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Diabetic Retinopathy Classification Using Deep Learning Technique

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Abstract*—Diabetic Retinopathy is a disease that damages the eyes and is caused by a consequence of diabetes. If blood sugar levels aren't controlled for an extended period of time, the disease can develop. It is mainly caused due to the damage of blood vessels in the retina. Retinopathy is the main cause of blindness in the world. Doctors can diagnose blindness before it occurs using Artificial Intelligence and Deep Learning. Medical imaging plays a very crucial role in a variety of medical issues and at all major levels of health issues. Medical imaging can be used to identify a variety of common eye illnesses. However, for a variety of reasons, including uneven lighting, picture blurring, and low contrast and brightness, poor-quality retinal images are ineffective for further diagnosis, particularly in automated analysing systems. Ophthalmologists' manual Diabetic Retinopathy diagnostic procedure is time-consuming, requires more work, costly, and might result in misdiagnosis. Basing on the vision like having trouble in reading distant objects or seeing distant objects, blindness or any other changes may happen in eye retina that affects diabetes. Diabetic retinopathy is one of the most frequent eye illnesses, affecting mostly diabetics. This model using deep learning convolution neural networks can assist the opthmologists by providing clear images of the retina, and also blood vessel extracted images. There are three phases in this diabetic retinopathy detection and classification technique. These three phases are pre-processing, blood vessel and exudates detection, feature extraction and classification. In this work, From the presented retinal fundus pictures, we utilised the Res-Block model to classify and diagnose diabetic retinopathy with 92% of accuracy.

Keywords—Diabetic Retinopathy, Deep Learning, Fundus, Artificial Intelligence, Medical Imaging

I. INTRODUCTION

Diabetic Retinopathy is a diabetic complication that affects eyesight. Damage to the blood vessels in the tissue surrounding the back of the eye causes diabetic retinopathy. A risk factor is poorly regulated blood sugar. Early symptoms include blurriness, floaters, dark patches of vision, and difficulty identifying colours. Blindness is a possibility. With appropriate diabetes treatment, mild instances can be managed. Laser treatment or surgery may be necessary in extreme cases. Medical imaging is an important part of medical practice in today's environment. The best method to avoid visual loss is to keep diabetes under control. As a result, the eye attempts to create new blood vessels. These new blood vessels, on the other hand, may not develop properly and are prone to leaking. New blood vessels do not grow in non-proliferative diabetic retinopathy (NPDR) in the early stages of diabetic retinopathy. When a person has NDPR, the walls of the blood vessels in the retina degenerate. As additional blood vessels get clogged, NDPR can evolve from moderate to serious. A more severe type of advanced DR is proliferative diabetic retinopathy (PDR). In this kind, damaged blood vessels close off, causing new, abnormal blood vessels to form in the retina. These new blood vessels are fragile, and they risk leaking into the clear, jellylike fluid that fills the centre of your eye. Serious visual impairments can occur as a result of complications. Diabetic retinopathy cannot always be avoided. Regular eye checkups, proper blood sugar and blood pressure control, and early detection of visual disorders can all assist to avoid serious vision loss.

Medical imaging has revolutionised the healthcare industry, allowing doctors and scientists to learn more about the human body than ever before. Medical imaging can also aid in the treatment and monitoring of the condition. Medical imaging is improving, and it may now be able to alert clinicians to concerns that a basic surface examination could miss. Medical imaging provides accurate data that enables patients to obtain better, more comprehensive treatment.In today's world, pictures have emerged as the most effective means of providing answers to a wide range of issues. . Images would play a major part in practically all disciplines such as medical, sports, social networking, and many more in everyday life. By taking a photo of the back of your eye using a high-resolution camera, retinal imaging allows your optometrist

to better analyse the health of your eye. The retina, optic disc, and blood vessels are all visible in this image. This can assist your optometrist in detecting specific eye or health concerns, which can help avoid the advancement of dangerous diseases. Retinal pictures may be compared over time to track your eye health and spot small changes. They allow your doctor to discuss therapy in greater detail because you can study the photographs together, ensuring that your routine eye exam is as precise as possible. Early illness detection may lead to more treatments and a higher survival rate.

