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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 of the clinical eye care practice to identify better and cheaper ways of identifying, understanding, managing, diagnosing, and treating Retinal Diseases. The number of people suffering from Diabetic Retinopathy is much more when compared to that of the ophthalmologists present. So a computeraided diagnosis tool is required which detects and classifies the fundus retinal image. 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-toend 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 the RESNET model and increased the accuracy above 90 percent. The GUI we developed classified the images into different classes of DR. These classes include No DR, Mild DR, Moderate DR, and Proliferate DR.

Keywords: Diabetic Retinopathy, ResNet Model, Feature extraction, Image processing quality, classification.

Chapter 1

INTRODUCTION

1.1 Basic Concepts

Diabetic retinopathy (DR) is a common diabetes complication that occurs when the retina's blood vessels are damaged due to high blood sugar levels, resulting in swelling and leaking of the vessels. In an advanced DR stage, the vision may be lost completely. The percentage of blindness worldwide resulting from DR is 2.6%. Therefore, diabetes patients need regular screening of the retina to detect DR early, manage its progression and avoid the risk of blindness

1.1.1 Diabetic Retinopathy

Diabetic Retinopathy is a condition that may occur in people who have diabetes. It causes progressive damage to the retina, the light-sensitive lining at the back of the eye. Diabetic retinopathy is a serious sight-threatening complication of diabetes. Diabetes interferes with the body's ability to use and store sugar (glucose). The disease is characterized by too much sugar in the blood, which can cause damage throughout the body, including the eyes. Over time, diabetes damages small blood vessels throughout the body, including the retina. Diabetic retinopathy occurs when these tiny blood vessels leak blood and other fluids. This causes the retinal tissue to swell, resulting in cloudy or blurred vision.

Diabetic retinopathy usually affects both eyes. The longer a person has diabetes, the more likely they will develop diabetic retinopathy. If left untreated, diabetic retinopathy can cause blindness when people with diabetes experience long periods of high blood sugar, fluid can accumulate in the lens inside the eye that controls focusing. This changes the curvature of the lens, leading to changes in vision. However, once blood sugar levels are controlled, usually the lens will return to its original shape and vision improves. Patients with diabetes who can better control their blood sugar levels will slow the onset and progression of diabetic retinopathy.

According to a 2018 American Eye-Q survey conducted by the AOA, nearly half of Americans didn't know whether diabetic eye diseases have visible symptoms (often which the early stages of diabetic retinopathy do not). The same survey found that more than one-third of Americans didn't know a comprehensive eye exam is the only way to determine if a person's diabetes will cause blindness, so the AOA recommends that everyone with diabetes have a comprehensive dilated eye examination at least once a year. Early detection and treatment can limit the potential for significant vision loss from diabetic retinopathy.

1.1.2 Symptoms of diabetic retinopathy

- Seeing spots or floaters.
- Blurred vision.
- Having a dark or empty spot in the center of your vision.
- Difficulty seeing well at night.

1.1.3 Stages of Diabetic Retinopathy

1. Mild Nonproliferative Retinopathy:

The first stage happens when the small blood vessels in the retina develop tiny bulges. Their development can cause blood to leak from the blood vessels. During this stage, you are likely to have no vision problems. It is ideal to go for constant medical checkups. Talk to your doctor about how to keep the condition from getting worse. Your blood sugar, cholesterol, and blood pressure will need to be under control. Your chances of progressing to the third stage are high if this first stage has affected both your eyes. You have a 25 percent risk of condition advancement within the next three years. It is ideal to go for the annual screening.

2. Moderate Nonproliferative Retinopathy:

This second stage is where the blood vessels inside your retina begin to swell. They cause physical alterations to your retina because of the inability to carry blood. Such changes can cause diabetic macular edema. Diabetic macula edema occurs when fluids and blood build up in your macula. The macula is a part of the retina responsible for the vision that is straight ahead. It aids when you are driving or reading. Reaching the second stage is a sign that your vision is at risk. Your doctor will recommend regular eye tests to mitigate further damage.

3. Severe Nonproliferative Retinopathy:

Your blood vessels become more blocked during this third stage. As a result, your retina receives less blood, and scar tissue begins forming. The low supply of blood triggers your retina to start developing other blood vessels. Your blood vessels can become blocked completely. As a result, you will have dark spots and blurry vision. Macular ischemia is the complete blockage of the blood vessels. You are most likely to lose your sight if you reach this third stage.

4. **Proliferative Diabetic Retinopathy (PDR):**

This stage is highly advanced. New weak and thin blood vessels start to grow into your retina, as well as in the fluid in the eye. The blood vessels can bleed and cause scar tissue. Retinal detachment can happen as the developed scar tissue grows smaller. The result of this is loss of straight-ahead and both sides' vision.

Figure 1.1 depicting the different lesions of the Diabetic Retinopathy in fundus retinal iamge

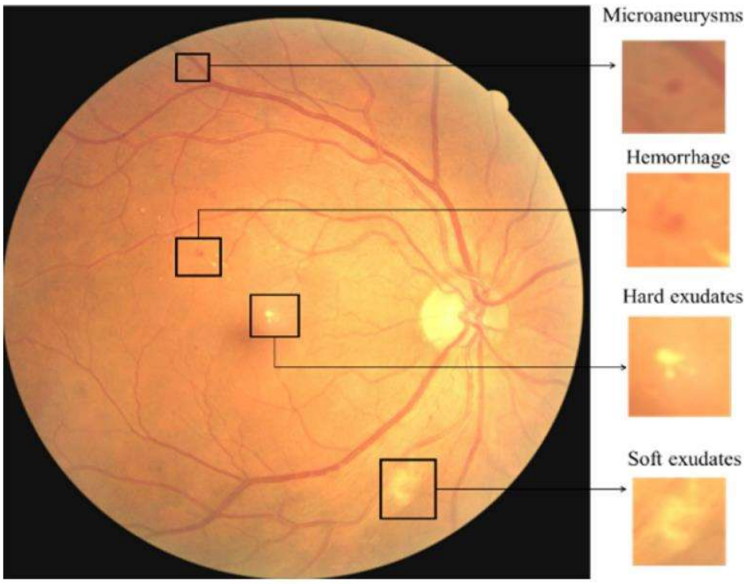


Figure 1.1: Different types of DR lesions

The leaking blood and fluids appear as spots, called lesions, in the fundus retina image. Lesions can be recognized as either red lesions or bright lesions. Red lesions involve microaneurysms (MA) and hemorrhage (HM), while bright lesions involve soft and hard exudates (EX) as shown in Figure 1.1. The small dark red dots are called MA and the larger spots are called HM. Hard EX appears as bright yellow spots, while soft EX, also called cotton wool, appears as yellowish-white and fluffy spots caused by nerve fiber damage. The five DR stages depend on the types and numbers of lesions on the retina image, as shown in Table 1.1. Samples of the various DR stages (no DR, mild DR, moderate DR, and proliferative DR) are shown in Figure 1.2.

Figure 1.2 depicting the different stages of Diabetic Retinopathy

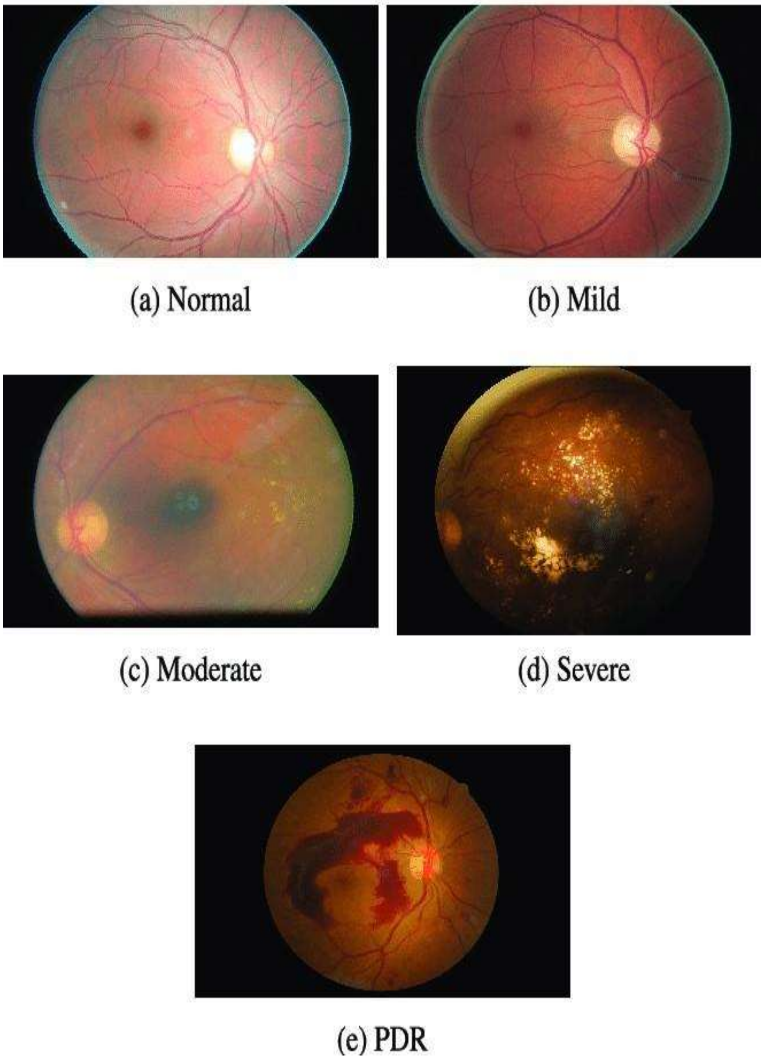


Figure 1.2: Different stages of DR

The manual diagnosis of DR by ophthalmologists is time-consuming, requires considerable effort, and is prone to disease misdiagnosis. Therefore, using a computeraided diagnosis system can avoid misdiagnosis and reduce overall cost, time and effort.

