY - 4

✳ **Title:** Diabetic Retinal Fundus Images: Preprocessing and Feature Extraction For Early Detection of Diabetic Retinopathy

✳ **Journal:** Biomedical & Pharmacology Journal

✳ **Methodology:**

- In this paper, pre-processing of raw retinal fundus images are performed using extraction of green channel, histogram equalisation, image enhancement and resizing techniques.
- The experiments are performed using Kaggle Diabetic Retinopathy dataset, and the results are evaluated by considering the mean value and standard deviation for extracted features.

✳ **Advantages:**

1. The result yielded exudate area as the best- ranked feature with a mean difference of 1029.7.

✳ **Disadvantages:**

1. Attributes such as red lesions, Kapoor entropy, edema are not extracted in this project.

2. Classification of diabetic retinopathy images in multiple classes based on the features values and performance is not done properly

LITERATURE SURVEY - 5

✳ **Title:** Diabetic Retinopathy Detection using Machine Learning

✳ **Journal:** International Journal of Engineering Research & Technology

✳ **Methodology:**

- This study proposes a machine learning method for extracting three features like exudates, haemorrhages, and micro aneurysms and classification using hybrid classifier which is a combination of support vector machine, k nearest neighbour, random forest, logistic regression, multilayer perceptron network.

✳ **Advantages:**

1. After voting of three classifiers, the testing set results in 82% accuracy.
2. This model provided better segmentation results.

✳ **Disadvantages:**

1. Out of 49 test samples, only 36 produced correct prediction.
2. It produced less accuracy when compared to other papers.

LITERATURE SURVEY - 6

✳ **Title:** A deep learning system for detecting diabetic retinopathy across the disease spectrum

✳ **Journal:** Nature communications

✳ **Methodology:**

- DeepDR is used to detect early to late stages of diabetic retinopathy in this paper. The DeepDR system consisted of three deep-learning sub-networks: image quality assessment sub-network, lesion-aware sub-network, and DR grading sub-network. They used transfer learning to transfer the DR base network to the three sub-networks of the DeepDR system, rather than directly training randomly initialized sub-networks.

✳ **Advantages:**

1. Rather than just generating a DR Grading, the system offers visual hints that help users to identify the presence and location of different lesion types.

2. The system achieved high sensitivity and accuracy in the whole-process detection of DR from early to late stages.

✳ **Disadvantages:**

1. This paper focused only on patients with referable DR who are then referred for specialist eye care.

2. Microaneurysms cannot be detected accurately using this DeepDR system

LITERATURE SURVEY - 7

✳ **Title:** Early detection of diabetic retinopathy based on deep learning and ultra-wide-field fundus images

✳ **Journal:** Scientific reports

✳ **Methodology:**

- This paper used deep learning for the detection of DR. Using the segmented ROI image, they employed the deep learning architecture, the residual network with 34-layer (ResNet-34) model as a classifier for the DR detection task.

✳ **Advantages:**

1. The ResNet architecture used this model provides advantages in an easier optimization and accuracy gain for deep networks.

2. The ETDRS 7SF photography was used to capture the retinal images. It captures approximately 90◦ of the retina that is around 30% of the retinal surface

✳ **Disadvantages:**

1. The data acquired in this paper is recognized as single-center, single-ethnicity, and single-device one. But for a thorough investigation, the acquisition of multi-center, multi-ethnicity, and multi-device data is essential.

2. The use of ETDRS 7SF requires skilled photographers and is time-consuming.

LITERATURE SURVEY - 8

✳ **Title:** Examination of Diabetes Mellitus for Early Prediction and Automatic Detection of Exudates for Diabetic Retinopathy

✳ **Journal:** International Journal of Innovative Technology and Exploring Engineering

✳ **Methodology:**

- In this paper the pre-processed image is segmented using simple linear iterative clustering algorithm. Later, optic disc is eliminated using key point extraction and template matching. Abnormal feature extraction is done using super pixel multivariable classification algorithm.

