Diabetic Retinopathy Detection

A

Synopsis

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As the partial fulfillment of the requirement for the degree of Bachelor in Information Technology

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CERTIFICATE

This is to certify that the following students have submitted the synopsis for the project titled

Diabetic Retinopathy Detection

At D. J. Sanghvi College of Engineering, Mumbai as a partial fulfillment of the requirement for the degree of Information Technology (Semester VI) of University of Mumbai in the year 2019 – 2020.

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Abstract

Diabetic retinopathy is a micro-vascular impediment of diabetes which causes deformities in the retina. It is the main source for the loss of vision and blindness. For effective treatment, early diagnosis of the disease is very important. The existing screening models send all captured retinal images to the hospital via VSAT for evaluation by the expert ophthalmologists. These systems are very costly and cause unnecessary data traffic on the internet as ophthalmologists have to evaluate all received images.

We have proposed an automated fundus image analysis system for early stage detection of diabetic retinopathy. Our proposed system captures retinal fundus images of patients by handheld fundus camera The captured images are accurately classified as normal or with Diabetic retinopathy using image processing techniques. The potential locations of different visual abnormalities associated with Diabetic retinopathy are highlighted on the images. An automated pre-screening system that determines whether or not any suspicious signs of Diabetic Retinopathy are present in an image significantly reduces the workload of experts. The proposed system implements two stage classification. Firstly, it classifies images into Diabetic retinopathy and non-diabetic retinopathy. Secondly, it identifies the potential lesions related to it in the images which are sent to base hospital for expert review.

The performance of the proposed method is evaluated using sensitivity, specificity and accuracy.

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1. Introduction

Vision loss due to diabetic eye diseases is on the rise and is expected to reach epidemic proportions globally in the next few decades. Almost all patients with type 1 diabetes mellitus and ~60% of patients with type 2 diabetes mellitus will develop retinopathy during the first 20 years from onset of diabetes. However, DR often remains undetected until it progresses to an advance vision- threatening stage.

Diagnosis of pathological findings in fundoscopy, a medical technique to visualize the retina, depends on a complex range of features and localizations within the image. The diagnosis is particularly difficult for patients with early stage diabetic retinopathy as this relies on discerning the presence of microaneursyms, small saccular outpouching of capillaries, retinal hemorrhages, ruptured blood vessels—among other features—on the fundoscopic images.

Diabetic Retinopathy (DR) is the most common microvascular complication of diabetes and can progress until a sudden loss of vision occurs. As the number of patients with diabetes is rapidly increasing, the number of retinal images produced by the screening programmes will also increase, which in turn introduces a large labour-intensive burden on the medical experts as well as cost to the healthcare services. This could be alleviated with an automated system either as support for medical experts' work or as a full diagnosis tool. Automated techniques for diabetic retinopathy diagnoses are essential to solving these problems. While deep learning for binary classification in general has achieved high validation accuracies, multi-stage classification results are less impressive, particularly for early-stage disease.
Early detection and prevention of DR are essential to mitigate the rising threat of DR.

- The current state of DR screening is based on assessment of colour fundus photographs by a retina specialist leaving a large proportion of patients undiagnosed and therefore receiving medical help too late.
- The objective is to bring portable, easy to administer, reliable, retinal screening to primary doctors' offices and health clinics.
- Initial retinal images taken with mobile cameras allow a first screening and first emergency decisions about the patient in hard to reach areas where there may be an absence of any ophthalmologist.

1.1 Motivation / Objective

The amount of the disease spread in the retina can be identified by extracting the features of the retina. The features like blood vessels, hemorrhages of NPDR image and exudates of PDR image are extracted from the raw images using the image processing techniques and fed to the classifier for classification.

Portable cameras able to help ophthalmologists have been a desired solution for a long time. Among the reasons for the need of an additional device to support the eye physician, on top of available fixed devices, is the fact that sometimes patients who need the visit of a doctor live in remote areas (or are housebound). In other hard to reach areas, there may be a total absence of any ophthalmologist able to collect medical information from patients. Initial retinal images taken with mobile cameras allow a first screening and first emergency decisions about the patient.

Together with telemedicine infrastructure, such retinal images taken with a mobile camera in remote places are transmitted to the ophthalmologist, who will thus be enabled to declare any pathology which can be assessed from the pictures. This is particularly useful, for instance, when screening cases of diabetic retinopathy: people with diabetes are at risk of developing diabetic retinopathy and therefore, need a regular screening with correct and timely diagnosis without the constraint of a long travel or needless waste of time, either for the eye care professional or for the patient: retinal images taken with mobile cameras are transmitted and analysed remotely, regardless of distance.

Nowadays, when we have very good smartphone cameras, it is quite simple to add optics to the mobile device and look through the pupils to capture the retina. However, these settings present also several challenges: first and foremost, hand motion, eye motion and the system itself which is not stabilized like in the clinic. Next, the optics are not ideal and include lots of artifacts, like shadows and reflections, together with some mist or foggy effect that will reduce contrast and make everything look blurred. Light conditions might also be far from ideal.

1.2 Major Challenges

The objective of the project deals with a lot of ideas that need to be researched to be able to execute properly. The project deals with a lot of research areas in Image Processing and Deep Learning which is in a preliminary stage. This becomes the core obstacles of the project which we need to overcome to be able to execute the project. Following are the major challenges which need to be tackled for the project lifecycle:

- *Prior Knowledge-*
  Before the detection begins, the system needs to gather prior knowledge to be able to start the test properly. The challenge lies in comparing the sample test cases and categorizing them as DR positive or negative.
- *Accuracy-*
  Like stated above the current algorithms and tools are too naive to carry out the objective as it gives a very low accuracy. The model needs to correctly analyze and improve its accuracy by tweaking and twisting current techniques.
- *Database Modelling-*
  There are no predefined datasets or knowledge information on the python question dataset and their answer. Thus, this becomes a big hurdle in creating our own database and framing question sets.

The current state of DR screening in the real world, based on assessment of color fundus photographs (CFPs) by a retina specialist or a trained grader, leaves a large proportion of patients undiagnosed and therefore receiving medical help too late, in part due to low adherence and access to retina screening visits. In-person expert examinations are impractical and unsustainable given the pandemic size of the diabetic population. Notwithstanding, early detection and prevention of DR progression are essential to mitigate the rising threat of DR

1.3 Report Overview

The report consists of the following sections:

1.) Introduction: This section provides an insight on the motivation and objective of selecting the problem statement, the healthcare domain and what are the problems faced by them.

2.) Literature Survey: It explores the different existing systems, their technologies, motivation, value proposition, their advantages and drawbacks. It also highlights upon how our system will try to improve upon any shortcomings. The literature survey covers the tools used by the systems and the reasons for using those particular tools. The aim behind the literature survey is to give us a reference for creating our product and to make the most feasible and appropriate decision in every stage of the product development.

3.) Proposed Methodology: It explains our proposed methodology for the project. It starts with defining the problem and then the scope of the project. The scope includes the assumption and the different constraints. The chapter then moves onto the proposed approach. We then move on to cover the System Architecture, the Use Case diagram and the Activity Diagram. Finally, the chapter ends with the benefits of our proposed solution.

4.) Feasibility study of proposed solution: It focuses on the feasibility study of our proposed product. The technical requirements, why they are required, their learning curve, their cost, their developer support have all been taken into consideration. A comparative study on the different languages, frameworks and tools was done to decide upon the final technologies to be used. This chapter also covers the operational feasibility of the project. What would be the operational requirements to use the product once it is deployed and whether they are viable. Finally, the cost of development of the product, the estimated Return on Investment (ROI) are covered to figure out the breakeven point for potential investors and to plan out the entire project.

5.) Conclusion: Finally the report will conclude with a study of the existing system, its risks and further improvements.

2. Literature Survey

This chapter deals with exploring the existing systems and frameworks in the market that are in lines to the project objective. Various algorithms and methodologies are discussed, explained and described that we might use for our proposed solution of the process. It also discusses under what scenarios and conditions the algorithms are best used, the technology and tools to achieve the desired outcome and what are the future scope of the existing research.