Other approaches, such as microaneurysm prognosis and early diagnosis for non-proliferative diabetic retinopathy, have been employed in the past [1]. Non-microaneurysm data, on the other hand, varies greatly, and collecting non-microaneurysm training data is a controversial matter, since the large training set not only consumes time but also generates class imbalance. Another method is to modify histograms and enhance contrast in digital images. Efficient Contrast Enhancement Using Adaptive Gamma Correction With Weighting Distribution[2]. Due to non-uniform contrast in images, the scales parameter cannot be held constant.If the image has a high density distribution in a limited range, it is not suited for the over-equalization effect problem. The retina is where the majority of eye problems exhibit themselves. Quantitative techniques for analysing fundus photographs are given special attention, with an emphasis on clinically relevant retinal vascular evaluation, retinal lesions identification, optic nerve head (ONH) shape assessment, retinal atlases construction, and automated retinal disease population screening [4]. However, when compared to radiologic imaging technologies, which can be 10 to 100 times more expensive, ocular imaging systems have a lower initial cost, explains part of this. Translation of basic scientific results in ophthalmology is predicted to stay rapid in the future. Enhancement Algorithm for Non-Uniform Illumination Images with Naturalness Preserved [5]. Image enhancement requires naturalness in order to obtain excellent quality. To preserve that naturalness during enhancement, It is proposed that a bright pass filter be used to breakdown a picture and identify details without disturbing the image's naturalness. However, because this enhancement technique ignores the relationship of illumination, it introduces flickering for video applications and scenes vary noticeably.

Ophthalmologists can manually detect Diabetic Retinopathy 1 or use automated technologies to do so. In the field of artificial intelligence, ophthalmology is being utilised to replace traditional detection methods in the early detection of diabetic retinopathy [8]. However, the success of Diabetic Retinopathy-based computer assisted systems is dependent on feature segmentation, i.e., feature extraction into diabetic retinopathy-related fundus pictures, which is computationally costly and prone to mistakes. Ophthalmologists must analyse retinal pictures and photos, which is a time-consuming and costly job.

II. METHODS AND MATERIALS

A. Analysis and Design

In order for users to perform their tasks, developers must incorporate functional requirements. As a result, they must be known by both the stakeholders and the development team. In general, functional requirements outline how a system responds in specific contexts.

The following items are in our project's list of hardware requirements:

• i7-11th GEN Processor

• 1TB hard drive

• Graphic card: NVidia • RAM: 8GB • Webcam: 2MP (4gb)

The following are some of our project's software requirements: Our project's environments are as follows:

• Microsoft Visual Studio code, Python IDLE, Anaconda

Our project uses the following programming languages and libraries: Python 3.8, Pandas, Keras, TensorFlow, Matplotlib, NumPy, and OpenCv.

Non-functional requirements explain how the system behaves, what features it has, and how it affects the user's experience. How successfully non-functional demands are recognised and implemented determines a system's ease of use, which is used to evaluate system performance. Non-functional criteria include things like product qualities and user expectations.