✳ **Advantages:**

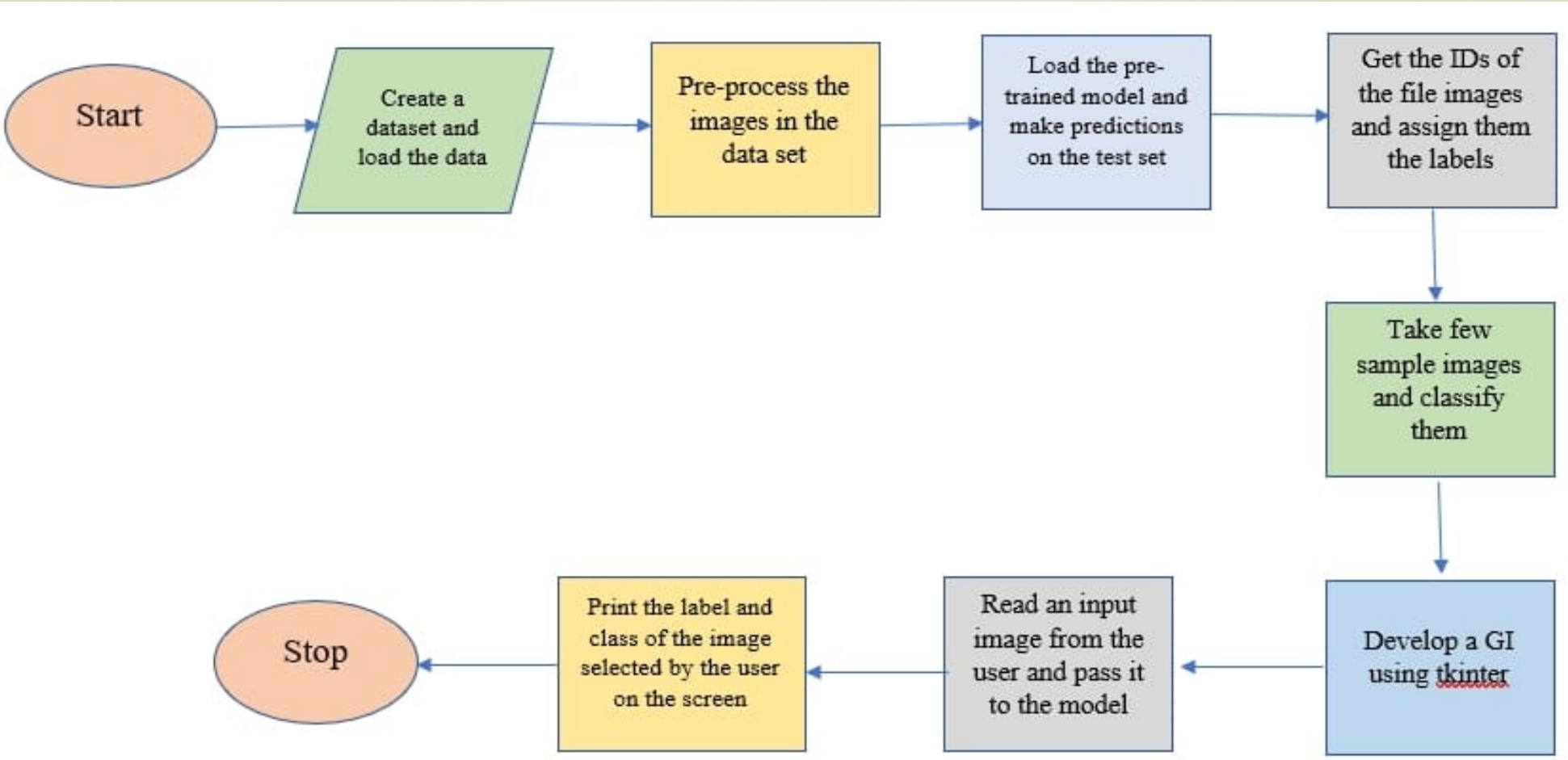
1. This paper worked on several datasets like messidor dataset, kaggle dataset to attain better accuracy.
2. This model showed an accuracy improvement from 2.05% to 12.4% across various models.

✳ **Disadvantages:**

1.Some of the images are misannotated.

2. Optic discs cannot be extracted using this model.

PROPOSED SYSTEM DIAGRAM



MODULES

* The project is divided into five different modules. They are:

1. Training the model
2. Testing the model
3. Developing a GUI

1. TRAINING THE MODEL:

A RESNET model with 152 layers is pretrained using pytorch with 3662 images.

2. TESTING THE MODEL:

Testing the trained model with a sample images of about 20 and classifying the images into different classes of DR. These classes include: No DR, Mild, Moderate, Severe, Proliferative DR.

3. DEVELOPING A GUI:

A user interface is developed which is user friendly developed using tkinter. This GUI asks for the retinal image and gives the report of the classified retinal image.