Table 1.1 describes about the severity levels of DR and their corresponding lesions

DR Severity Level	Lesions
0-No DR	No lesions.
1-Mild DR	MA only.
2-Moderate DR	More than just MA but less than severe DR.
3-Severe DR	More than 20 intra retinak HM in each of 4 quadrants; Definite venous beading in 2+quadrants; Prominent intra retinal

	microvascular abnormalities in quadrant and no signs of proliferative DR.
neovascularization	Neovascularization,pre-retinal HM.

Table 1.1: DR stages depending on lesions classification.

During the last decade, deep learning (DL) approach has emerged and been adopted in many fields, including medical image analysis. DL can identify features accurately from input data for classification or segmentation and typically outperforms all traditional image Sensors 2021, 21, 3704 3 of 22 analysis techniques.

Recent advancements in Artificial Intelligence (AI) and the increase in computational resources and capabilities have created the opportunity to develop Deep Learning (DL) applications for accurate DR detection and classification.

1.1.4 ResNet Model

ResNet, short for Residual Networks is a classic neural network used as a backbone for many computer vision tasks. The fundamental breakthrough with ResNet was it allowed us to train extremely deep neural networks with 150+layers successfully. Prior to ResNet training very deep neural networks were difficult due to the problem of vanishing gradients. AlexNet, the winner of ImageNet 2012 and the model that apparently kick-started the focus on deep learning had only 8 convolutional layers,and the ResNet 152 had 152 layers. There is a 34-layer plain network in the architecture that is inspired by VGG-19 in which the shortcut connection or the skip connections are added. These skip connections or the residual blocks then convert the architecture into the residual network.

1.2 Motivation

Diabetic retinopathy is one of the common eye diseases and is a diabetes complication that affects the eyes. Eventually, it can cause blindness. So the early detection of symptoms could help to avoid blindness.Our goal is to classify the patients having diabetic retinopathy and those not having the same, with a highresolution fundus image of the retina.

The classification of diabetic retinopathy (DR) is important for documenting the disease status of an individual patient and following changes over time. In the clinical setting, it is commonly used to provide an estimate of the severity of the disease and therefore can help guide the clinician in determining appropriate treatment or follow-up intervals.

1.3 Village Visited

Visited Pinnamaneni Siddhartha Medical College, Chinna Avutapalli, Andhra Pradesh.

1.4 Photo with the client

Figure 1.3 shows the photo with the client while explaining the project. Figure

Figure 1.3: Photo with the client

1.4 shows the photo with the client along with the guide

Figure 1.4: Photo with the client and guide

1.5 Problem Statement

Diabetic Retinopathy is a disease with an increasing prevalence and the main cause of blindness among the working-age population. The risk of severe vision loss can be significantly reduced by timely diagnosis and treatment. Systematic screening for DR has been identified as a cost-effective way to save health services resources. Automatic retinal image analysis is emerging as an important screening tool for early DR detection, which can reduce the workload associated with manual grading as well as save diagnosis costs and time. Many research efforts in the last years have been devoted to developing automated tools to help in the detection and evaluation of DR lesions. We are interested in automating this prediction using deep learning models. So we want 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 based on the features extracted.

1.6 Scope

The scope of our project is:

- Limited to all ophthalmologists and diabetic retinopathy affected patients.

- Images should be taken in proper lighting conditions.

- Classifies nearly 3000 images.

1.7 Objective

The Objective of our project is:

- To classify the retinal images into different stages of DR.

- To develop a user-friendly GUI.

1.8 Advantages

- Trained by nearly 3000 input retinal images.

- The disease if detected earlier can be treated quickly which prevents the loss of vision.

- Gives the output effectively.

- Time-saving.

- User-friendly GUI.

1.9 Applications

- Used by ophthalmologists to classify the retinal images.

- Used by the common people to check if the diabetic retinopathy is present or not.

Chapter 2

LITERATURE SURVEY

2.1 Diabetic Retinopathy Detection [12]

Journal: International Journal of Engineering and Advanced Technology(IJEAT)

Methodology: This paper uses image processing for the detection of diabetic retinopathy. It is used to enhance and extract useful information from the images which undergone the process based on characteristics and features associated with that image. The methodology in Image processing follows (1) Image acquisition,
(2) pre-processing (3) edge- detection, (4) segmentation, (5) Image restoration, and (6) output processed image. It reduces the noise, and segments and enhances them for improved quality which accurately detects the focus of diseases and communicates medical and pathological information of a particular image by visual representation. There are two stages namely proliferative Diabetic Retinopathy (PDR) and non-proliferative Diabetic Retinopathy (NPDR). At the stage of NDPR, the retinal blood vessels get damaged and become wet and swollen. The PDR stage occurs when abnormal blood vessels appear in various areas of the retina. This paper used only 20 to 50 images in each of the six classes and achieved accuracy above 95%.

Advantages:

- The model developed by this paper is not only helpful for Diabetic retinopathy affected people but can also be used by the melanoma and myeloid leukemia disease affected people.
- This system attained higher accuracy even with less number of dataset.

Disadvantages:

- A negative AI-based finding may give PCPs and patients a false sense of security about the totality of their ocular status.
- Overfitting occurs when this model learns the random noise and irrelevant details from the image dataset.

2.2 Detection of Retinal Hemorrhage from fundus images using ANFIS classifier and MRG segmentation [13]

Journal: Biomedical Research

Methodology: In this paper ANFIS classifier and MRG segmentation are used for the detection of retinal hemorrhage from the fundus images. Retinal fundus images were apprehended with the help of a fundus camera. . With the fluoresce angiograms; ophthalmologists can perceive hemorrhages and microaneurysms. They have also developed a graphical user interface (GUI) model that establishes the classification and segmentation performance metrics.The projected hemorrhage detection procedure experiments in the working platform of MATLAB 2015a with the system configurations as an i5 processor with 4GB RAM and the assessment is done in respect of the classification and also the segmentation. Subsequently, in the segmentation, the performance evaluation is carried out in terms of sensitivity, specificity, accuracy and some performance parameters. The segmentation process they used attained 92.56% accuracy. The accuracy level attained in this paper has clearly demonstrated that the projected algorithm is decidedly efficient in perceiving the affected portions of the retinal image.

Advantages:

- The accuracy level has demonstrated that the algorithm used in this paper is decidedly efficient in perceiving the affected portions of the retinal image. • Splat based image representation makes it easier for clinicians to annotate the boundaries of target objects which may lower the cost of attaining reference standard information for training.

Disadvantages:

- The raw retinal fundus images are difficult to process by machine learning algorithms.
- This model works only for hemorrhage detection.

Journal:

2.3 Diabetic retinal and fundus images: Pre-processing and feature extraction for early detection of diabetic retinopathy [14]

Biomedical & Pharmacology Journal

Methodology: Image processing is the main methodology involved in the extraction of features and for the early detection of Diabetic Retinopathy in this paper. Due to the sensitivity of eye fundus to some vascular diseases, the fundus imaging technique is more suitable for non-invasive kind of screening. The result of the screening approach is directly related to the quality and accuracy of the fundus image extraction technique coupled with efficient image processing methodologies for identifying the abnormalities.

In this paper, pre-processing and feature extraction of the diabetic retinal fundus image is done for the detection of diabetic retinopathy using machine learning techniques. The pre-processing techniques such as green channel extraction, histogram equalization and resizing were performed using DIP toolbox of MATLAB. Out of the total extracted features, seven most significant features are used for comparison and ranking these features is very simple and fundamental in the process of identifying a normal and a diabetic fundus image.

Advantages:

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

Disadvantages:

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

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

2.4 Diabetic retinopathy detection using machine learning [15]

Journal: International Journal of Engineering Research & Technology (IJERT)

Methodology: In this paper several classifiers in machine learning are used for diabetic retinopathy detection. In the proposed method they are implementing a hybrid classifier. That is they are using combination of five classifiers, Support vector machines, K nearest neighbors, Random forest. SVM classifier with kernel radial bias function and degree 3 is used. Training and testing set are prepared in ratio 80:20. In this proposed method hemorrhages, exudates and microaneurysms are detected. For exudate detection green channel extraction, masking, smoothing, bitwise AND are done which results in better calculation and extraction of exudates. For detection of hemorrhages and micro aneurysms, morphological operations are performed like opening. For diabetic retinopathy detection, count the number for MA occurred, count the number of hemorrhages occurred and count the number of exudates occurred in the image so as to decide the condition of image. Then features are calculated and feed to both SVM, KNN, Random Forest classifier. Voting of three classifiers are chosen as final prediction .In this paper, the overall accuracy attained is 82%. Out of 49 test samples 36 produced the correct output.