B. Proposed System

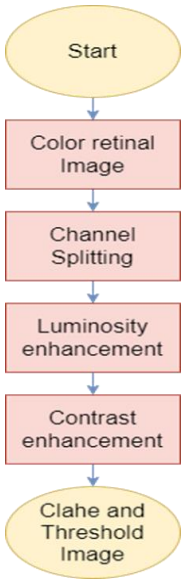

Fig 1: Data pre-Prossesing

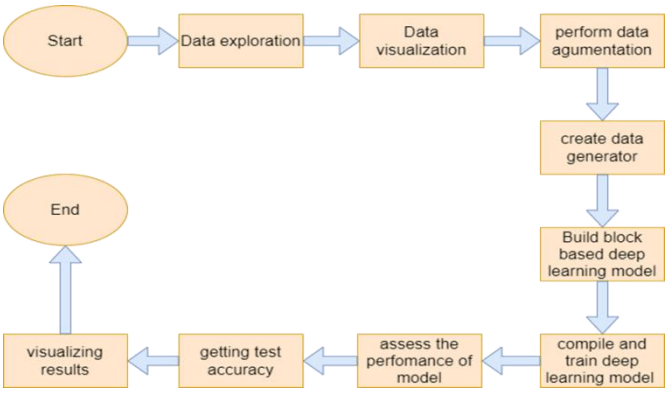

Fig 2: Classification Model

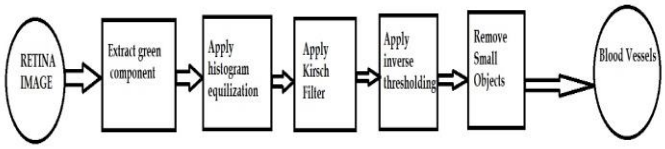

Fig: 3.The Blood vessel Extraction

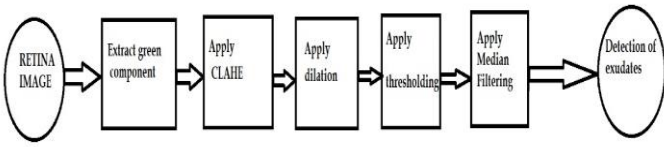

Fig 4: Exudates Extraction

C. METHODOLOGY

Our work is divided into 4 modules
1.data pre processing
2. Diabetic retinopathy feature extraction -Blood Vessels segmentation
3. Exudates extraction
4. Building a deep learning block model and Classification of DR

i. Data pre-processing
When dealing with pictures acquired/captured from various sensors, views, or timings, image pre-processing is a critical task. By employing numerous ways to illustrate the accurate efficacy depending on application, aim, and goals, this procedure improves the information or data in input photos for subsequent calculations or outcomes. We use CLAHE(Contrast Limited Adaptive Histogram Equalization) and adaptive threshold approaches in the picture pre-processing stage to improve image quality.
ii. Diabetic retinopathy feature extraction
-blood vessels extraction
Because the blood artery looks brighter in the green channel picture, it is detached. The noise in the input picture is then removed using the Kirsch filter. The Kirsch Edge module uses eight compass filters to identify edges. The image is subjected to all eight filters, with the best kept for the final image. A simple compass convolution filter is rotated eight times to create the eight filters. The filtered picture is subjected to histogram equalisation..
-Exudates extraction
Exudates are detected using the green channel. The use of morphological operations is used. CLAHE is an adaptive Histogram Equalization extension that aids in the dynamic preservation of an image's local contrast characteristics. To dilate the picture, we use morphological operations. Dilation is the first step in the closure process, followed by erosion (median filter). In a binary picture, erosion causes items to shrink.
iii. Classification based on Res-block model
In this we perform data exploration and visualize images for each of the classes present in the dataset and then get the list of images in a given class. We check images in each class in the training set and then perform data augmentation and shuffle the data and split it into training and testing. Now we create run time augmentation on both the training and testing dataset training data generator, we perform normalization, zooming range ,shear angle and horizontal flip for testing data, we only normalize the data, creating data generator for training, validation and test dataset. We create a deep learning model based on (CNN) convolutional neural networks and residual blocks. Then we should compile and train deep learning model, halting training early if validation loss does not decrease after a specific number of epochs (patience), and save the best model with the lowest validation loss. Evaluate the training model's performance by giving label names to the associated indexes providing retinal images and their predictions, and determining the test accuracy and then visualizing the outcomes.

D. Implementation

ALGORITHMS

1. Image Enhancement (pre –processing)

Step 1: Import libraries that are required
Step 2: Load and display the image
Step 3: Create a grayscale image for the retinal images.
Step 4: Next, we'll examine the grayscale image's histograms then find the distribution of intensities in that image.
Step 5: Then we use cv2.equalizeHist() function for the purpose of equalizing the contrast of a given grayscale image this cv2.equalizeHist() function normalizes the brightness of the image and then increases the contrast.
Step 6: Obtain the Gray Scale Histogram equalized retinal image.
Step 7: Apply Contrast Limited Adaptive Histogram Equalization