STEPS FOR TRAINING THE MODEL:

- Import all the required packages.
- Load the data from the trained data set. The training dataset consists of 3662 images in which the images are already classified into 5 classes.
- Visualize the trained data set.
- Visualize the test data set which consists of 1928 images which should be trained.
- Perform the preprocessing on each image of the data set. By using the compose function present in the transforms module we resize and normalize the images.
- Load the sample training and validation data from the train data set and load the sample test data from the test data set.

- Now, load one batch from the sample test set and check the images and their corresponding labels.
- Save the trained model in a file named classifier.pt and save the file in the working directory.
- Now, for each epoch pass the images in the corresponding sample train data and the corresponding sample validation data to the model to test and validate the data set.
- Repeat the above step till all the epochs are completed.

STEPS FOR TESTING THE MODEL:

- Import all the required packages.
- Create a sample data set from the test data set.
- Preprocess each image in the dataset created using the Compose function present in the transforms module.
- Now load the model to predict the labels for the loaded test dataset.
- Unfreeze the layers present in the pretrained model and pass the images present in the test data set to the model.

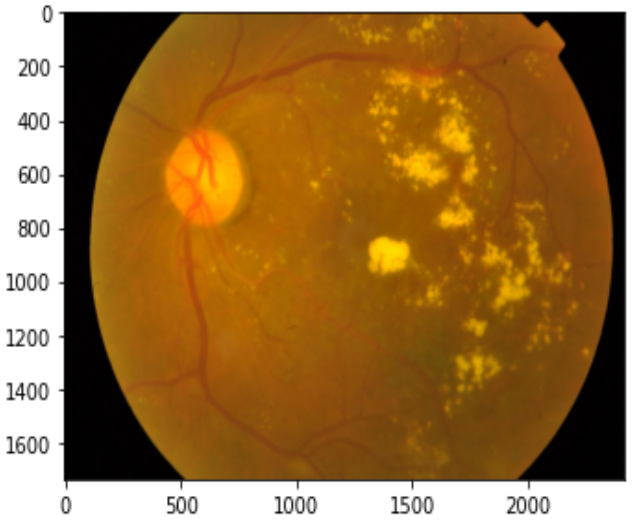
- Store the resultant output labels in an array.
- All the images present in the test data set are now classified into different classes.
- Now, provide the path of the folder where the sample images are present.
- Now perform all the above steps and print the predicted labels and classes for all the images present in the folder specified.

STEPS FOR DEVELOPING A GUI

- Import all the required packages.
- Create a window with the required title and background color.
- Add a label asking the user the choose an image.
- Now add the button correspondingly.
- Define a function which takes the input image from the user and shows the report of the image read.
- In the function defined, pass the input image read to the model that is built earlier.
- It returns the value and class of the image. Now display the report of the image on the screen.

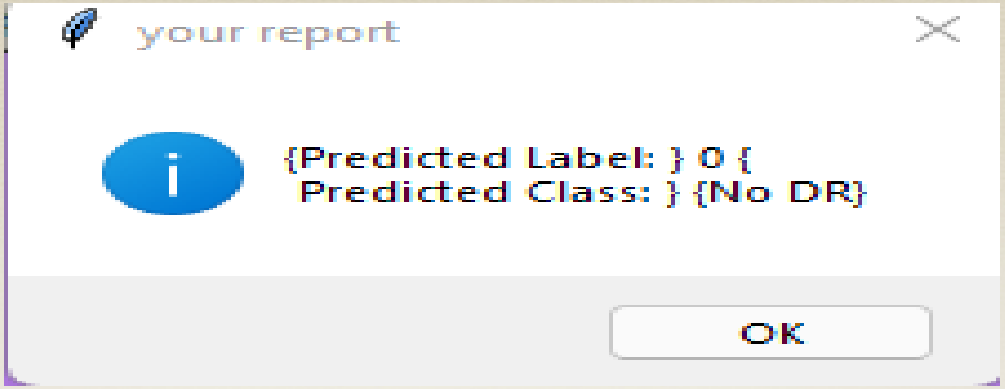
OUTPUTS

```
C:\Users\Dell\OneDrive\Desktop\Retinal_blindness_detection_Pytorch-master\sampleimages\0104b032c141.png
Value: 2
Moderate
```