Advantages:

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

Disadvantages:

- Out of 49 test samples, only 36 produced correct predictions.

Journal:

- It produced less accuracy when compared to other papers.

2.5 A deep learning system for detecting diabetic retinopathy across the disease spectrum [16]

Nature Communications

Methodology: This paper used deep learning system for the detection of Diabetic Retinopathy. To facilitate the screening process, they developed a deep learning system, named DeepDR, that can detect early-to-late stages of diabetic retinopathy. DeepDR is trained for real-time image quality assessment, lesion detection and grading using 466,247 fundus images from 121,342 patients with diabetes. Evaluation is performed on a local dataset with 200,136 fundus images from 52,004 patients and three external datasets with a total of 209,322 images. Several deep learning algorithms with high specificity and sensitivity have been developed for the classification or detection of certain disease conditions based on medical images, including retinal images. Finally, they developed an automated, interpretable, and validated system that performs real-time image quality feedback, retinal lesion detection, and early- to late-stage DR grading. With those functions, DeepDR system is able to improve image collection quality, provide clinical reference, and facilitate DR screening.

Advantages:

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

Disadvantages:

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

Journal:

2.6 Early detections of diabetic retinopathy based on deep learning and ultra-wide-field fundus images [17]

Scientific reports

Methodology: In this paper, Resnet-34 model is used for the detection of Diabetic Retinopathy. The proposed DR detection system requires an automatic segmentation of the ETDRS 7SF to remove undesirable components such as eyelashes and skin. Using the segmented ROI image, they employ the deep learning architecture, the residual network with 34-layer (ResNet-34) model21 as a classifier for the DR detection task. To evaluate the DR detection performance, they compared their system with the one based on the ROI containing only the ETDRS Field 1 and Field 2 (F1–F2) in terms of several metrics. In this study, they configured a deep learning system for DR detection using the ETDRS 7SF image extracted from the UWF fundus image. Although the UWF imaging provides a wide captured area, the far periphery of the retina in UWF images may contain eyelids and eyelashes. By segmenting the ETDRS 7SF from UWF photography, we can save the time and effort for capturing the ETDRS 7SF photography using a single-field fundus camera. They attained an overall accuracy of 83%.

Advantages:

- The ResNet architecture used this model provides advantages in an easier optimization and accuracy gain for deep networks.
- The ETDRS 7SF photography was used to capture the retinal images. It captures approximately 90◦ of the retina which is around 30% of the retinal surface

Disadvantages:

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

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

2.7 Examination of diabetes mellitus for early prediction and automatic detection of exudates for diabetic retinopathy [18]

International Journal of nnovative Technology and Exploring Engineering (IJITEE)

Methodology: In this paper, the major objective of the proposed methodology and Hypothetical Research Survey Analysis for recognition of Exudates in diabetic retinopathy images for diverse categories of image considerations. It is constructed on studying texture insight competencies in fundus images to distinguish vigorous patients from DR images. The former discovery of diabetic retinopathy using state of art of image technologies will have several applications based on the hypothetical analysis survey in this paper. The strategy talked about where less human correspondence offering increment to amazingly sterile procedure and making the framework recognizable proof completely programmed. The study will be supported for the discovery & its pertinent constraints Wide-ranging collected works survey has been done in the hypothetical analysis in the domain of medical solicitations. In the reference of hypothetical analysis to give a vision into numerous AI models and its prognostic exactness in relations of the recital, accuracy improvement from 2.05% to 12.4% across various models.

Advantages:

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

Disadvantages:

Journal:

- Some of the images are misannotated.
- Optic discs cannot be extracted using this model.

2.8 Automatic Classification of Preliminary Diabetic Retinopathy Stages using CNN [19]

Journal: International Journal of Advanced Computer Science and Applications(IJACSA)

Methodology: This paper used Convolutional Neural Networks for detecting diabetic retinopathy. The approach mainly replaces the old-fashioned manual diagnosis of (DR), with a modern automated method. The aim of this proposed system is to be able to automatically detect and classify the various Diabetic Retinopathy stages using a “5-Stages” model architecture, in which deep learning mainly depends on raw colored Retinal Fundus images as its source of input. The main goal of this software is to automatically detect the early stages of Diabetic Retinopathy and classify the level of the disease in the patient’s body.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. This research is additionally centered around distinguishing and immediately perceiving the characteristics and qualities of (DR) for ideal precision during the classification operation. The overall accuracy attained by this paper is 84%.

Advantages:

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

Disadvantages:

- The trained model in this paper has a huge variation from the real data.

- Several other models may be designed which offers better results than this model.

Chapter 3

ANALYSIS AND DESIGN

This chapter includes the analysis of requirements for the proposed project. This chapter contains

- Functional Requirements.
- Non-Functional Requirements.

3.1 Functional Requirements

Functional requirement analysis entails a thorough examination, analysis, and description of software requirements and hardware requirements in order to meet actual and also necessary criteria in order to solve an issue. Analyzing functional Requirements includes a number of processes. The Functional Requirements include:

Software Requirements PyTorch:
PyTorch is an open source machine learning framework based on the Torch library that may be used for applications like computer vision and natural language processing. The framework is designed to accelerate the transition from research prototyping to implementation.

Jupyter Notebook:
JupyterLab is the latest web-based interactive development environment for notebooks, code, and data. Language of choice Jupyter supports over 40 programming languages, including Python, R, Julia, and Scala. Share notebooks can be shared with others using email, Dropbox, GitHub and the Jupyter Notebook Interactive Output Your code can produce rich, interactive output: HTML, images, videos, LaTeX, and custom MIME types. Explore that same data with pandas, scikitlearn, ggplot2, TensorFlow. In this project, the code is written in a jupyter notebook.

Image processing:

Image processing is a technique for performing operations on an image in order to improve it or extract relevant information from it. It's a sort of signal processing in which the input is an image and the output is either that image or its characteristics/features.

Tkinter:
Tkinter is Python's standard GUI library. Python and Tkinter make it simple and quick to design graphical user interfaces. Tkinter gives the Tk GUI toolkit a robust object-oriented interface. Tkinter should be imported.

Python:
Python is a high-level, interpreted, general-purpose programming language. Its design philosophy emphasizes code readability with the use of significant indentation. Python is dynamically-typed and garbage-collected. It supports multiple programming paradigms, including structured (particularly procedural), objectoriented and functional programming. Requires a version of python 2.7 and above.

Modules:
OpenCV, Keras, NumPy, etc. are some of the modules in Python that are used in the project. These modules are used for image pre-processing, training the model, and testing the model.

Hardware Requirements

- Modern Operating System (windows 7 or 10/Mac OS X 10.11 or higher)
- x86 64-bit CPU
- Disk Space - 4GB SSD
- RAM/Main Memory - 4GB DDR4 3200Mhz

3.2 Non-Functional Requirements

Non-functional requirements describe how a system must behave and establish constraints of its functionality. This type of requirements is also known as the system's quality attributes.

The Non-functional requirements of this project are:

Availability: Availability is gauged by the period of time that the system's functionality and services are available for use with all operations. So, scheduled maintenance periods directly influence this parameter. And it's important to define how the impact of maintenance can be minimized.

Scalability: Scalability requirements describe how the system must grow without negative influence on its performance. This means serving more users, processing more data, and doing more transactions. Scalability has both hardware and software implications. For instance, you can increase scalability by adding memory, servers, or disk space, can compress data, use optimizing algorithms, etc.

Usability: Usability defines how difficult it will be for a user to learn and operate the system. It is assessed by using Efficiency of use, Intuitiveness, Low perceived workload.

Security: Security requirements ensure that the software is protected from unauthorized access to the system and its stored data. It considers different levels of authorization and authentication across different user roles. For instance, data privacy is a security characteristic that describes who can create, see, copy, change, or delete information. Security also includes protection against viruses and malware attacks.

Efficiency: Efficiency means a level of performance that describes how to use the smallest number of inputs to produce the largest output so with minimal system requirements and processing power we should be able to detect exudates accurately.

Performance: Performance is a quality attribute that describes the responsiveness of the system to various user interactions with it. Poor performance leads to negative user experience. It also jeopardizes system safety when it is overloaded.

Accuracy: Accuracy is the quality or state of being correct or precise or accuracy refers to the closeness of the measurements to a specific value. The output in detecting the exudates should be more accurate.

Reliability: The model is said to be reliable if it is consistently good in quality or performance and it can be trusted to work in all conditions. The CNN model should be reliable irrespective of the input of any kind of retinal image.