2.1 Existing Work

2.1.1 Literature Related to Existing System

PAPER 1:

In this paper an automated detection system is described to easily and effectively identify the stages of DR. For the detection process the artificial neural network is used that uses the identifier and a wide number of training sets for specific results. They have implemented a method by which mobile phones and 20D or 28D lenses are used to take the retina image, so that the system can be available to any place at any time. The system is developed to provide a method to perform a mobile phone based indirect ophthalmoscopy for the identification of Diabetic retinopathy stages using artificial neural networks and discrete wavelet transform.[1]

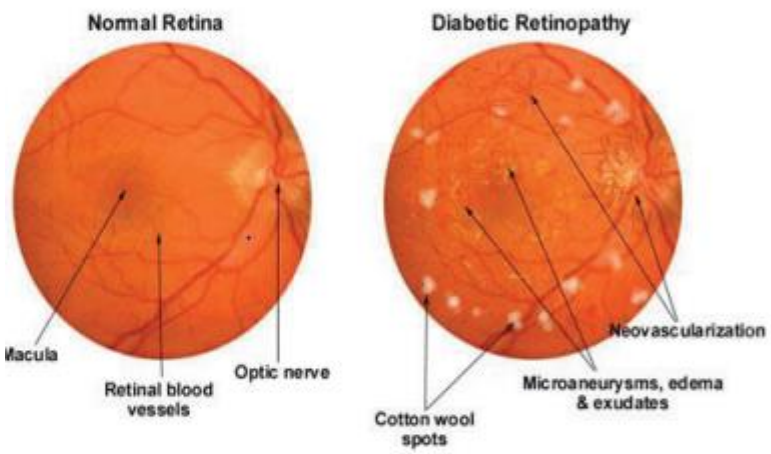

Figure 1:Retinal image

PAPER 2:

This paper focuses on detection aspects of a mobile application developed to perform DR screening in real time. The application described in this paper is powered by a tensor flow deep neural network architecture that is trained and tested on 16,798 fundus images. The images are pre-processed to remove noise and prepare them to be fed into the neural network. Pre-processing steps involve averaging all the images using a 5x5 filter to improve the quality of images and then these images are resized to 256x256 pixels. After pre-processing the input dataset is fed into the neural network. The convolutional neural network model used in this project is Mobile Nets, which is used for mobile devices. The neural network has 28 convolutional layers and after each layer there is a batch norm and ReLU nonlinear function except at the final layer. The output from the last layer is a class label either DR or no DR. The model was optimized to work on mobile devices and does not require Internet connection to $run.$ [2]

PAPER 3:

A quick inexpensive automatic computer aided DR pre-screening system is needed to efficiently pre-screen patients in a massive fashion to reduce these problems. Nowadays there are many commercial retinal lenses embedded in a camera that can take an image of a retina with a mobile phone. Fig. 1 shows examples of a few lenses made from different companies to work with mobile phones.

Figure 2: Portable retinal lenses on mobile phones from different companies

A retinal image obtained from a mobile phone usually has a lower quality than that from a standard fundus camera used in the major hospital. The optic disk and the vessels in images from a mobile phone usually have noticeable blurrier edges and fainter colour than those from a standard fundus camera. At the left or right side of the edge of the retina, there may exist a bright region emerging due to external light entered during the time of image capturing. An image produced by a mobile phone with a portable lens normally has a narrower field of view compared to that produced by the standard camera. That means a mobile-phone retinal image can show only limited area in the retinal. Figure 2 shows a close comparison of images taken by a mobile phone with portable lens and a standard fundus camera from the same patient. A dotted circular boundary in the image of a standard fundus camera represents the field of view from a mobile phone.

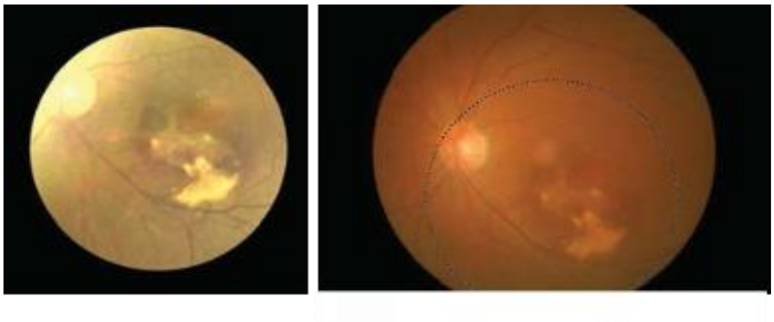

Figure 3:Examples of a retinal image taken from an Iphone with a portable lens from Volk in view company (left) and a retinal image taken from a standard fundus camera (right) with a mapped field of view from an Iphone shown in a dotted contour.

Hemorrhages and exudates are major signs of abnormality in the retina. Hemorrhages are caused by the broken retinal blood vessels while exudates are caused by fat or protein leaking from blood vessels. When a spot of either a hemorrhage or an exudate is present in the retinal of a patient, DR is concluded. In this work, only exudate detection is $focused$.[3]

PAPER 4:

This review paper restricts itself to the recent articles published in last three years, covering the latest techniques for DR detection. Automatic and earlier detection of diabetic retinopathy is an active research area as evident from the increased number of published research articles. A reliable automated detection and screening system for diabetic retinopathy is a desirable goal for the researchers worldwide. In the pre-processing stage, green channel response is the most popular step in reported literature as it reliably provides maximum contrast to distinguish between the microaneurysm, hemorrhages and exudates while histogram equalization and image normalization has equal importance. A significant number of the articles reported employing support vector machine classifiers in the classification stage, demonstrating appreciable $results$.[4]

PAPER 5:

An automatic eye fundus investigation technique using digital fundus images. This modern teleophthalmology system captures retinal fundus images of patients by handheld fundus camera at the screening camp site. The captured images are accurately classified as normal or with DR using image processing techniques. From the campsite, only DR affected images will be sent to expert ophthalmologists through the internet. An automated pre-screening system that determines whether or not any suspicious signs of DR are present in an image significantly reduces the workload of experts. The proposed system implements two stage classification, firstly at the screening camp it classifies images into DR and non-DR, secondly to identify the potential lesions related to DR in the images which are sent to base hospital for expert review. In this paper holo-entropy enabled the decision tree classifier for the classification purpose is implemented. The experimental evaluation is performed on the publicly available database DIARETDB1 as shown below:

Figure 4:Fundus image. having MA and HM

The proposed system implements two stage classification, firstly at the screening camp it classifies images into DR and non -DR, secondly to identify the potential lesions related to DR in the images which are sent to base hospital for expert $review$.[5]

2.1.2 Literature Related to Methodology

PAPER 1:

Mobile phones with good camera quality, light-emitting diode (LED) and 28D lens are used in place of fundus camera to take the patient's retina image

The paper describes the methodology as follows:

1. First hold the phone in one hand and lens in other hand then light up the retina by using an LED and take a picture of it.
2. The technique is simple and acts as an indirect ophthalmoscope.
3. The retinal image database which contains images of various diabetic retinopathy signs are collected and analysed.
4. The patient's retina image capture by using a mobile phone along with a condensing lens
5. The image is processed and features are extracted using DWT
6. After finding energies of the query image and database images the sub-bands are compared using the Euclidean Distance Metric.
7. This metric is used by Artificial Neural Network to retrieve the most relevant $images$[1]

The image given below shows the retinal images captured by the smartphone

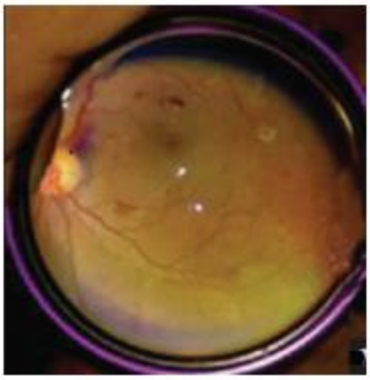

Figure 5:retinal images captured by the smartphone

PAPER 2:

The image dataset is using Kaggle's database as shown below. The application was made to do the binary class categorization on the input images that are fed to the application via a mobile camera in real time. The classification category includes: DR and no DR. The image dataset includes 26% of the DR and 74% of no DR images.

Figure 6:A glimpse of fundus image dataset.

1.Data Pre-processing

Averaging:

The images in the dataset contained noise such as: low contrast, colour variation, and uneven light reflections. To make images more consistent and smooth, a convolution filter of size 5x5 is used. The technique used in averaging is known as **Box blur.**

The images in the dataset contain noise such as varying lighting condition, low contrast, and different sizes. To make the image smooth one can use a 2d convolution filter. The one used in this project is a 5×5 filter:

$$F = \frac{1}{25}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

The above filter adds all the pixels that come under it while running over the image and then takes the average of it. After that, it replaces the centre pixel intensity with the new average value. This operation was applied to all the images in the training dataset.

Resize: The images in the dataset are of size 4928x3264 pixels to make it suitable to be fed to the neural network. Resize is accomplished by using **bilinear interpolation.** This process contributed to the neural network taking less time to train and made the data consistent

2. Training

After pre-processing the data, was fed into a neural network. The neural network model used in this project is the Mobile Nets, which has 28 convolution layers. The technique used in this project for making the neural network learn the input data is referred to as **transfer learning**. In this technique, a pre-trained network is utilized which was trained with millions of images from ImageNet dataset. This model is stored in the form of a graph file and one can make use of this graph file to generate a new graph file with updated weights and biases. This process is much faster and more efficient than creating a neural network from scratch and try to fit such a large dataset to it can take several days of training and requires high GPU power. After training the neural network model outputs generated were: graph file and class labels. Graph file contains all the nodes and operations that are performed during the training of the network. The whole neural network was built using a tensor flow library that has a built-in tool for removing all the nodes that are not needed for a given set of inputs and outputs.