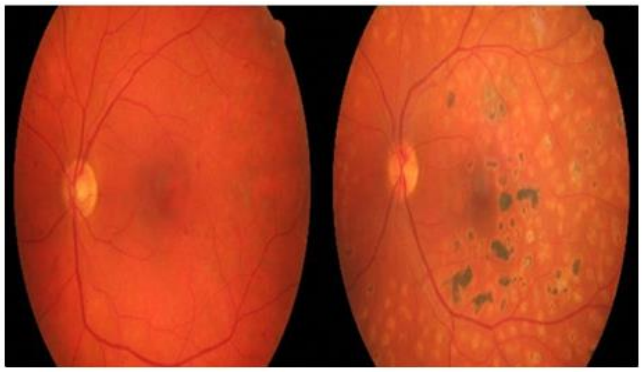

Fig: 5.1: Original Retinal Images

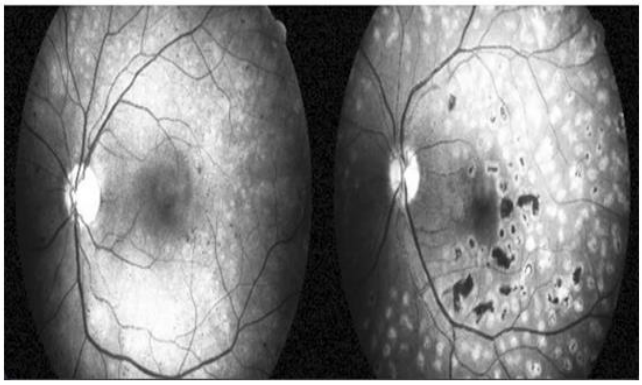

Fig 5.2: Gray Scale Images

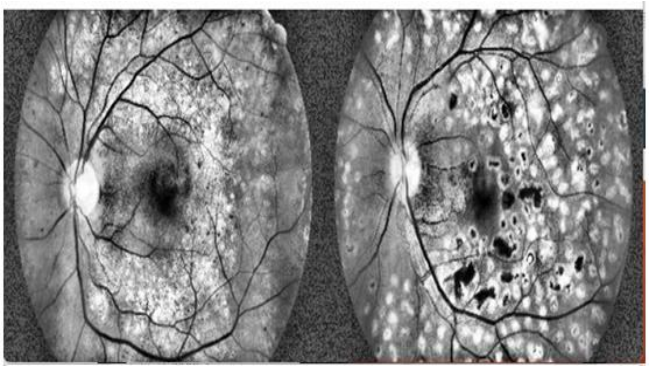

Fig 5.3: CLAHE Images

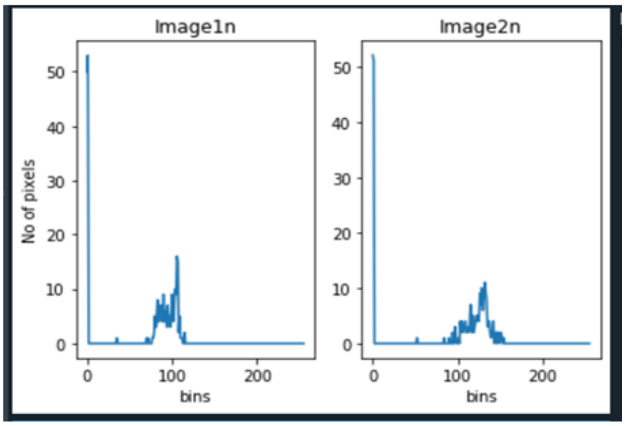

Fig 5.4: Histogram Of Retinal Images

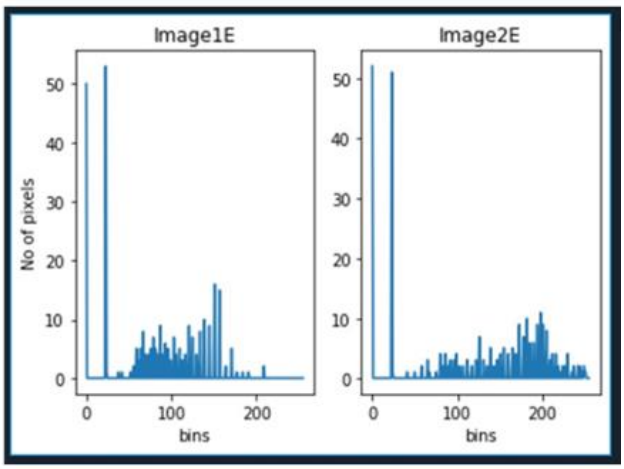

Fig 5.5: Histogram Equalization

2. Diabetic Retinopathy Detection - Blood Vessel Detection

Step 1: Extracting the green channel alone by slicing the array.
Step 2: Apply Histogram Equalization.
Step 3: Apply Kirsch Filter to Histogram.
Step 4: Apply Basic Thresholding with Inverse.
Step 5: Apply Morphological Operations to remove small objects.

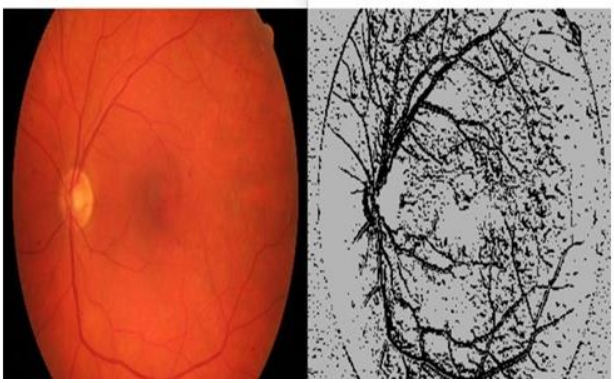

Fig 5.6: Blood Vessel Detection

3. Exudates Detection

Step 1: Extracting the green channel alone by slicing the array.
Step 2: Apply Contrast Limited Adaptive Histogram Equalization (CLAHE).
Step 3: Apply Morphological Operation – Dilation after Creating Structuring Element.
Step 4: Apply Thresholding with Complement/Inverse.
Step 5: Apply Median Filter in order to remove noise.

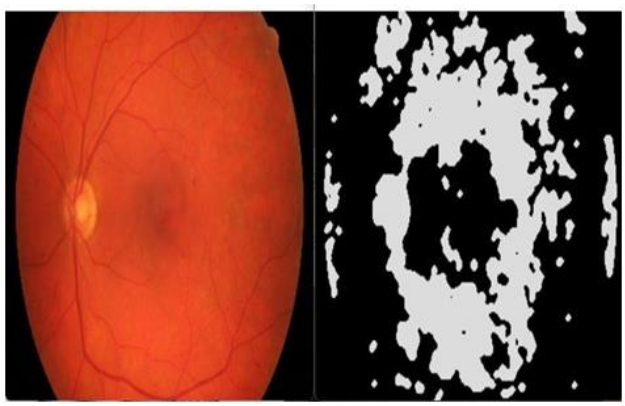

Fig 5.7: Exudates Detection

4. Classification based on Res-Block model

Step 1. Import all the necessary libraries
Step 2. Explore the data and then visualize the data
2.1 for each class visualize images in the dataset
2.2 get the list of images in a given class
2.3 check the number of images present in each class in the train dataset
Step 3. Perform data augmentation and then create data generator
3.1 shuffle the data and split it into training and testing
3.2 create run-time augmentation on both datasets training and testing.
3.2.1 for training data generator, we add normalization, zooming the range, shear angle and horizontal flipping
3.3 for data of test generator, we only normalize the data.
3.4 creating data generator for training, validation and test dataset. Step 4. Convolutional neural networks (CNN) and residual blocks
Step 5. Build block based deep learning model
Step 6. Compile and train deep learning model
6.1 use early stopping to exit training. (if validation loss is not decreasing even after certain epochs).
6.2 save the model with lower validation loss
Step 7. Now Assess the performance of the obtained model
7.1 Evaluate the model performance.
7.2 Assign label names to the associated indexes
7.3 Loading images along with their predictions
7.4 Obtaining the test accuracy
7.5 Visualize results.