3.3 Design Diagrams

Figure 3.1 shows various layers that are present in the ResNet model

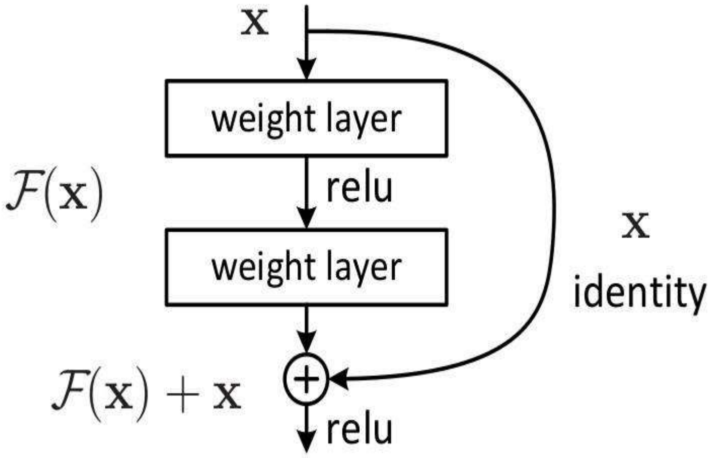


Figure 3.1: Different layers of ResNet

Figure 3.2 shows about how a ResNet model works when a retinal image is sent as input

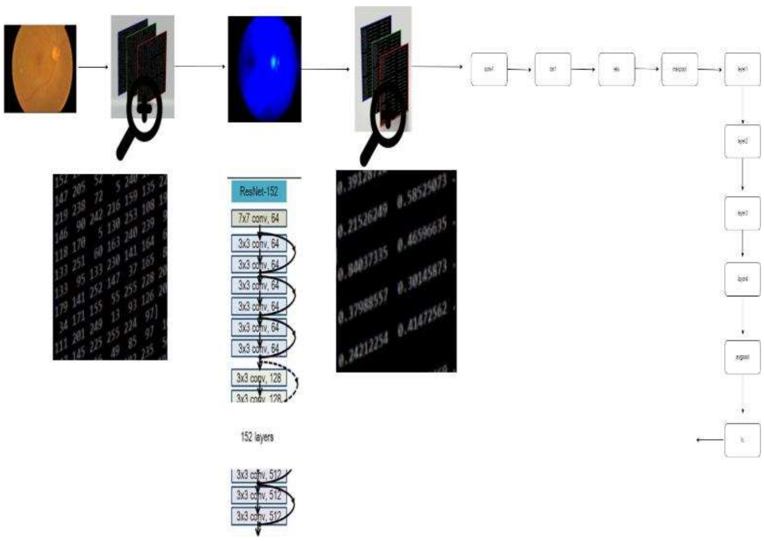


Figure 3.2: Figure describing how ResNet model works

Chapter 4

PROPOSED SYSTEM

4.1 Process Flow Diagram

Figure 4.1 depicts the flow chart of the implementation of the model

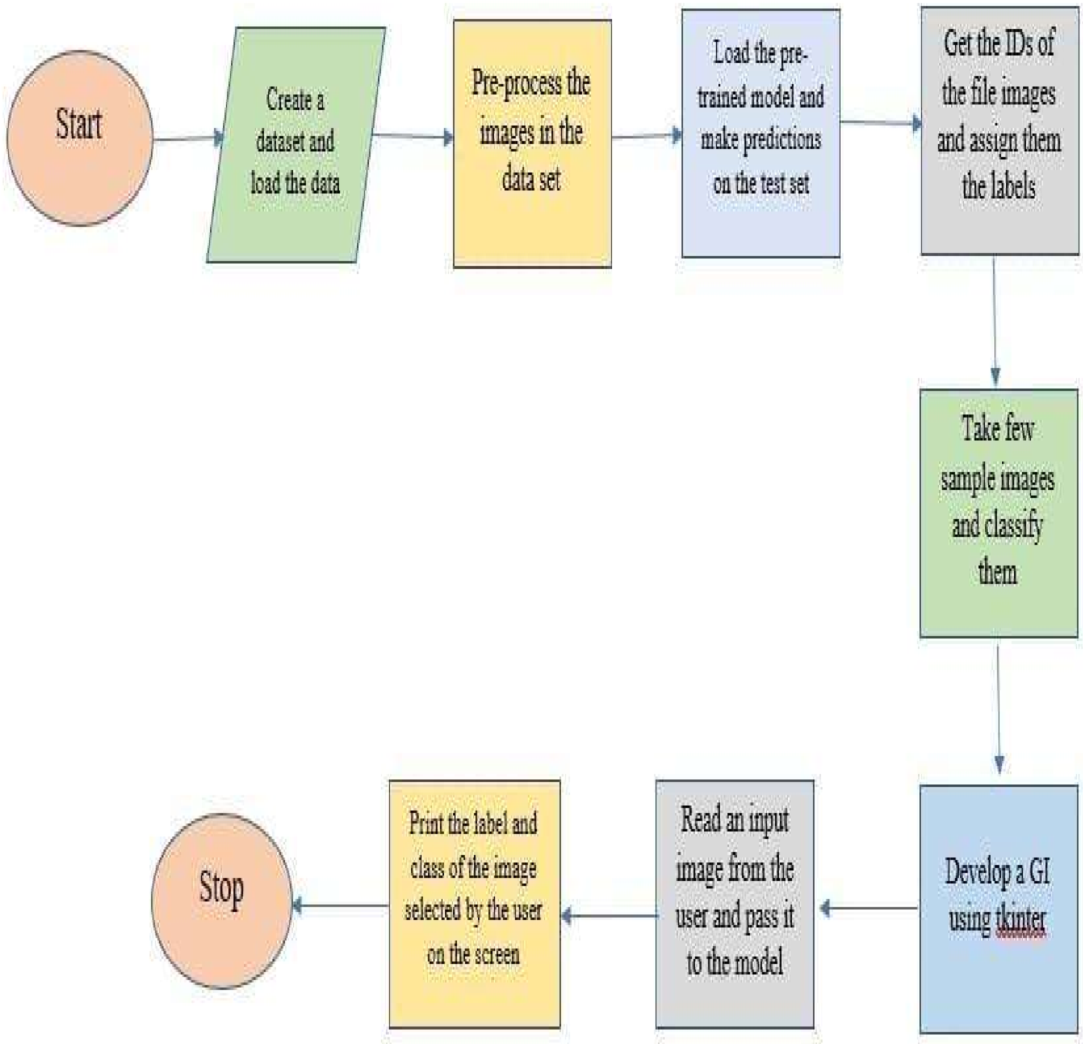


Figure 4.1: Process flow diagram

4.2 Proposed Methodology

ResNet model is used to classify the images. The model is built using PyTorch in which the pre-processing is done internally. The ResNet model consists of 152 layers. The depth of the deep network plays a pivotal role in their performance. With the increase in layers, the model gives better performance.

However, it has also been observed that the addition of layers may increase the error rate. This is named as an issue of vanishing gradients. The residual neural network, also known as ResNet, was introduced to address this problem.

Figure 4.2 shows the building block of a residual network showing ReLu activation function and various convolution layers (1 × 1 64, 3 × 3 64, 1 × 1 256).

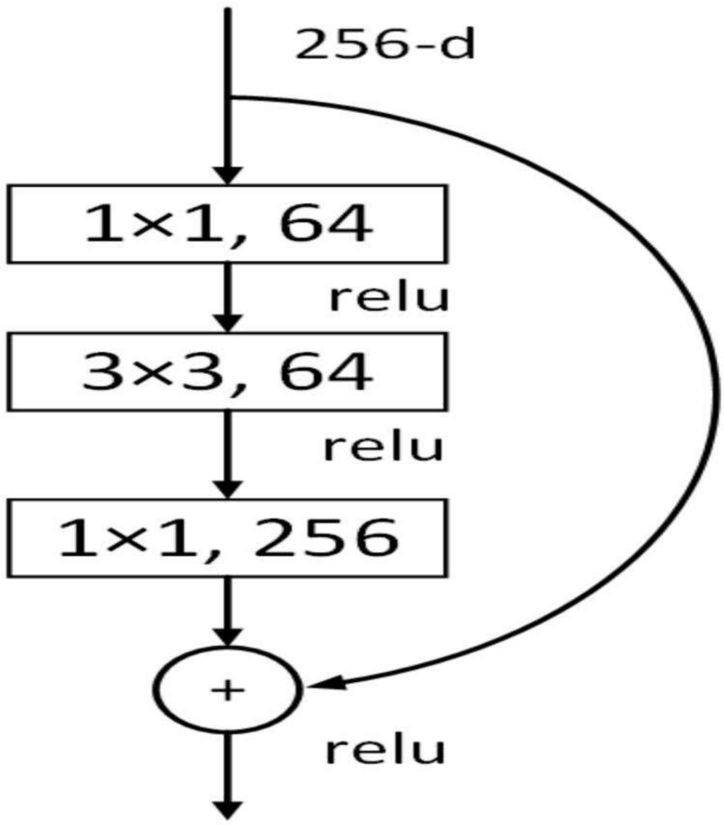


Figure 4.2: Building block of Residual Network

Residual Network uses the skip connection to indiscriminately allow some input to the layer to incorporate the flow of information and also to prevent its loss, hence, addressing the problem of vanishing gradients (which also suppresses the generation of some noise). Suppressing the noise means averaging the models, which keeps a balance between precision and generalization. To achieve higher precision and an estimated level of traversal, the most efficient way is to increase more labeled data. The structure of ResNet speeds up the training of ultra-deep neural networks and increases the model's accuracy on large training data.