The developed Android application was tested in real time on test dataset images. Since the test dataset contained images of both categories of DR and no DR, so it was used as source for real time image analysis as one would be capturing image of an actual subject. The application was made to run in real time on test dataset images and images were acquired using the built-in camera of the mobile device. Once an image is captured it is fed into the neural network, which then displays the output label as one of the two classes: DR or no DR. The output is then shown in the form of $probability$.[2]

PAPER 3:

The flowchart in Fig 3 illustrates our methods for detecting exudates.

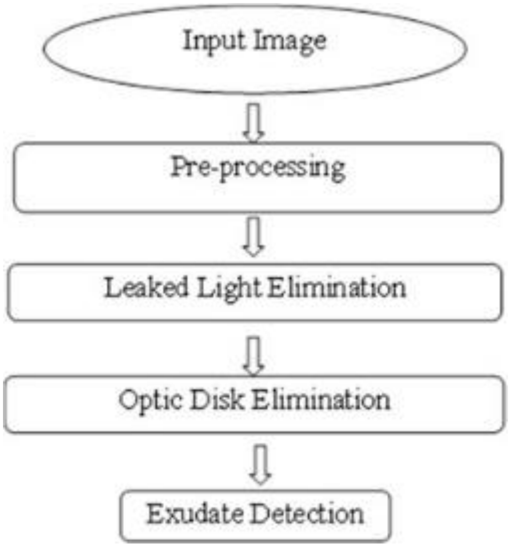

Figure 7:A flowchart depicting processes for detecting exudates

1. Pre-processing

We mainly use the green channel of RGB space for exudate extraction because this channel offers the best image quality in terms of clarity of details of the retinal components. Fig 1 depicts the retinal images in three different channels.

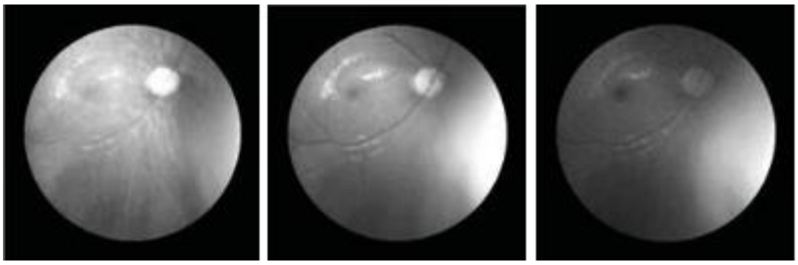

Figure 8: Examples of images in different channels: red (left), green (middle) and blue (right)

As there can be noise in the image, the median filtering is first applied to remove it. Then the image is converted to gray scale. Next, the contrast-limited adaptive histogram equalization (CLAHE) is applied for enhancing the contrast of the local areas in selected channels.

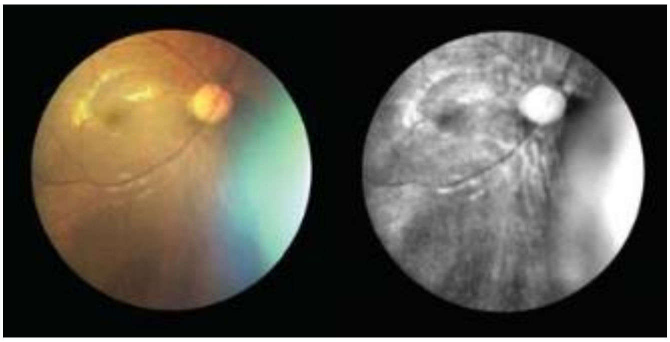

Figure 9: Examples of a mobile-phone retinal image before (left) and after pre-processing (right).

2.Exudate Detection

2.1 External light region removal

In some cases, as the intensity range of the external light region and exudate are close, the external light region is removed to avoid misdetection. To this aim, the region growing technique is applied.Fig.3 depicts the area of the retina after light correction is done.

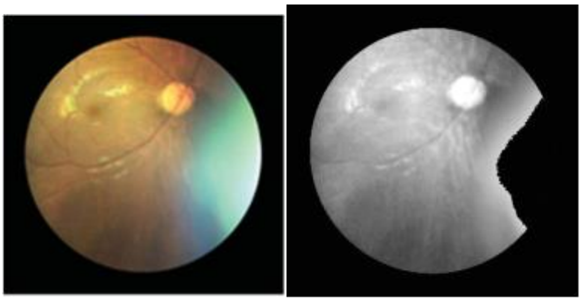

Figure 10: Excessive light sample image (right) Image after external light removal (left)

2.2 OD removal

Due to the fact that the optic disk (OD) and exudates share the close range of intensity, thus OD elimination is also needed to avoid misdetection. It is worth noting that in case that the OD isn't present in the image, the Mahfouz-Exclusion method can also detect that there is no OD. The

OD region is segmented using the region growing technique with a seed point set to an OD location returned from the Mahfouz-Exclusion method.

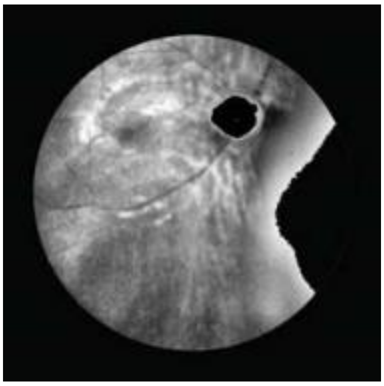

Figure 11: Illustration of a retinal image after OD removal

2.3 Bright region classification

At this stage, the image is assumed to contain only regions of interest. As an exudate on a fundus image appears bright or having high intensity in the green channel space, we utilize the Adaptive thresholding method and find all regions having high intensity in the region of interest. For each region, information on the average intensity and the image average intensity was collected. A collection of such features are split into training and testing sets. A well-known classification method so called Support Vector Machine (SVM) is used to train the feature data in the training set to find the separation line that can be used to classify data into a class of regions that are exudates and a class of regions that are not exudates.

2.4 User Interface

For convenience, a Matlab user interface was made so that a nurse or a technical staff can use this system easily. The program consists of a panel to be used to display the input retina image and the result image, has two modes of reading input: single or multiple images, a mode of selection of areas of interest, which in this work is currently only exudate. The program performs the exudate detection, displays the boundary of exudate regions and also shows the number of detected exudate regions in the displayed panel when $finished$.[3]

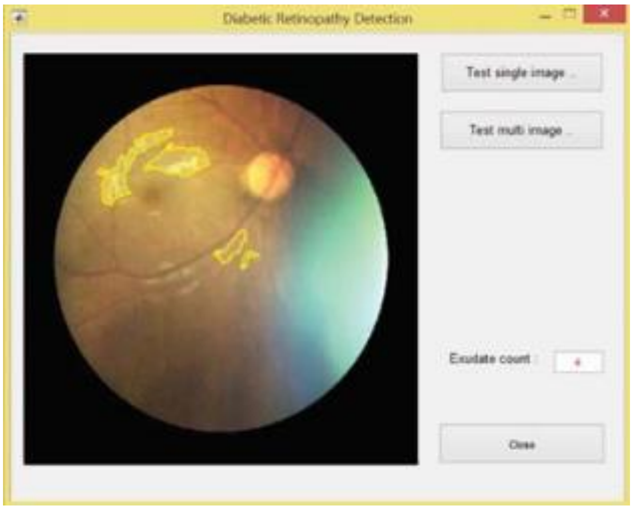

Figure 12: Matlab User Interface

PAPER 4:

1. Green Channel

Retinal features can be discriminated from each other by utilizing color as a feature descriptor. Pathological signs of diabetic retinopathy like MAs, HMs appear as red spots in RGB fundus images while EXs appear as yellow spots in RGB fundus images.

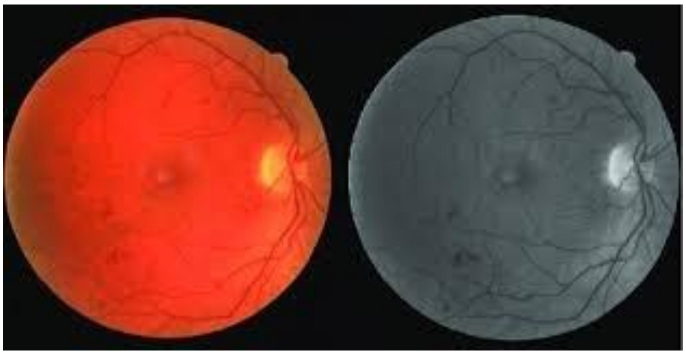

Figure 13:Green channel of RGB colour space

2. Image Normalization

Image normalization is used to minimize intra-image variability in fundus images. It is proposed that color normalization can be utilized for brightness correction, color modification and contrast enhancement.They investigated that there is a gradual intensity variation in the background from central macular region to periphery region which can affect the process of vessel segmentation. To minimize this, they subtracted an estimate of background from the original image which was computed by applying 31 x 31 arithmetic mean kernel.