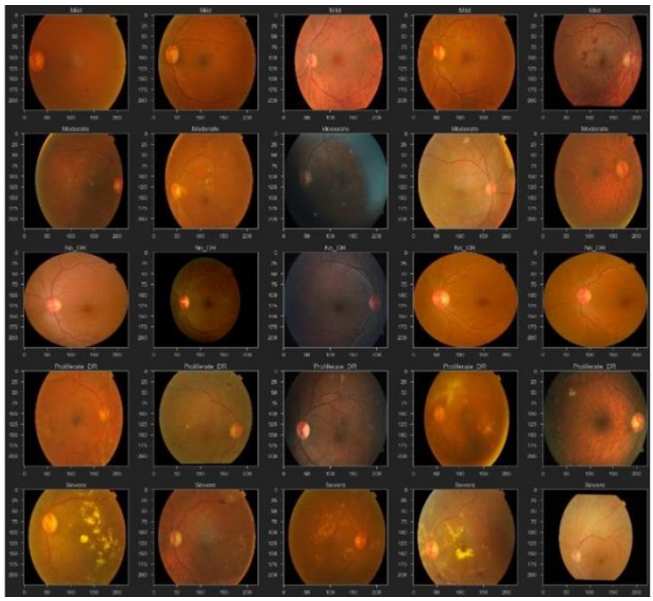

Fig 5.8: Dataset of our Retinal Images

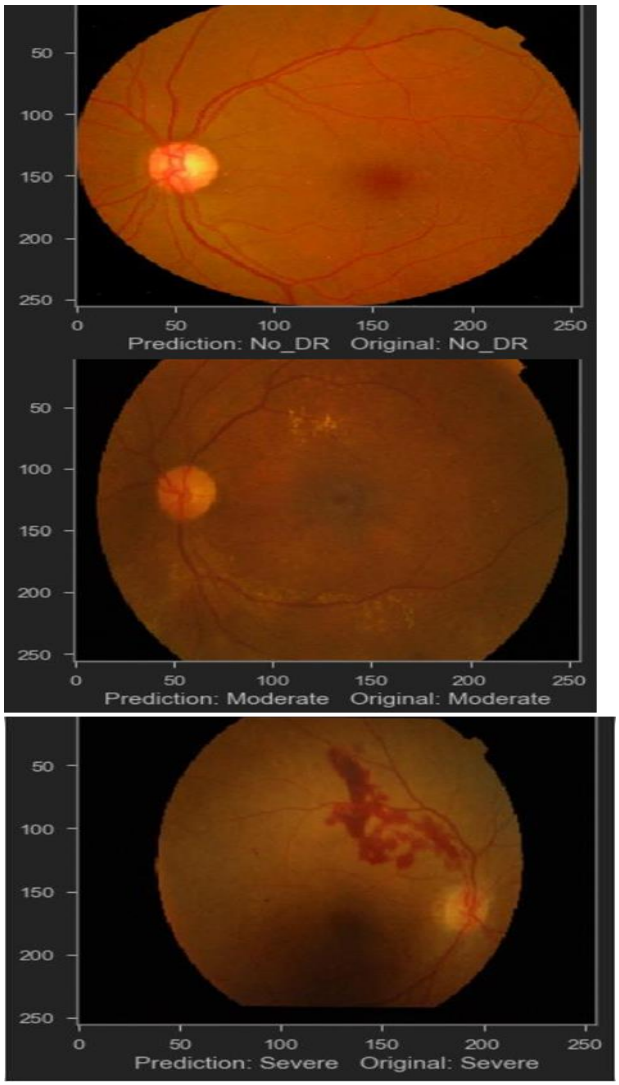

Fig 5.9: Predictions of our Model

E. Results and Analysis

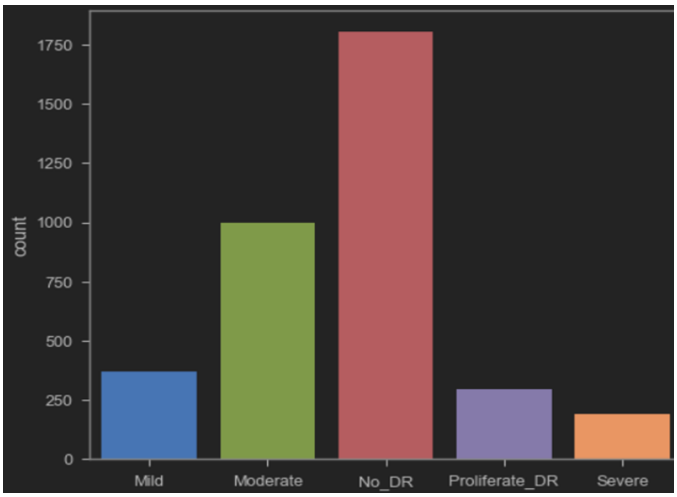

Fig 6.1: Count Plot For All Classes

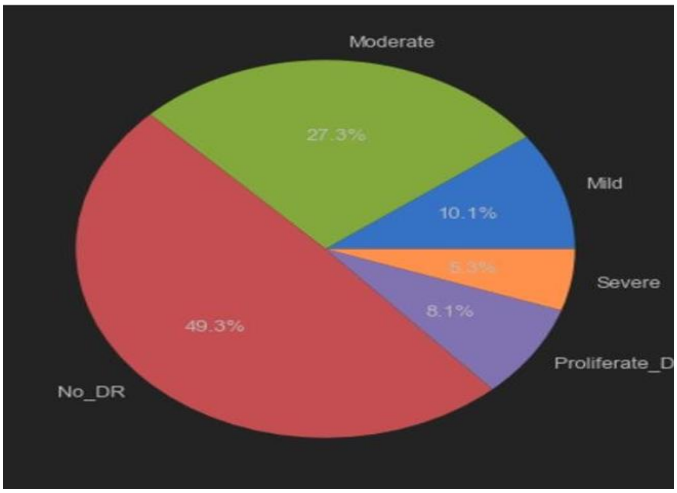

Fig 6.2: Represents a pie chart showing the percentage of samples per class

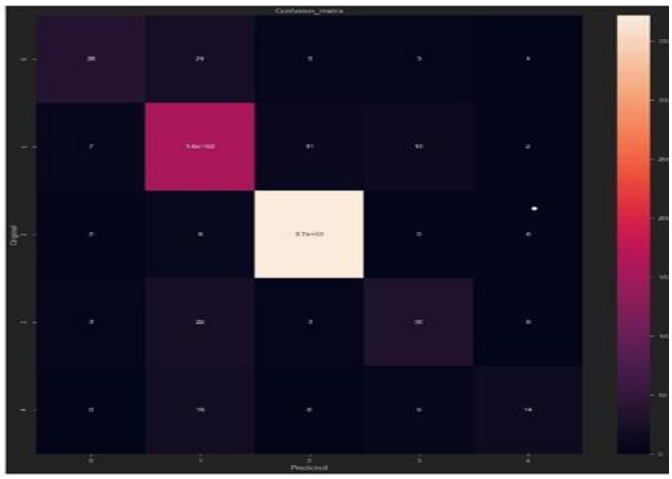

Fig 6.3: Represents Confusion Matrix

F. Conclusion & Future Works

We installed software on a computer i.e. Anaconda, where we can have multiple ways to execute our programs. We directly placed the dataset from different sources like hospitals, physical diagnosis, localized patients. The input data is uploaded with corresponding structure format according to the hierarchies designed by medical expertise and physical diagnose professionals. First and foremost, there is much more work to be done before an algorithm like this can be widely employed. We'd be able to manage more of our training data if we could. We could improve our algorithm's accuracy by training it more. In addition, we employed simple feature selection and scaling algorithms, as well as possible. More complex strategies for picking and producing characteristics might help us get better outcomes. Using attributes from retinal pictures, we attempted to build an ensemble to predict if a patient had diabetic retinopathy. The accuracy we achieve after training and testing the model is comparable. For more accurate findings, we'd want to expand our work by applying a variety of machine learning algorithms like as SHIFT, Deep Convolution Neural Network (DCNN), and others.

G. References

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