This model is first trained and is later tested inorder to classify the images. The training of the data set is done using 3662 images and the testing is for approximately 1900+ images. At a later stage, a GUI is developed using Tkinter in python which asks the user to upload the image of a fundus retinal image and then gives the predicted label as the output.

4.3 Architecture

ResNet includes the skip connection feature which enables the training of 152 layers without vanishing gradient issues.The approach behind this network is instead of layers learning the underlying mapping, we allow the network to fit the residual mapping.

Figure 4.3 shows the architecture of the ResNet model.

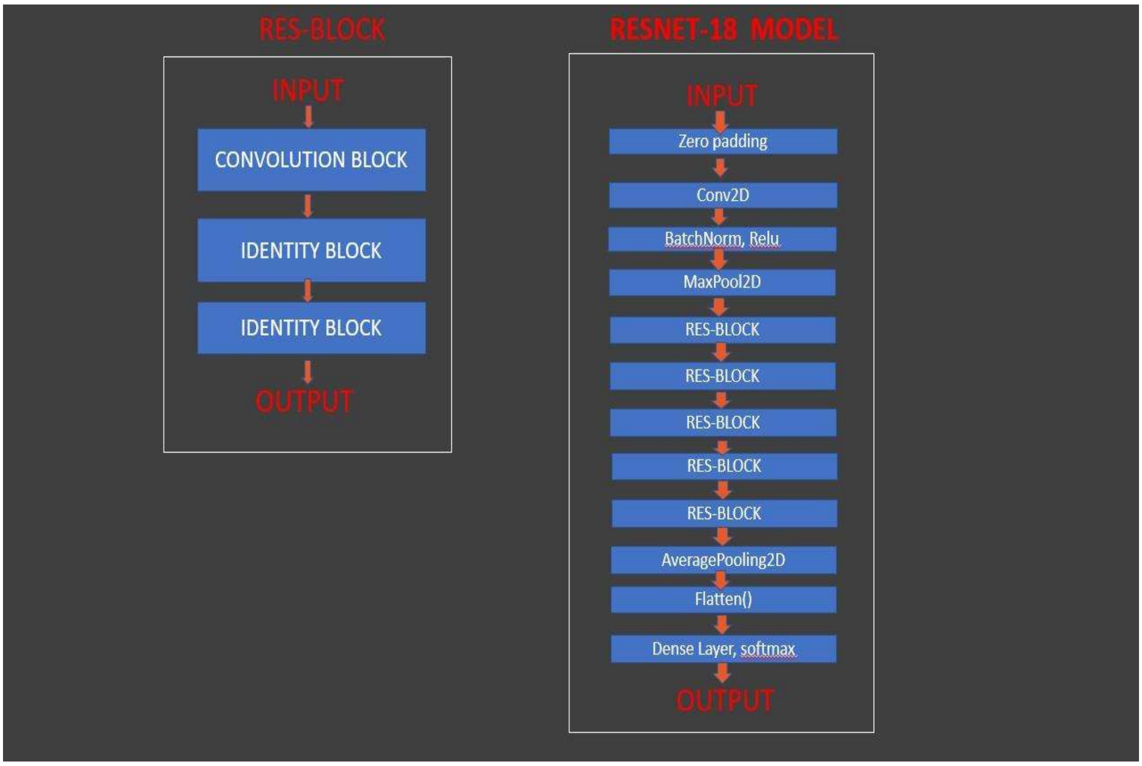


Figure 4.3: Architecture

So, instead of say H(x), initial mapping, let the network fit, F(x) := H(x) – x which gives H(x) := F(x) + x. where: x = shows the input of building block.
F(x) = shows the output of the layer within the building block of the residual network.
The advantage of adding this type of skip connection is that if any layer hurt the performance of architecture then it will be skipped by regularization. So, this

results in training a very deep neural network without the problems caused by vanishing/exploding gradient.

4.4 Algorithms

4.4.1 Algorithm for training the data

1. Start
2. Import all the required packages.
3. Load the data from the trained data set. The training dataset consists of 32 images and the images are already classified into 5 classes.
4. Visualize the trained data set.
5. Visualize the test data set which consists of 1928 images that should be trained.6. 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.
7. Load the sample training and validation data from the train data set and loadthe sample test data from the test data set.
8. Now, load one batch from the sample test set and check the images and theircorresponding labels.
9. Save the trained model in a file named classifier.pt and save the file in theworking directory.
10. Now, for each epoch pass the images in the corresponding sample train dataand the corresponding sample validation data to the model to test and validate the data set.
11. Repeat the above step till all the epochs are completed.
12. Stop

4.4.2 Algorithm for testing the data

1. Start
2. Import all the required packages.
3. Create a sample data set from the test data set.
4. Preprocess each image in the dataset created using the Compose function present in the transforms module.
5. Now load the model to predict the labels for the loaded test dataset.

6. Unfreeze the layers present in the pre-trained model and pass the images presentin the test data set to the model.
7. Store the resultant output labels in an array.
8. All the images present in the test data set are now classified into differentclasses.
9. Now, provide the path of the folder where the sample images are present.
10. Now perform all the above steps and print the predicted labels and classes forall the images present in the folder specified.
11. Stop

4.4.3 Algorithm for developing a GUI

1. Start
2. Import all the required packages.
3. Create a window with the required title and background color.
4. Add a label asking the user the choose an image.
5. Now add the button correspondingly.
6. Define a function that takes the input image from the user and shows the reportof the image read.
7. In the function defined, pass the input image read to the model that is builtearlier.
8. It returns the value and class of the image. Now display the report of the imageon the screen.
9. Stop

4.5 Dataset Collection

We collected the real-time dataset from Dr.Pinnamaneni Siddhartha Institute of Medical Sciences, Chinnaoutpalli, Vijayawada. Around 3000 images of Diabetic Retinal Eyes are collected and trained properly.

Sample link:
https://drive.google.com/drive/folders/1Q09Ym2dkasve4GNZmNC0zIcjQLfPqO7
The fundus retinal pictures in the dataset are from patients who visited Pinnamaneni Siddhartha Institute of Medical Sciences in Chinnaoutpalli, Vijayawada.

Chapter 5

IMPLEMENTATION

5.1 Output Screenshots

Figure 5.1 shows the output of the code after executing in the jupyter notebook.