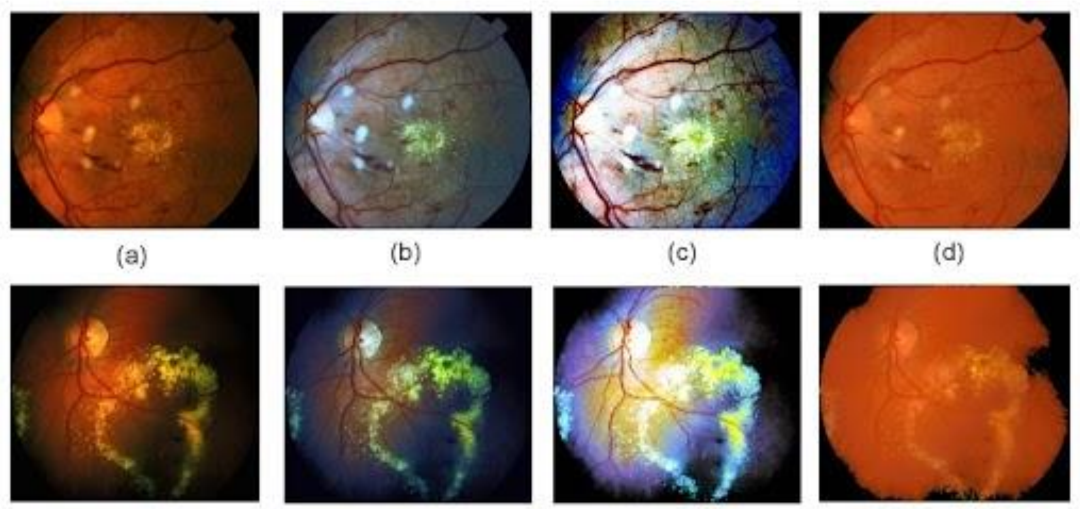

Figure 14: Image Normalization of retinal images

3. Histogram Equalization

The purpose of histogram equalization is to redistribute the intensity value in the input image so that the intensity values in the output images are uniformly distributed. They utilized histogram equalization in combination with smoothing filters to enhance the contrast of retinal image. They also used contrast limited adaptive histogram equalization (CLAHE) in which local histogram was applied to the distinct sections of input image. In CLAHE, contrast limitation is applied on each neighbourhood pixel which prevents over amplification of noise. Similarly, Adaptive histogram equalization was utilized for contrast enhancement purposes

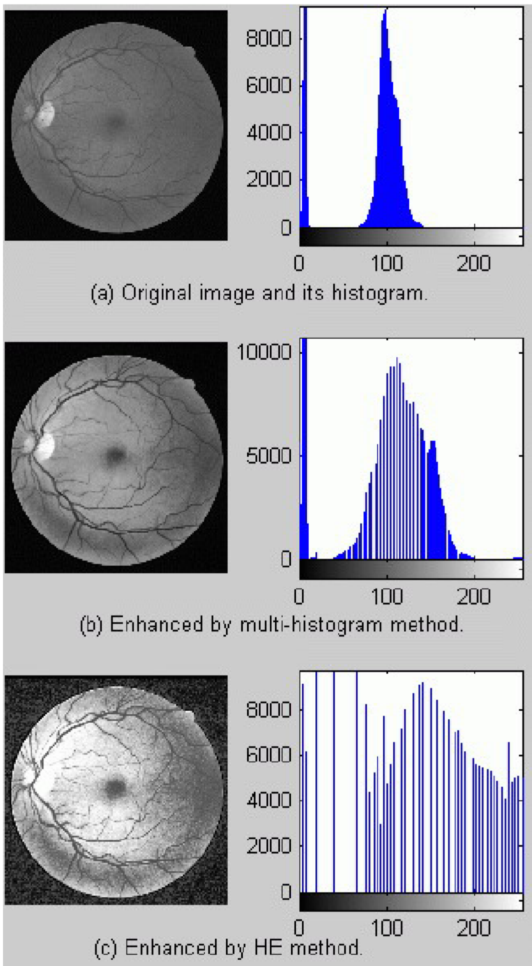

Figure 15:Retinal Image Enhancement

4. Correction of Non- Uniform Illumination

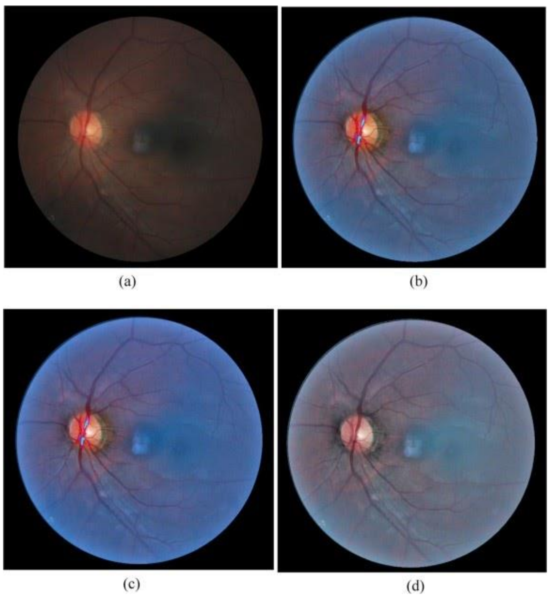

Figure 16:Non-uniform Illumination correction

Non uniform illumination causes vignetting effects in fundus images reported. Non uniform illumination can alter statistical characteristics of an image and can affect the performance of automated detection of diabetic retinopathy. These effects may not be visible to human observers but can cause problems in feature extraction and classification. The formula used for correction of non uniform illumination:

$f' = f + \mu d \; \mu i$ (1)

where in equation 1, μd and μi are desired average intensity and local average intensity and f and f' are the original and new pixel intensities.

2.1.2.5. Morphological Operations

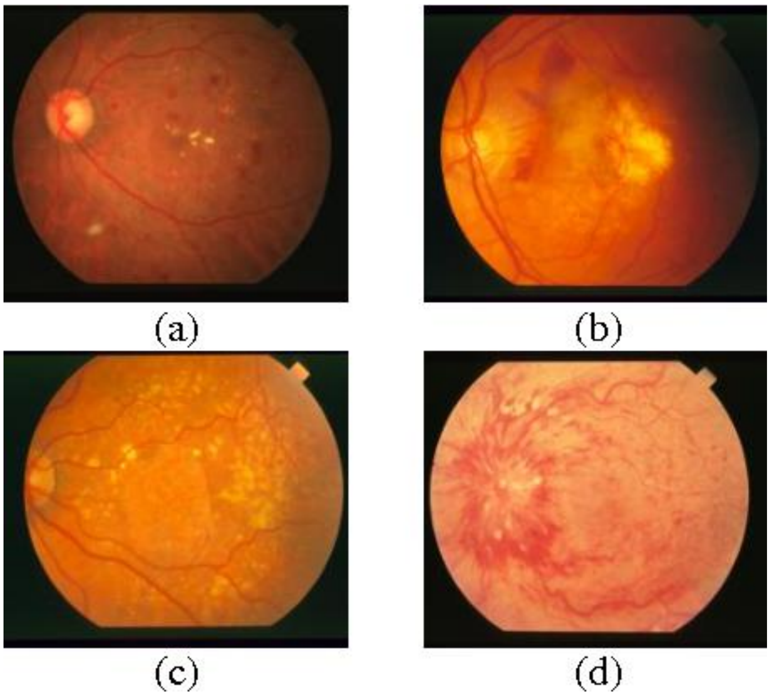

Figure 17:Morphological Operations performed on an image

They proposed morphological openings for smoothing optic discs and bright lesions. Their proposed approach also utilized to remove bright lesions. They utilized top hat and bottom hat transform for both contrast enhancement and for good prominence of dark lesions with minimal background variations. They also proposed morphological top-hat transform for vessel *enhancement*. [4]

PAPER 5:

The prevention of the loss of vision due to DR is possible only when DR is diagnosed at the early stage. The teleophthalmology system developed was accurate, efficient, low cost, portable and user friendly so that the screening camps can be easily conducted throughout the entire region including rural places. This helped to bridge the gap between physician and patients screening is a helpful method for early detection of DR.

The architecture of the proposed modern teleophthalmology system is shown below.