Output after testing the sample images

GUI developed


your report
{Predicted Label: } 0 {
Predicted Class: } {No DR}
OK

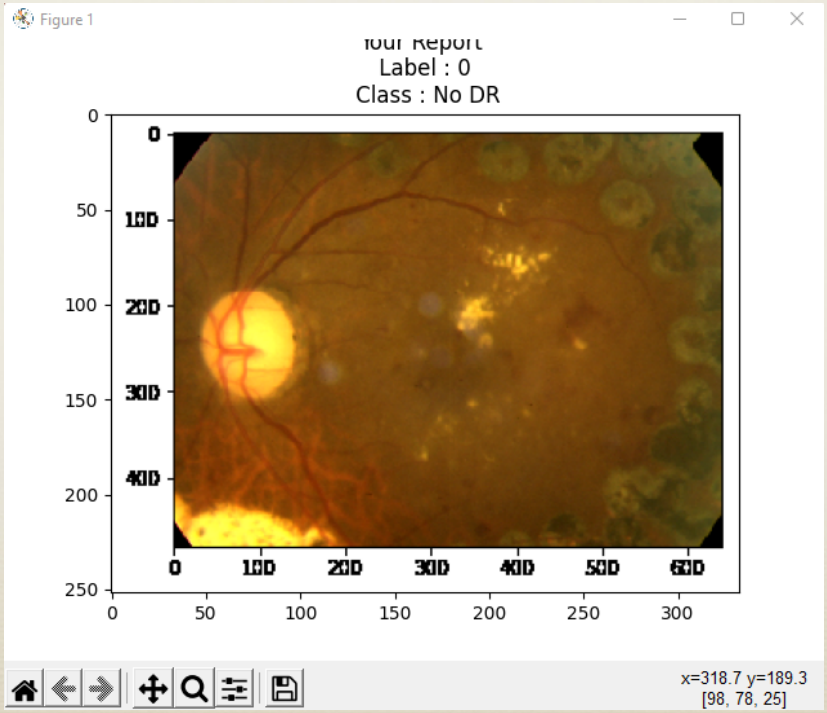


Figure 1
Label : 0
Class : No DR
x=318.7 y=189.3
[98, 78, 25]

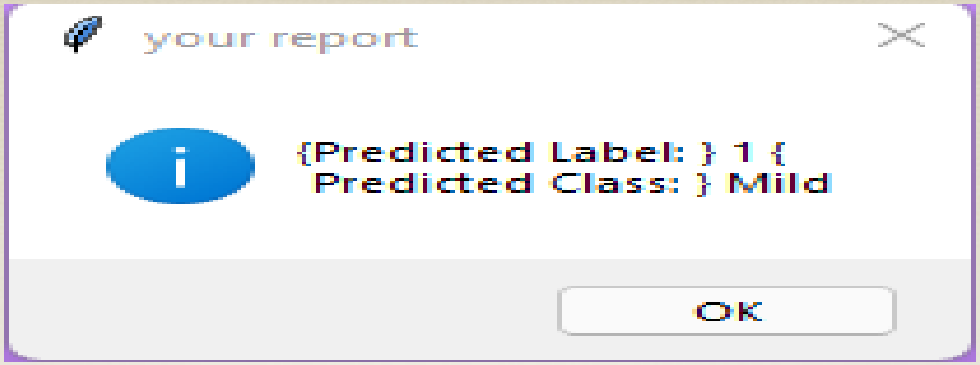
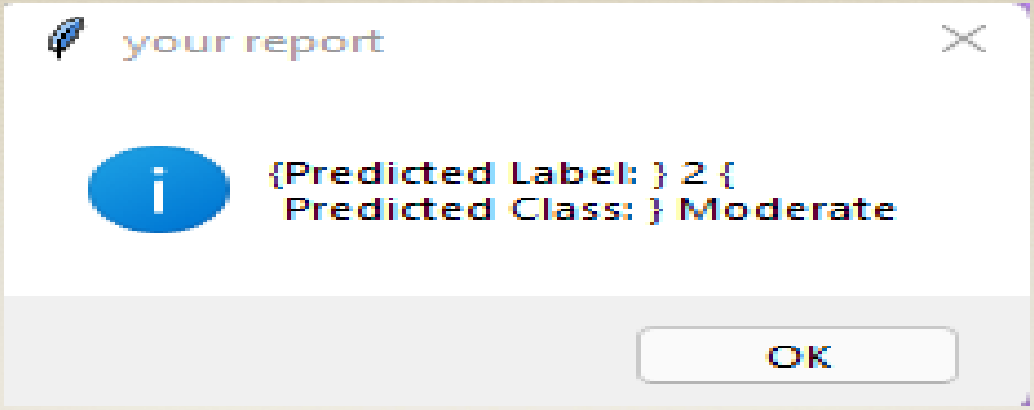