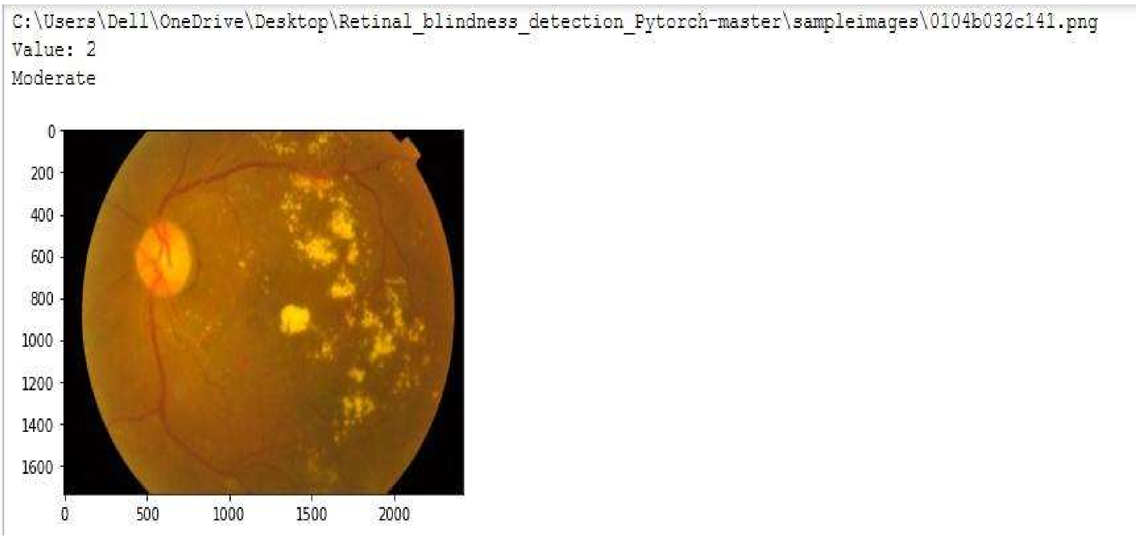


Figure 5.1: Output after testing the sample images

Figure 5.2 shows the GUI developed

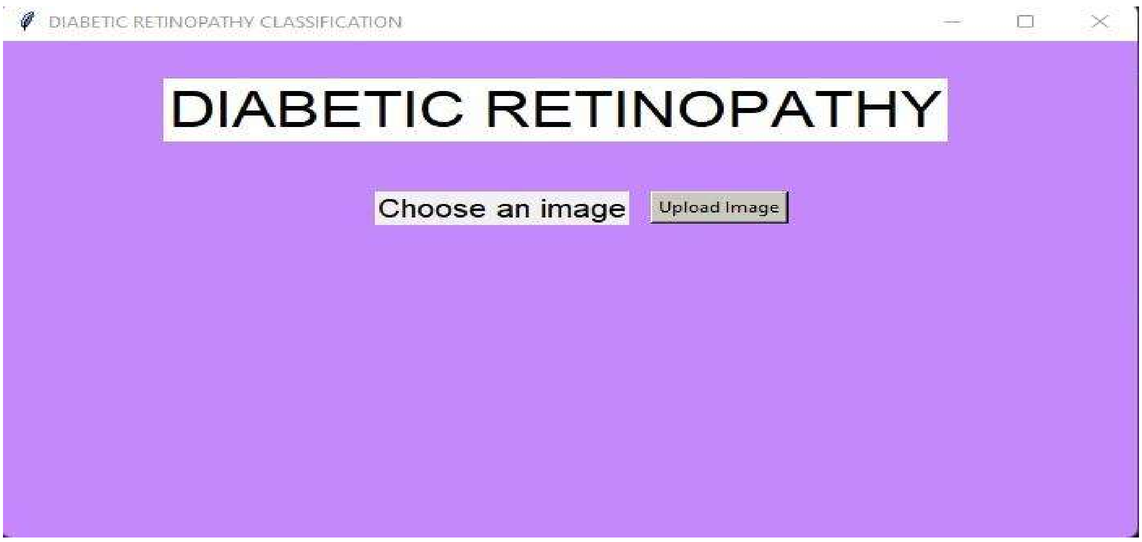
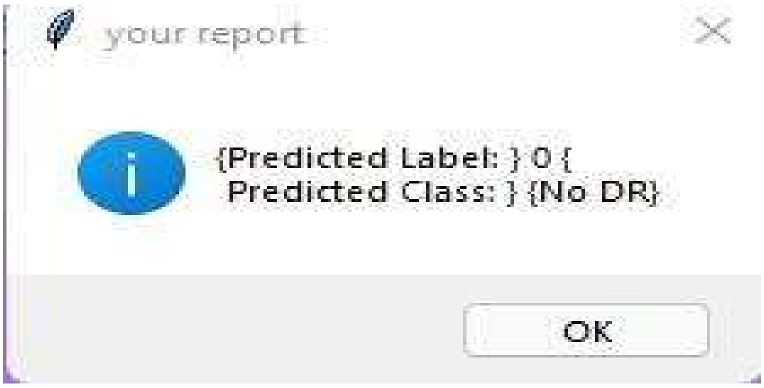


Figure 5.2: GUI developed

Figure 5.3 shows that the predicted class label is No DR



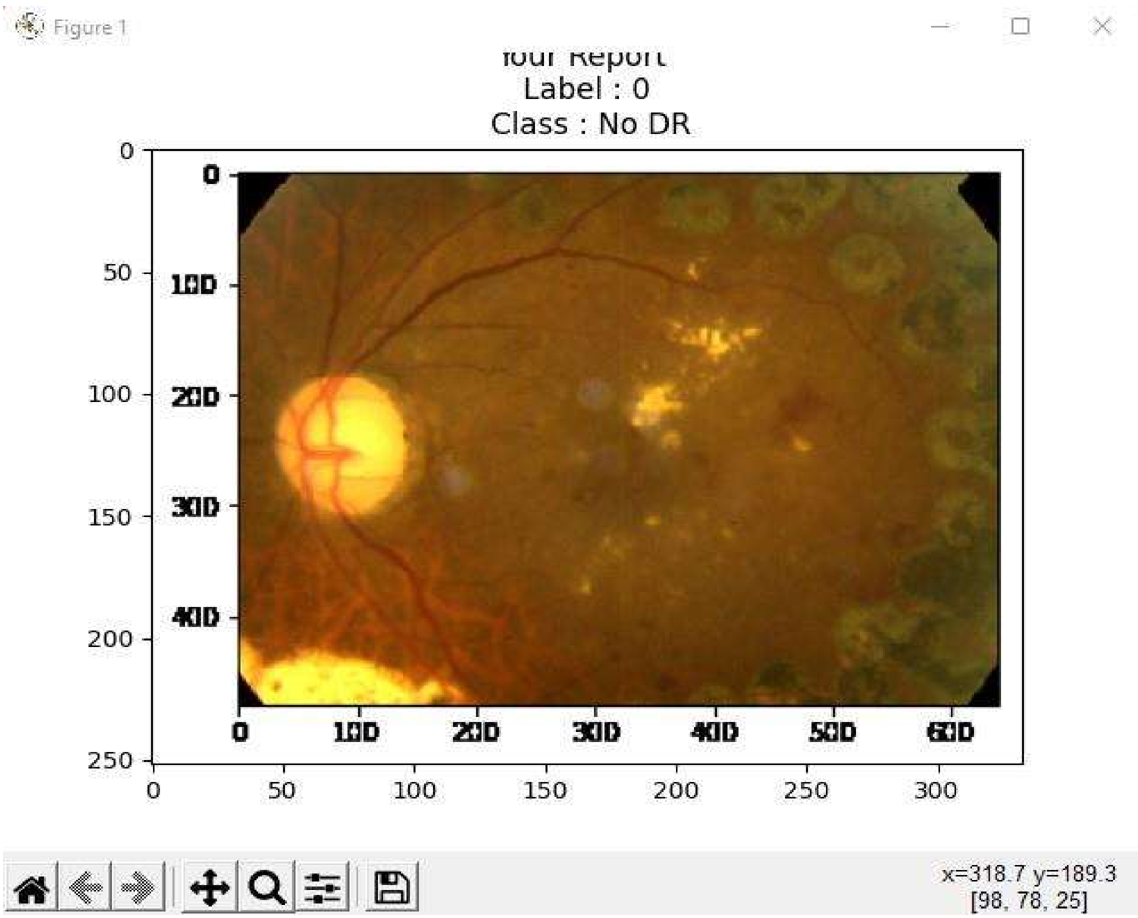
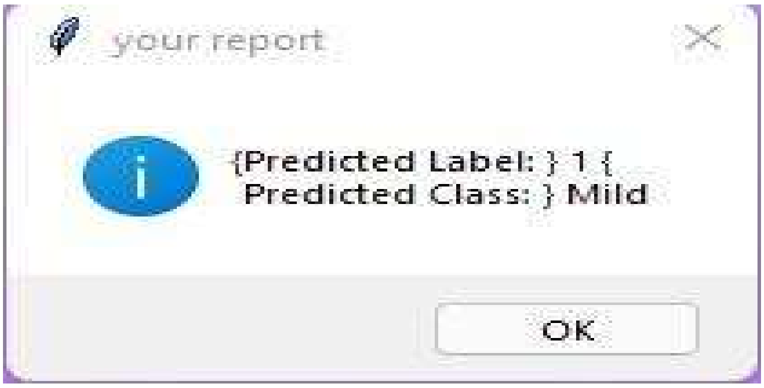