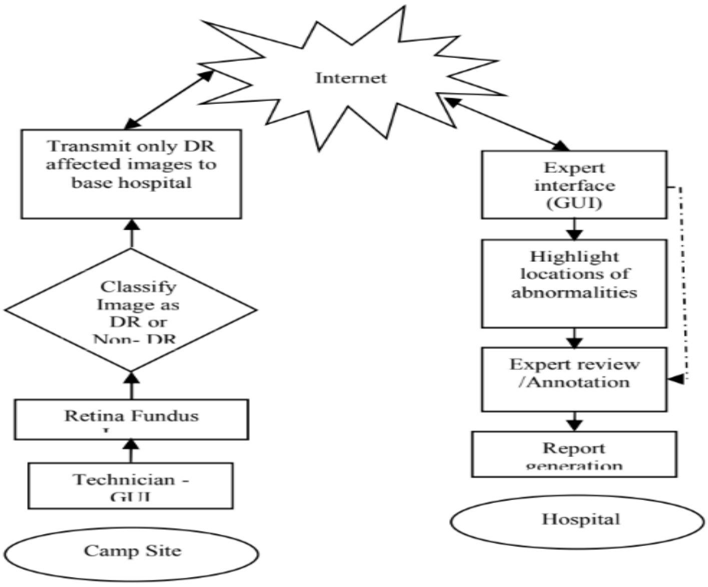

Figure 18:The architecture of the proposed modern teleophthalmology system

1. Classifications of DR images at screening camp sites

The proposed technique implements the major steps such as pre-processing, optic disc segmentation, blood vessel segmentation, feature extraction and classification.

1.1 Pre-processing**:** Retinal fundus images are pre-processed to make input images suitable for subsequent processes. The retinal colour fundus images are converted to grayscale. The gray scale image is binarized, a low threshold value is fixed for optical disc segmentation. The segmented output is then processed to find whether any disc regions are found out using the initial threshold. If no region is found, the threshold value is increased and the process is repeated until the optic disc region is found out.

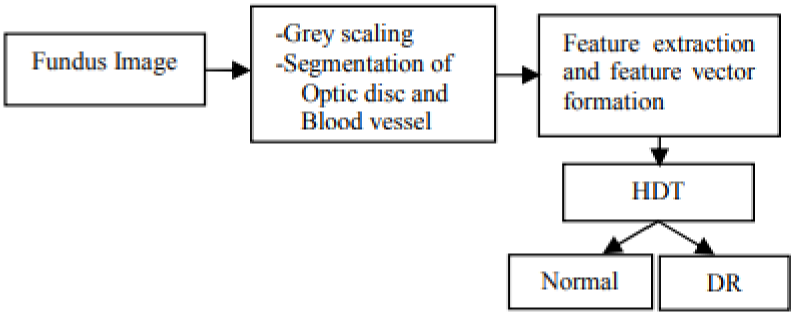

Figure 19:. DR image classification using Holoentropy enabled Decision tree

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1.2 Hybrid feature extraction: The decision tree develops the system for classification with minimum computational processes. It is constructed using steps such as selection of the best feature as a node, split the feature to progress the tree and finally label the class. The node with the best feature is selected using holo-entropy instead of entropy. The holo-entropy has been calculated for each feature from the feature vector. The feature having highest holo-entropy is chosen as the best feature to construct the decision tree.

1.3 Classification using Holo-Entropy Enabled Decision Tree: The decision tree develops the system for classification with minimum computational processes. It is constructed using steps such as selection of the best feature as a node, split the feature to progress the tree and finally label the class. The node with the best feature is selected using holo-entropy instead of entropy. The holo-entropy has been calculated for each feature from the feature vector. The feature having highest holo-entropy is chosen as the best feature to construct the decision tree.

The process is executed to all the samples recursively. The labelling of the last node that is leaf node is performed by selecting the group to which the large amount of data is fulfilled with the same node. The HDT is formed for the set of training images. The new retinal fundus image is tested against the constructed decision tree by extracting the hybrid features. The final outcome of the testing will be classifying the test image as DR or Non-DR

2. Identification of lesions of DR in images at base hospital

2.1 Candidate MA Region Extraction: The pre-processing of the fundus images is required to improve the quality of an input retinal fundus image. The accurate segmentation of blood vessels is important to decrease the occurrence of false MAs and to improve the overall accuracy of the system.

The green plane of the input colour fundus image is selected for further processing. The adaptive histogram equalization is performed to remove brightness variations in the fundus image. The Gabor filter is applied to the pre-processed image for blood vessel enhancement.

The figure below shows MA detection at base hospital

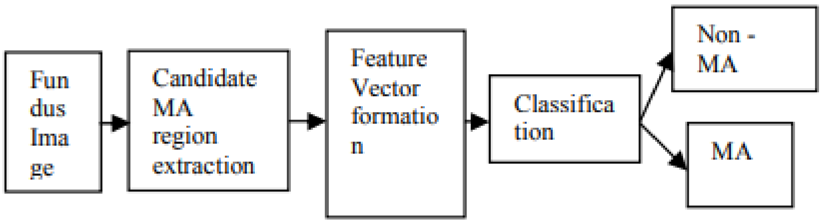


Figure 20:MA detection at base hospital

2.2 Feature Vector Formation: The extracted candidate MAs includes both lesion and non lesion regions. GLCM features are used for extracting information related to intensity of the candidate regions. For the wavelet features, first level DWT transforms for 2D images are applied to obtain coefficient matrices for approximation, horizontal details, vertical details and diagonal details sub- bands.

2.3 Classification: The testing set is formed by features of candidates in test input fundus image. All the candidates were individually classified as MAs or Non MAs. The holoentropy enabled classifier is utilized for the classification purpose.

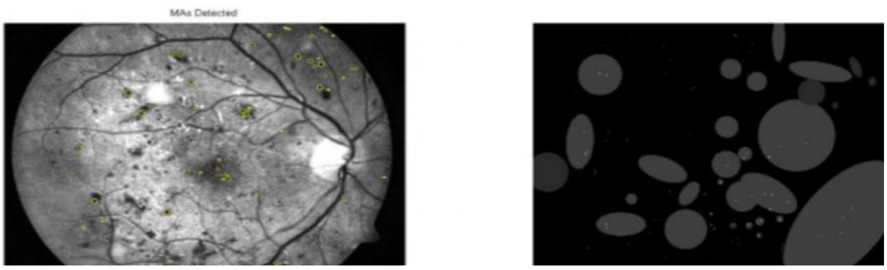


Figure 21:MAs detected and its ground truth

2.1.3 Literature Related to Algorithms

PAPER 1:

1. Artificial Neural Networks

A. Artificial Neural Network An Artificial Neural Networks (ANN) is the processing system which is modelled to simulate the way the human brain analyses the information. ANN is the base of Artificial Intelligence and clarifies the issues that look impossible to solve by human or statistical measurements.

Artificial Neural Networks consist of a number of nodes that act like neurons of the human brain. The neurons are joined and cooperate with each other by networks. Each node has the ability to take data input, process it and send it to the next neuron. The result created at each node is known as node value. Data that move through the network can change the format of ANN as a neural network learn and develop on the basis of input & output

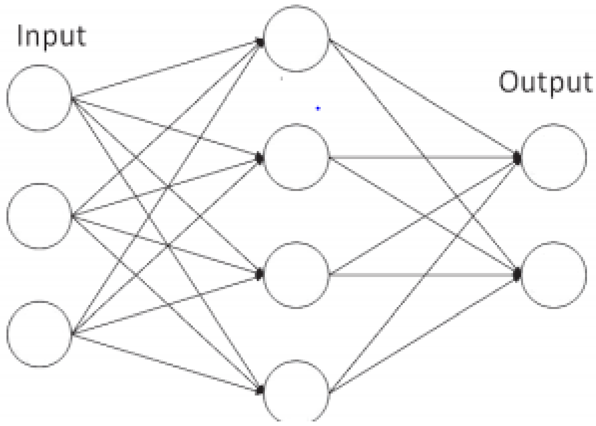


Figure 22:. ANN dependency graph

2 Discrete wavelet Transform

DWT is the multi resolution characterization of an image that decodes constantly from low to high resolution. It divides the image into low and high frequency elements. The high frequency has the information of corner elements and the low frequency is again divided into high and low frequency elements

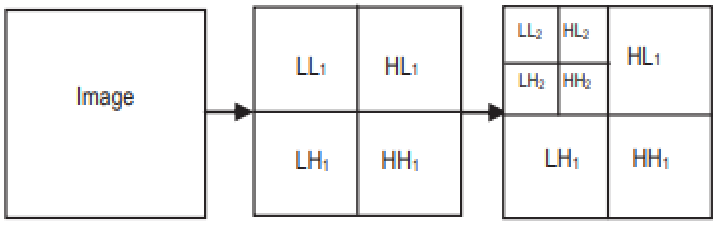


Figure 23:. Two-level discrete wavelet decompositions

Algorithm

1. Capture the retina image (query image) of the patient by using a mobile phone and 28D lens.
2. Input the query image.
3. Convert the RGB query image into Gray image.
4. Resize image to 256×256.
5. Decompose the image into four sub-images by applying Discrete Wavelet transform (DWT). Calculate the energy of all decomposed images at the same scale.
6. Create the retinal image database which contains images of various diabetic retinopathy signs. Reading all the retinal images from the database and repeating the step 3 to 6 for each and every database image. Calculate Euclidean distance between the features of the query image and database images.
7. Arranging them in a sorted order and on the basis of order label the relevant images.