your report
{Predicted Label: } 1 {
Predicted Class: } Mild
OK


Figure 1
Your Report
Label : 1
Class : Mild
0
50
100
150
200
250
300
350
400
0
100
200
300
400
500
600
x=436. y=192.
[236, 8, 33]


your report
{Predicted Label: } 2 {
Predicted Class: } Moderate
OK

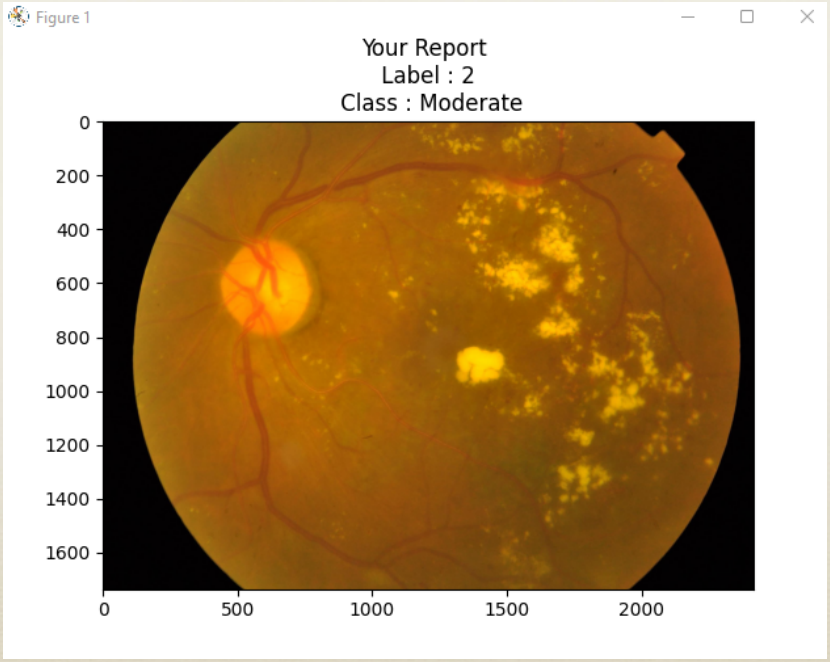
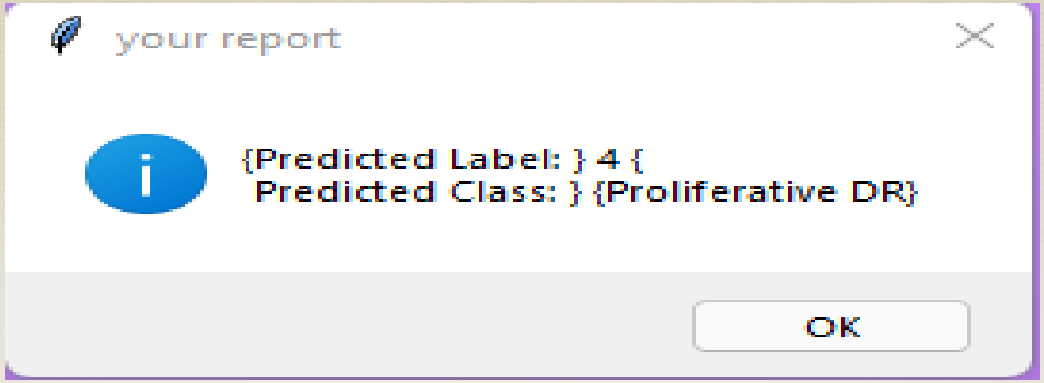


Figure 1
Your Report
Label : 2
Class : Moderate
0
200
400
600
800
1000
1200
1400
1600
0
500
1000
1500
2000