Figure 5.3: Retinal image - predicted as No DR

Figure 5.4 shows that the predicted class label is Mild



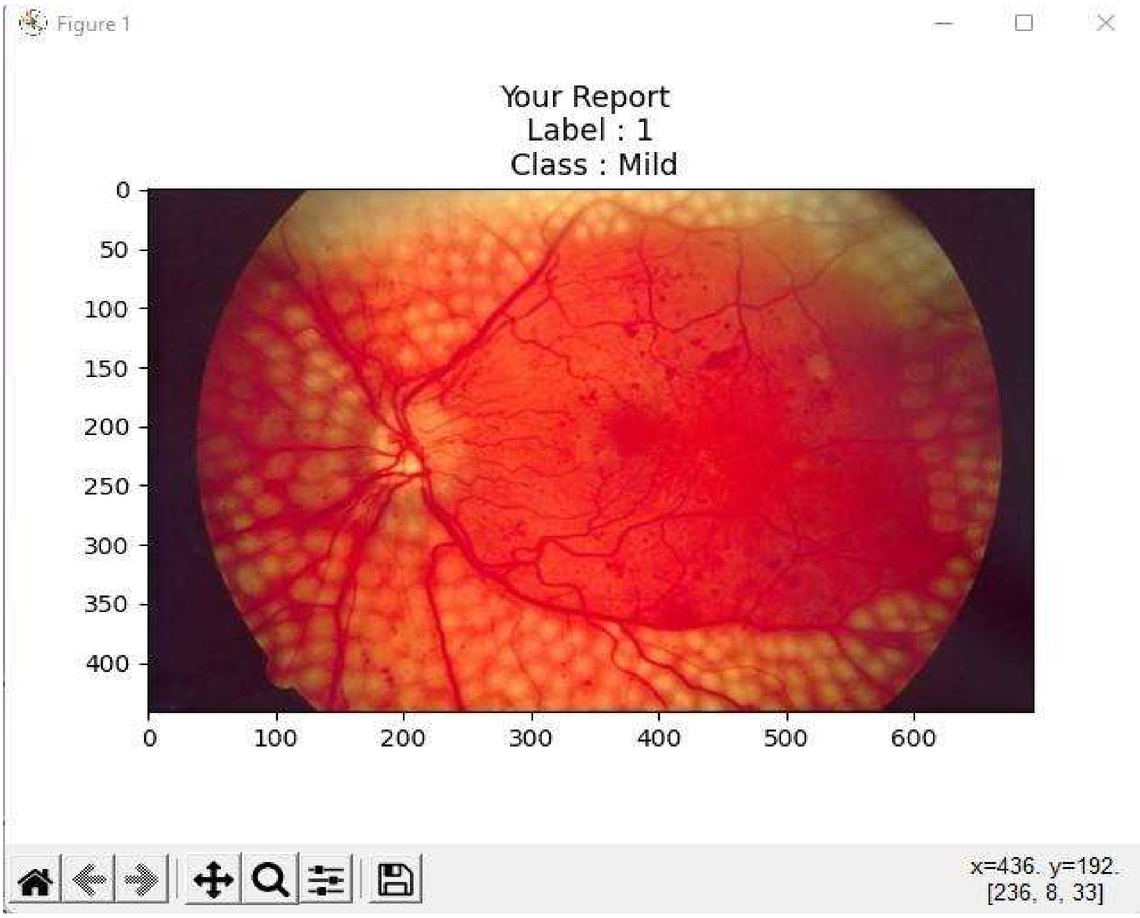


Figure 5.4: Retinal image - predicted as Mild

Figure 5.5 shows that the predicted class label is Moderate

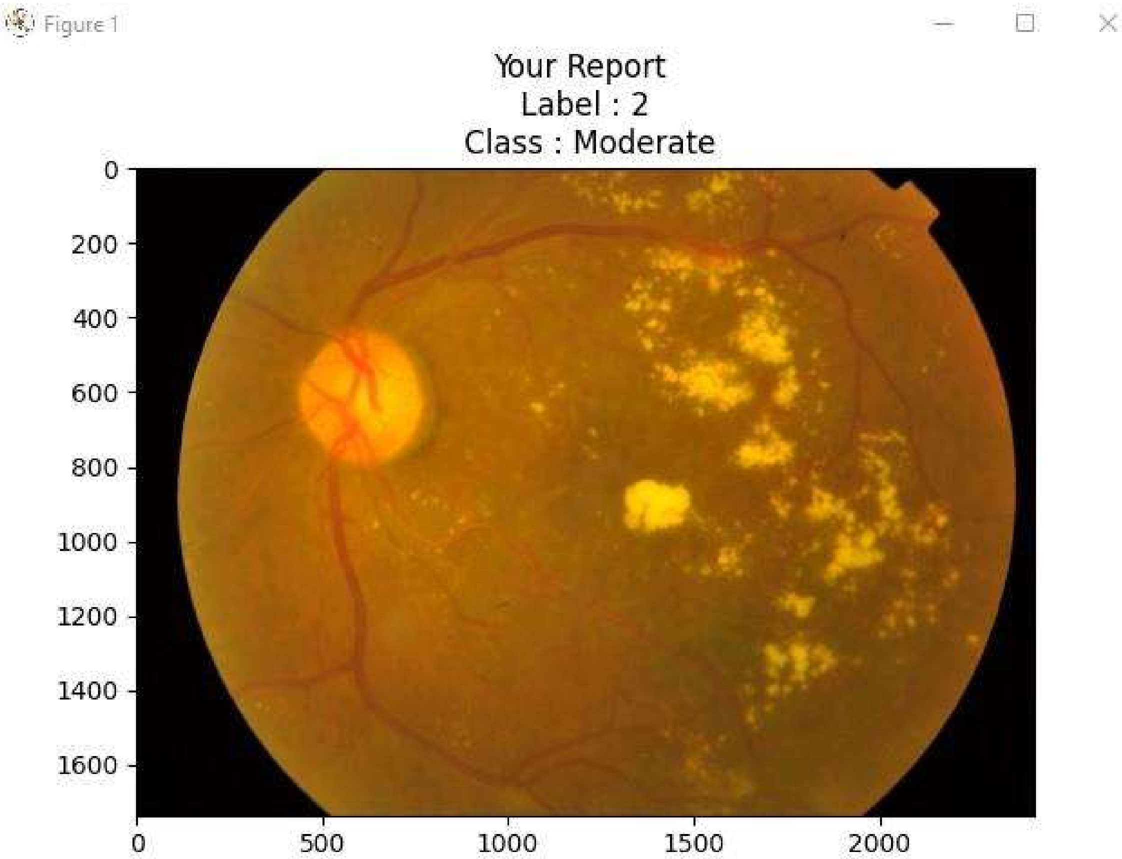
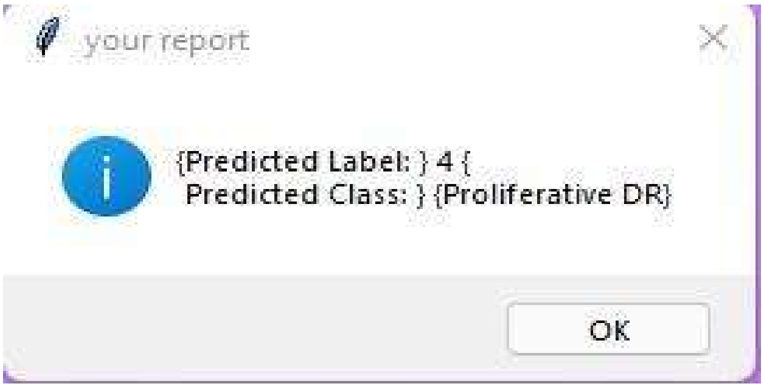