Output:

- The experiment result shows that the finite numbers of retina images were retrieved with 63% precision and 57% recall rate to cut down the analysis time.

PAPER 2:

1. MobileNets

1. The utilized neural network architecture is based on MobileNets.
2. This network is built on depth-wise convolution layers which are further divided into depth-wise and pointwise convolution, except for the first layer which is a fully connected layer.

3. Depth-wise convolution is used for applying a single filter on every input channel while pointwise convolution is used to form a linear combination of the output from the depth-wise layer.
4. There are two non-linearity used: batch norm and ReLU after each layer
5. The depth-wise layer is represented as:

$$G_{k,l,m} = \sum_{i,j} K_{i,j,m} \cdot F_{k+i-1,l+j-1,m}$$

where k is a depth-wise kernel.

6. Computation cost of depth convolution:

$$D_k \,.\, D_k \,.\, M \,.\, D_F \,.\, D_F$$

7. Depth-wise convolution is a way to filter the channels but it does not combine them in order to generate new features. So for combining we use 1×1 pointwise convolution.

The figure below shows the MobileNets model:

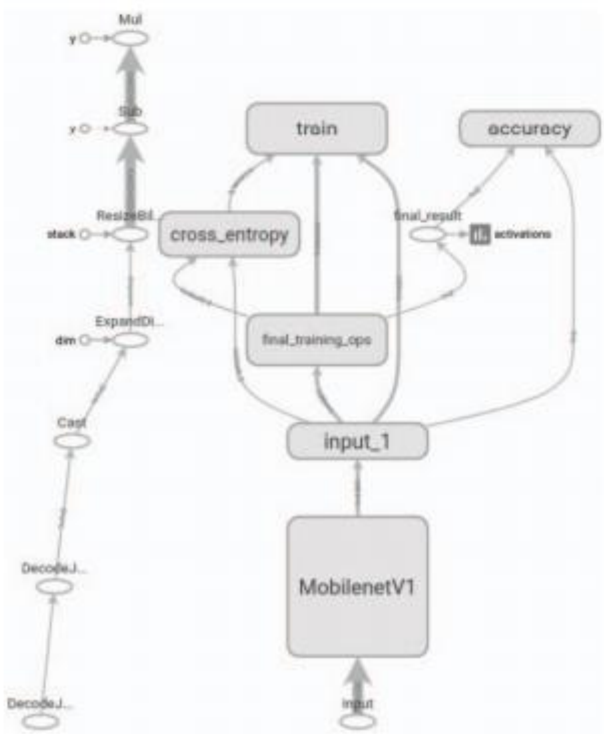


Figure 24:MobileNets model

Table 1:MobileNets Architecture

Type/Stride	Filter Shape	Input Size
Conv/s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw/ s1	$3 \times 3 \times 3 \times 32$ *dw*	$112 \times 112 \times 32$
Conv/s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw/s2	$3 \times 3 \times 64$ *dw*	$112 \times 112 \times 64$
Conv/s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw/s1	$3 \times 3 \times 128$ *dw*	$56 \times 56 \times 128$
Conv/s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw/s2	$3 \times 3 \times 128$ *dw*	$56 \times 56 \times 128$
Conv/s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw/s1	$3 \times 3 \times 256$ *dw*	$28 \times 28 \times 256$
Conv/s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw/s2	$3 \times 3 \times 256$ *dw*	$28 \times 28 \times 256$
Conv/s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5 \times$ Conv dw/s1 Conv/s1	$3 \times 3 \times 512$ *dw* $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw/s2	$3 \times 3 \times 512$ *dw*	$14 \times 14 \times 512$
Conv/s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw/s2	$3 \times 3 \times 1024$ *dw*	$7 \times 7 \times 1024$
Conv/s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool/s1	Pool 7×7	$7 \times 7 \times 1024$
FC/s1	1024×1000	$1 \times 1 \times 1024$
Softmax/s1	Classifier	$1 \times 1 \times 2$

Output:

- The accuracy of the model comes out to be about 73.3 %
- The sensitivity of the model is 74.5 % and specificity is 63%.

PAPER 3:

The images are taken by using a Volk iNview lens that works with an iPhone 6 camera. The images are in JPEG file format. There are 50 fundus images in the experiments- 25 images have exudates and another 25 has no exudate. The ground truths of exudate regions and the DR screening results for these images are provided by an ophthalmologist. The SVM in exudate classification contains 500 regions and 90% is used for training and 10% is for testing. We also used ten fold cross-validation in order to reduce the bias in the testing setSensitivity = TP / (TP + FN)

Specificity = TN / (TN + FP)

Precision = TP / (TP + FP)

Accuracy = (TP + TN) / (TP + FP + TN + FN)

where TP, TN, FP, and FN are the number of true positive, true negative, false positive, and false negative, respectively.

Output:

	Percentage
Sensitivity	96
Precision	75
Specificity	68
Accuracy	82

PAPER 4:

1. Classification of Microaneurysm and Hemorrhages

Microaneurysm (MAs) are small red spots which are the first pathological signs of diabetic retinopathy and appear at the earliest stage of this diabetic complication. MAs are caused by dilatation of thin retinal blood vessel . As the disease progresses, the weakened walls of MAs or thin blood vessel may rupture and produce dot hemorrhages and later blot hemorrhages which are the next pathological signs of diabetic retinopathy. They proposed splat features classification for the detection of retinal hemorrhages. Total 357 splat features were used which includes colour, DoG filter bank, Gaussian & Schmid filter bank, local texture filter and area, orientation, solidity, extent of splat. The features selection procedure was also carried out by filter approach and feature selection with a wrapper approach. The authors utilized k-nearest neighbour (k-NN) classifier and achieved 0.87 area under the curve (AUC) for receiver operating characteristics (ROC) and obtained the specificity of 66% and sensitivity of 93%.

2. Classification of Exudates and Cotton wool spots

The exudates (EXs) and cotton wool spots appear as white lesions in DR. The thin blood vessels burst in DR causing the formation of MAs and HMs. As the disease progresses, cotton wool spots and hard exudates start to appear on the retinal surface. The patient can lose the central vision if the exudates and cotton wool spot reach the macula and fovea where the central vision is focused.

PAPER 5:

1.Database used: DIARETDB1 is a public database for benchmarking DR detection from digital images used for experimental evaluation. This database covers 89 colour fundus images, of these eighty four images reveal at least mild non- proliferative signs of the DR and the rest of the 5 images are thought to be normal with no signs of diabetic retinopathy. These classifications of images were made by experts. The data is highly associated with practical circumstances and hence, the images are comparable in determining the general performance of diagnostic schemes.

1.1 Holo-entropy Enabled Decision Tree

The decision tree develops the system for classification with minimum computational processes. It is constructed using steps such as selection of the best feature as a node, split the feature to progress the tree and finally label the class. The node with the best feature is selected using holo-entropy instead of entropy. The holo-entropy (HLE) has been calculated for each feature from the feature vector. The feature having highest holo-entropy is chosen as the best feature to construct the decision tree.

$$HLE(attribute_i) = 2\left(1 - \frac{1}{1 + \exp(-Entropy(attribute_i))}\right) \times Entropy(attribute_i)$$

The process is executed to all the samples recursively. The labelling of the last node that is leaf node is performed by selecting the group to which the large amount of data fulfilled with the same node. The HDT is formed for the set of training images. The new retinal fundus image is tested against the constructed decision tree by extracting the hybrid features. The final outcome of the testing will be classifying the test image as DR or Non-DR

The splitting of the selected best feature to construct the decision tree has performed by selecting the best possible split. This process is performed by utilizing holo-entropy information gain (HLEIG) and conditional holo-entropy (CHLE)

The process is executed to all the samples recursively. The labelling of the last node that is leaf node is performed by selecting the group to which the large amount of data is fulfilled with the same node. The HDT is formed for the set of training images. The new retinal fundus image is tested against the constructed decision tree by extracting the hybrid features. The final outcome of the testing will be classifying the test image as DR or Non-DR. The images with DR will be sent to the base hospital for further processing and evaluation by experts.