your report
{Predicted Label: } 4 {
Predicted Class: } {Proliferative DR}
OK

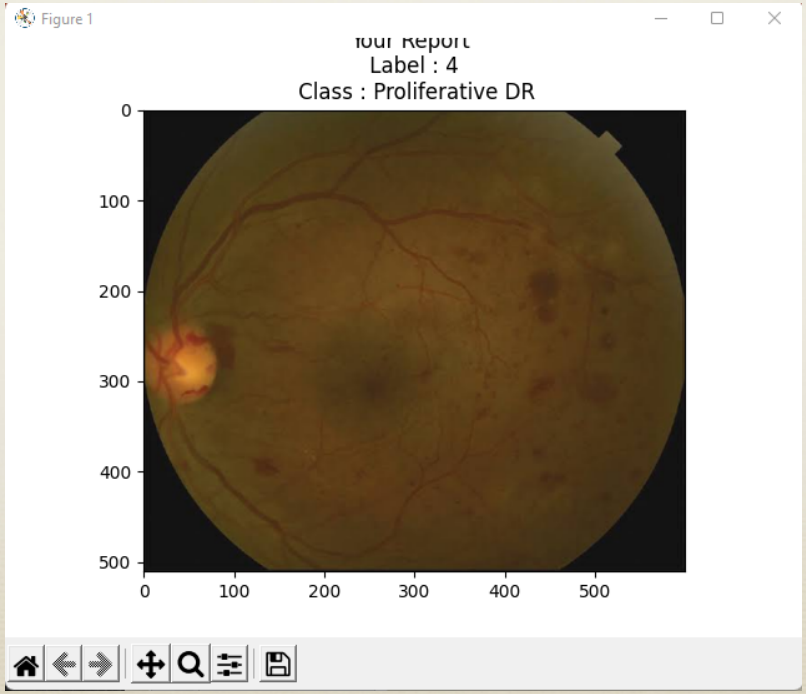


Figure 1
Label : 4
Class : Proliferative DR
0
100
200
300
400
500
0
100
200
300
400
500

```
C:\Users\Dell\OneDrive\Desktop\Retinal_blindness_detection_Pytorch-master>gui.py
Imported packages
Model loaded Succesfully
GUI SYSTEM STARTED...
C:/Users/Dell/OneDrive/Desktop/Retinal_blindness_detection_Pytorch-master/sampleimages/eye8.jpg
Transforming your image...
Passing your image to the model....
Predicted Severity Value:  1
class is:  Mild
Your image is printed:
Thanks for using the system !
```

Output in the console

CONCLUSIONS AND FUTURE WORK

In this project, we are able to classify the images into different stages of DR using the pretrained RESNET model. The GUI we developed will be helpful for both doctors and also the common people.

Our future work is to convert the GUI into a mobile application. We are also trying to improve the accuracy.

REFERENCES

1. Walter, T., Klein, J.-C., Massin, P., Erginay, A. ‘A contribution of image processing to the diagnosis of diabetic retinopathy — detection of exudates in color fundus images of the human retina.’ IEEE Trans. Med. Imaging 21 (10) (2002): 1236–1243

2. Xiaohui, Z., Chutatape, A. ‘Detection and classification of bright lesions in color fundus images.’ In Proceedings of the International Conference on Image processing (ICIP 04), 2004, vol. 1, pp. 139–142

3. Varun Gulshan, Subhashini Venugopalan and Rajiv Raman, "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs", JAMA, vol. 316, no. 22,2016, pp. 2402-2410.

4. A. Osareh, B. Shadgar, and R. Markham, “A computational-intelligence-based approach for detection of exudates in diabetic retinopathy images,” IEEE Trans. Inf. Technol.., 13(4): pp. 535–545 (2009).

5. L. Math and R. Fatima, "Adaptive machine learning classification for diabetic retinopathy", Multimedia Tools Appl., vol. 80,Oct. 2020,pp. 5173-5186.

6. I. U. Morphological, E. Detection, A. Aquino, M. E. Gegúndez-arias, and D. Marín, “Detecting the Optic Disc Boundary in Digital Fundus Feature Extraction Techniques,” 29(11): pp. 1860–1869 (2010).

7. R.GargeyaandT.Leng,“Automated identification of diabetic retinopathy using deep learning,” Ophthalmology, vol. 124, no. 7, pp. 962–969, 2017.

8. L. W. Yun, U. R. Acharya, Y. V. Venkatesh, C. Chee, L.C. Min and E.Y.K. Ng, "Identification of different stages of diabetic retinopathy using retinal optical images", Information Sciences, vol. 178, 2008, pp. 106-121.

9. Tang L, Niemeijer M, Reinhardt J, Garvin MK, AbramoffM. "Splat feature classification with application to retinal hemorrhage detection in fundus Images". IEEE TransactMed Imag 2013; 32: 364-375.

10. Hatanaka Y, Nakagawa T, Hayashi Y, Hara T, Fujita H.Improvement of automated detection method of hemorrhages in fundus Images. J Med Imaging 2008; 978:5429-5432.

11. N. Patton, T. M. Aslamc, M. MacGillivrayd, I. J. Dearye, B. Dhillonb, R. H. Eikelboomf, et al., "Retinal image analysis: Concepts applications and potential", Retinal and Eye Research, vol. 25, 2006,pp. 99-127.

THANK YOU😆