Figure 5.5: Retinal image - predicted as Moderate

Figure 5.6 shows that the predicted class label is Proliferate DR



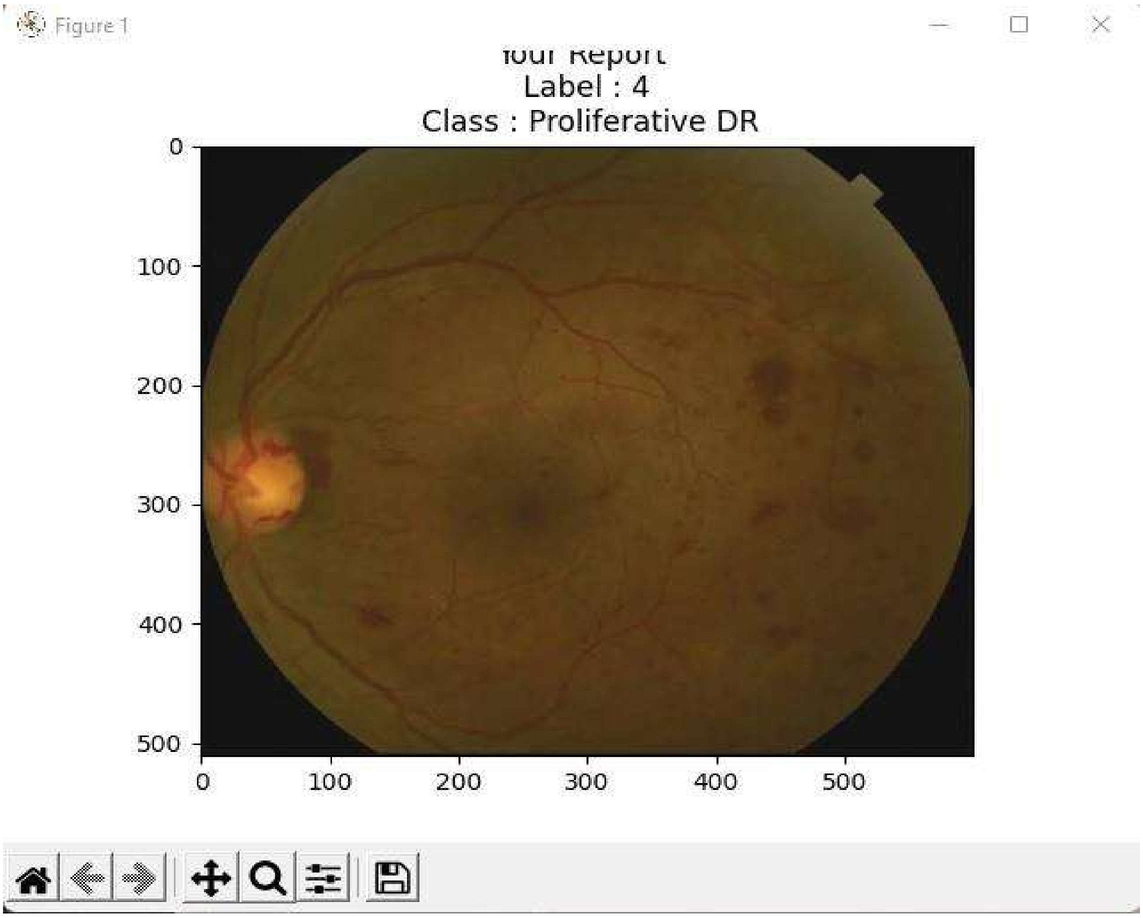


Figure 5.6: Retinal image - predicted as Proliferative DR

Figure 5.7 shows the output in the console

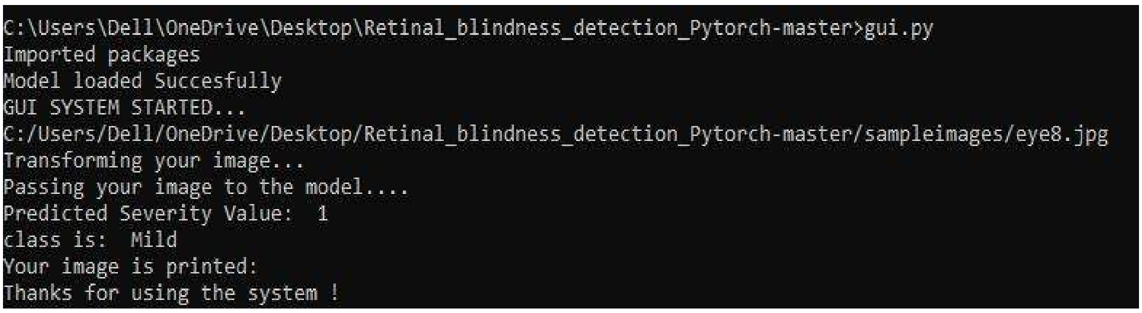


Figure 5.7: Output in the console

5.2 Test Cases

The figures shown below depicts the expected label and the output label

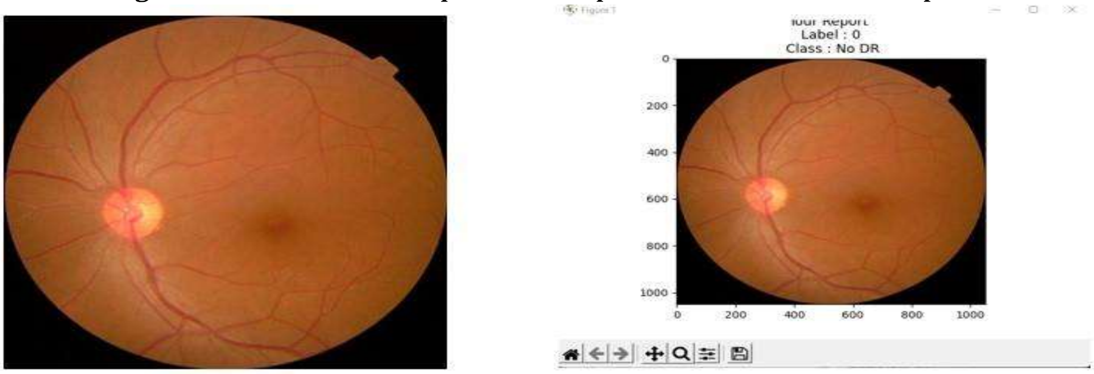


Figure 5.8: Expected label: No DR vs Output Label

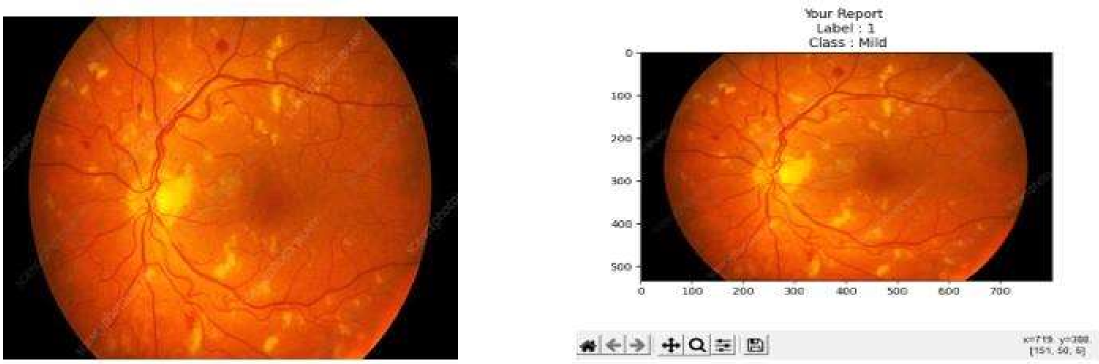


Figure 5.9: Expected label: Mild vs Output Label

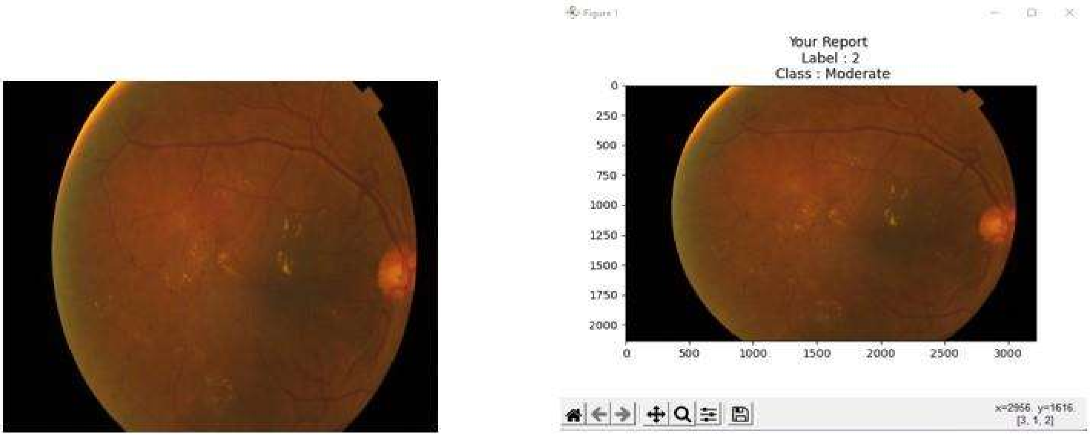


Figure 5.10: Expected label: Moderate vs Output Label

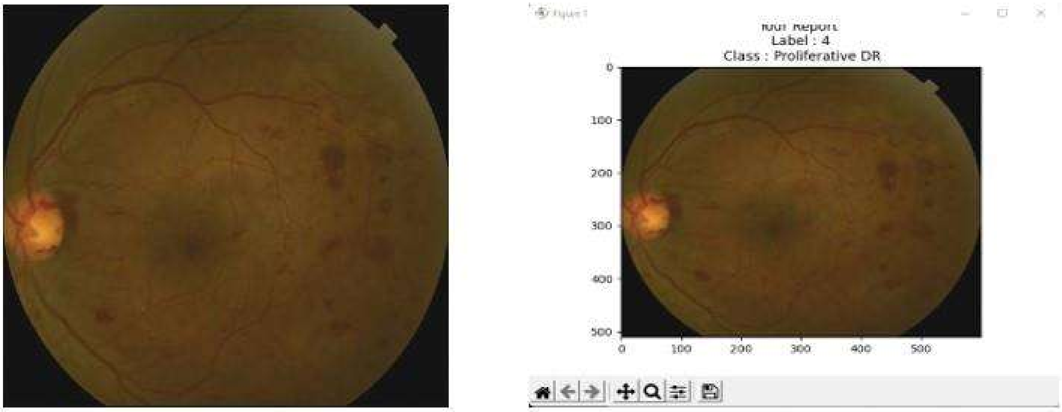


Figure 5.11: Expected label: Proliferate DR vs Output Label

Figure 5.12: Expected label: Mild vs Output Label (Wrong Output)

5.3 Results and Analysis

Out of 52 sample images we have taken for testing, 31 images are classified into class 0, 12 images are classified into class 1, 6 images are classified into class 2 and 3 images are classified as class 4 that means, 31 images are classified as ‘No DR’, 12 images are classified as ‘Mild DR’, 6 images are classified as ‘Moderate DR’ and 3 images are classified as ‘Proliferative DR’. From the above result, we observe that there are very few images that belong to the class Proliferative DR. From the images that are classified into different stages of Diabetic Retinopathy. 48 images out of 52 images were predicted correctly leading to an accuracy of approximately 92%. Our model has less error rate thus having higher efficiency.

Chapter 6

CONCLUSION AND FUTURE WORK

Diabetic Retinopathy is a well-known kind of vision loss caused by diabetes. Diabetic Retinopathy affects people who have been diagnosed with diabetes. If detected and identified early on, it can be significantly reduced. In this project, we are able to classify the input retinal images into different stages of DR using the pre-trained ResNet model. Additionally, we showed that our GUI was accurate at predicting four stages of diabetic retinopathy: no DR, moderate DR, mild DR, and proliferative DR. The GUI we developed is helpful for both doctors and also the common people is the fundus retinal image is available with them. After uploading the image to the GUI, it predicts the stage of the disease. Our future work is to convert the GUI into a mobile application. We are also trying to improve the accuracy and classify the disease into few more levels rather than just classifying into four levels.

Chapter 7

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