2.1.4 Literature Related to Technology / Tools / Frameworks

Table 2:Literature to Technology, Tools and Framework

PAPER 1	PAPER 2	PAPER 3	PAPER 4	PAPER 5
TensorFlow Keras	TensorFlow RMSProp Android Studio 3.1	Matlab user interface TensorFlow Image Processing	Image Processing, TensorFlow	Internet Fundus Camera OpenCV

2.2 Observations on Existing Work

Table 3: Observations on Existing Work

Characteristics	PAPER 1	PAPER 2	PAPER 3	PAPER 4	PAPER 5
Dataset	Live dataset using fundus lens	Dataset from Kaggle	Images taken from a hospital	Already existing dataset.	Already existing dataset.
Methodology	Image processing and Deep Learning	Image processing and Deep Learning	Images processing and Machine Learning	Images processing and Machine Learning	Image processing and Deep Learning
Algorithms	Artificial Neural networks (ANN) and Discrete Wavelet Transform (DWT)	MobileNets - Neural network Model	Support Vector Machine (SVM)	Support Vector Machine (SVM) and k-nearest neighbor (k-NN) classifier	Support Vector Machine (SVM)
Advantages	The system can be made available at any time, any place ideal for rural region.	The application can be used for Android devices, Linux and Windows Operating System	High accuracy, quick processing, portability, ease of use, and economy	The system significantly reduces the workload of experts. The system is accurate, efficient, portable and user friendly.	The system significantly reduces the workload of experts. The system is accurate, efficient, portable and user friendly.

3. Proposed Methodology Approach

Diabetic retinopathy (DR) is one of the leading causes of preventable blindness globally. Performing retinal screening examinations on all diabetic patients is an unmet need, and there are many undiagnosed and untreated cases of DR. The objective of this study is to develop robust diagnostic technology to automate DR screening. Referral of eyes with DR to an ophthalmologist for further evaluation and treatment would aid in reducing the rate of vision loss, enabling timely and accurate diagnoses.

A fully data-driven artificial intelligence–based grading algorithm can be used to screen fundus photographs obtained from diabetic patients and to identify, with high reliability, which cases should be referred to an ophthalmologist for further evaluation and treatment. The implementation of such an algorithm on a global basis could reduce drastically the rate of vision loss attributed to DR.

3.1 Problem Definition

Traditional retinal cameras are expensive, large, immovable and require special training to operate. Without regular check-ups, it is possible that retinopathy may go undiagnosed, which has adverse effects.

Hence, a novel, cheaper and convenient approach to capture high definition retinal images and detect the likeliness of DR using deep learning techniques is suggested. A compact mobile phone -based result finding system which helps in early detection of diabetic retinopathy is presented. The use of neural networks and image processing techniques on color fundus images for the recognition task of diabetic retinopathy staging is demonstrated. The retinal images taken with a mobile camera which has a lens mounted on its camera in remote places are transmitted to the ophthalmologist, who will thus be enabled to declare any pathology which can be assessed from the pictures.Also , the likeness of the presence or occurrence of other associated complications such as amputations, high blood pressure, glaucoma, etc. Is predicted.

3.2 Scope

- The system is easy to use, and the only hardware requirements are a lens and a smartphone.
- The solutions to various challenges come from image processing techniques.
- It is possible to identify and use automatic focus detection, to find the ideal focus for the image of the eye.
- The scanned images will be processed and the reports will be available to doctors to analyse.
- At the end of the process, an in depth analysis will be performed to provide an insight to the doctor and patient regarding the condition
- We reduce the processing speed and the memory requirements of the entire process.
- We also predict the likeness of the presence or occurrence of other associated complications such as amputations, high blood pressure, glaucoma, etc., which helps the patients to get it tested immediately and take the necessary precautions.
- It will be accessible by any person with or without a medical knowledge, although it is advisable to trust the decision of a medical personnel
- Data will be collected from the patients in real-time.
- The proposed solution would be an app/website portal.

3.2.1 Assumptions and Constraints

The product design is based on following assumptions. System hold the right to change the methodology if any of the assumptions fail to fulfill the requirements.

- The use of a fundus lens is mandatory for the working of this system, as it needs to be mounted on a smartphone to take clear, more accurate retinal images.
- The presence of a smartphone is of utmost importance as the fundus lens needs to be mounted on it, and it is required to apply the algorithms on images.
- An internet connection is also important for the smooth functioning of the system.
- Since Machine Learning tasks require some time for processing, the time required to process each reply cannot be ignored and may affect the real time system.
- Since we require data from people from various medical backgrounds, we rely on their co-operation to do the same.
- We rely on the efficiency and accuracy of the prediction algorithms for predicting other complications related to diabetes, and state that this is just a prediction based on analysis, and may or may not hold true for every single patient.

3.3 Proposed Approach to Build Diabetic Retinopathy Detection

Retinal imaging is the most widely used method for screening due to its high sensitivity. Traditional retinal cameras are expensive, large, immovable and require special training to operate. Without regular check-ups, it is possible that retinopathy may go undiagnosed, which has adverse effects. Hence, we suggest a novel, cheaper and convenient approach to capture high definition retinal images and detect the likeliness of DR using deep learning techniques. In this method, we offer to mount an external lens on a smartphone camera, which can then be used by anyone as per their needs. This lens can take live images of subjects who need to undergo diagnosis. The images taken will then have various image processing and machine learning algorithms applied on it, which will eventually predict the possibility of having the condition. We will also be predicting the possibility and likeness of other diabetes related complications that may occur. Our proposed approach consists of the following steps:

- *Data Collection*: We will be collecting various samples of images from patients with and without the condition, so that we can predict the possibility of the patient being tested positive on the basis of the dataset.
- *Live testing:* A person who needs to be tested can take their image with the smartphone which has a mounted lens specially for retinal imaging. The diagnosis can be done immediately and effectively.
- *Evaluation report*: A detailed analysis of the patient's condition will be presented. The necessary steps to be taken after a positive diagnosis can be given by the doctor.
- *Predicting other diabetes related complication*s: Our model also compares retinal images of patients with other diabetes related complications and predicts the chances of it occurring for the patient based on comparison of retinal images.

3.3.1 Features of Proposed System

- *Image Processing:* 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.
- *Deep Learning*: A deep learning AI-system applied to a relatively small retinal image dataset could accurately identify the severity grades of diabetic retinopathy and macular edema and that its accuracy was improved by using high resolution and quality images.
- *Classification*: DR is divided into two major forms: non-proliferative and proliferative, named for the absence or presence of abnormal new blood vessels emanating from the retina. These stratifications have been useful for analysis of treatment efficacy in the literature and general indicators for treatment strategies. However, each patient with DR has a unique combination of findings, symptoms, and rate of progression, which necessarily requires an individualized approach to treatment in the effort to preserve vision.
- *Ease of operation*: Presently, ophthalmologists rely extensively on specially trained personnel to capture images using the fundus cameras. Our system simplifies the task of image collection independent of the operator.
- *Decision-making capability*: In contrast to other systems which require interpretation of images by an ophthalmologist, our system provides a first-hand assessment of conditions to general practitioners and emergency room physicians.
- *Portability*: Our compact system is easy-to-deploy on field locations that are hundreds of miles away from specialists. This is unlike present-day heavy equipment.
- *Cost-efficiency*: Existing methods include costs incurred for expensive sophisticated fundus cameras and operating technicians. Our system, on the other hand, uses a low-cost direct ophthalmoscope and smartphone.
- *Convenience*: Any doctor can use this system during a general check-up of a patient to diagnose diabetic retinopathy. It can also be used by a lay-man, although the correct steps to be taken after a positive diagnosis need to be taken by a mediical professional only.

3.4 Proposed System Architecture

The below diagram is the system architecture of our proposed system. It includes abstract relations with proposed features.

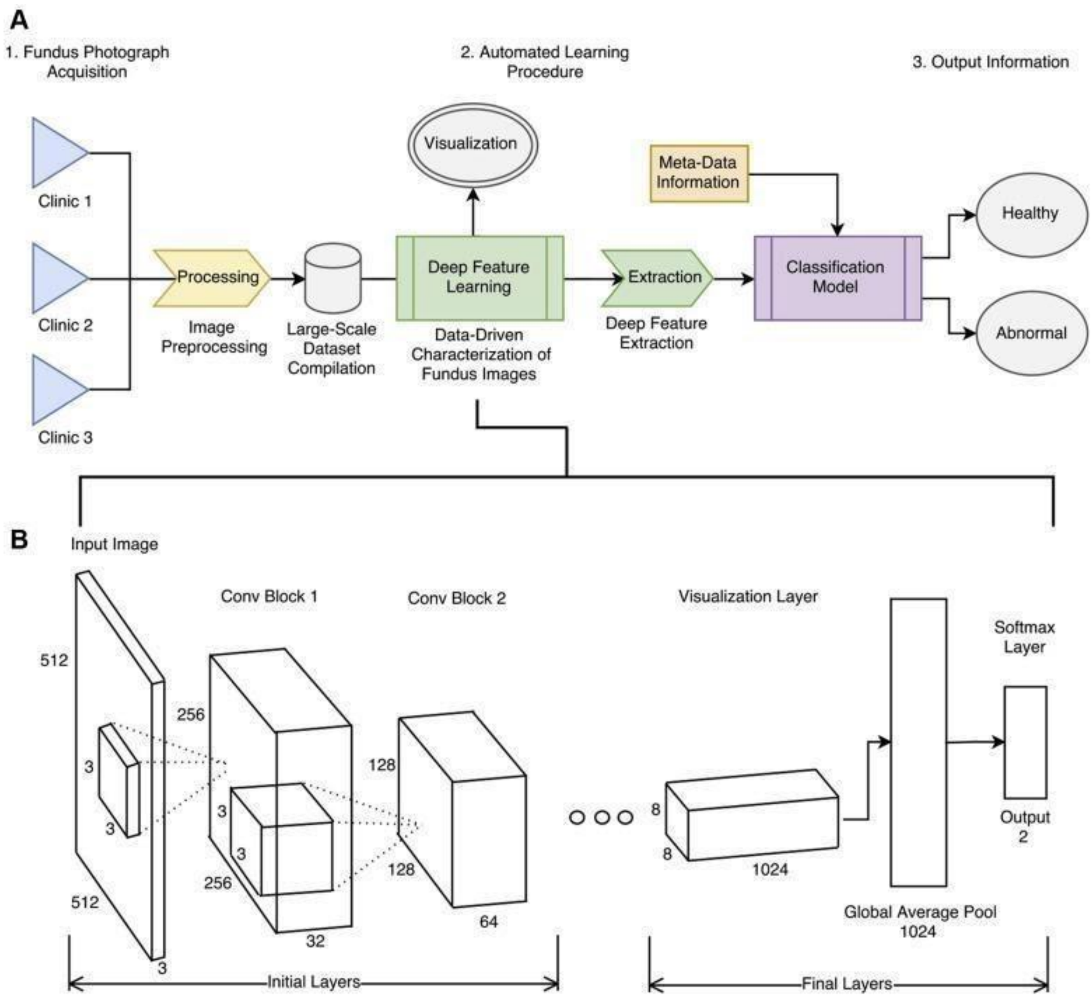
A- Integration of our algorithm in a real diagnostic workflow.

B -Abstraction of the deep neural network.

Figure 1A represents an abstraction of the algorithmic pipeline. The fundus images will be compiled and preprocessed across various sources into a large-scale data set. The deep learning network learned data-driven features from this data set, characterizing DR based on an expert-labelled ground truth. These deep features will be propagated (along with relevant metadata) into a tree-based classification model that outputs a final, actionable diagnosis.

Figure 1B represents an abstraction of this feature learning architecture.

As is standard in deep convolutional networks, each convolutional layer used batch normalization and the ReLU nonlinearity function to ensure smooth training and prevent overfitting, while using 2-class categorical cross-entropy loss for class discrimination



1. **Data Acquisition**

The data set is a set of color fundus images obtained from the clinics.

Each image will be associated with a diagnostic label of 0 or 1 referring to no retinopathy or DR of any severity, respectively, determined by a panel of medical specialists.

2. **Data Preprocessing and Compilation**

To account for image variation within our data, multiple preprocessing steps will be performed for image standardization before deep feature learning. Image pixel values will be scaled to values in the range of 0 through 1. Images will be downsized to a standard resolution pixel.

To preprocess images further before learning, data set augmentation methods will be applied to encode multiple invariances in our deep feature learning procedure. Data set augmentation is a method of applying image transformations across a sample data set to increase image heterogeneity while preserving prognostic characteristics in the image itself. Other important characteristics such as the color and brightness of the image (having invariance to varying color contrast between images), can be encoded using brightness adjustment. Grayscale Conversion,

Filtering, Smoothening, can also be used depending on the necessity.
These image transformations will aim to improve our model's ability to classify varieties of retinal images obtained in unique lighting settings with different camera models.

3. Deep Feature Learning and Extraction

Our novel approach to feature learning for DR characterization will leverage deep learning methods for automated image characterization. Specific, deep convolutional neural networks will be used for automated characterization of fundus photography because of their wide applicability in many image recognition tasks and robust performance on tasks with large ground truth data sets. These networks use convolutional parameter layers to learn iteratively filters that transform input images into hierarchical feature maps, learning discriminative features at varying spatial levels without the need for manually tuned parameters. The convolutional layers will be positioned successively, whereby each layer will transform the input image, propagating output information into the next layer.

4. Metadata Information

To enhance the diagnostic accuracy of our final prediction, we can append multiple metadata features related to the original fundus image to our feature vector useful in characterizing the original image. Such as original pixel height of the image, original pixel width of the image, and field of view of the original image.

5. Classification Model

To generate a final diagnosis, the feature vector will be trained on a second-level gradient boosting. Gradient boosting classifiers can be used for capturing fine-grained correlations in input features. Decision Tree classifier can be used because of its speed of implementation and robustness against overfitting. This classifier will be trained by using the categorical cross-entropy loss function, yielding the probability that the input image will be pathologic.

3.5 Use Case Diagram

The system has 2 actors: Local practitioner and patient and use cases like pre-processing of the image, classification, scaling, filtering, getting classified results etc. Figure below conveys the different use cases available for users to interact with or perform on the system. Local practitioner will take the retinal images of the patient using a smartphone The smartphone will have a fundus lens mounted on it.

The retinal images are the preprocessed using filtering, scaling and are transformed from RBG color format to grayscale format. The dataset undergoes training using deep learning algorithm. Depending upon the accuracy then it is predicted whether the patient has diabetic retinopathy or not.

This determines if the patient needs to visit an ophthalmologist or not.

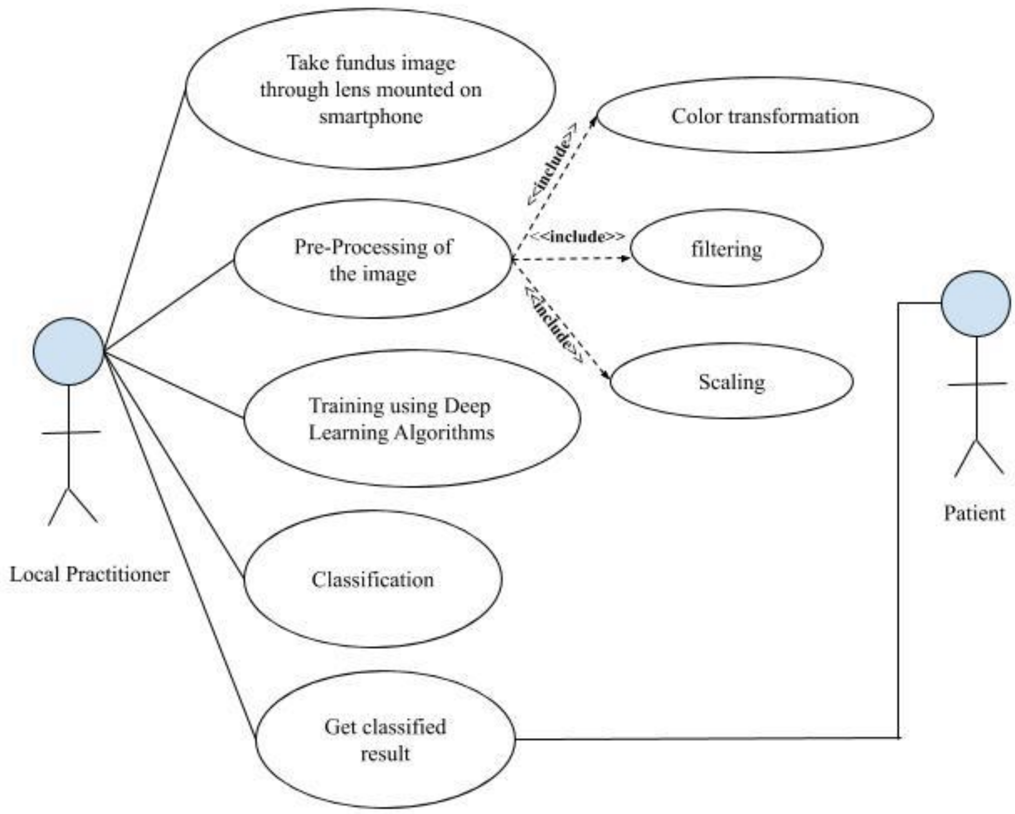


Figure 25:Use Case Diagram

3.6 Activity Diagram

The activities include data acquisition, image pre-processing , training using neural networks, indexing and retrieval, DR identification etc. It is depicted in below[figure3] activity diagram.

Data acquisition: It is a process of collecting patient's retinal images with the help of the fundus lens mounted on the smartphone.

Image pre-processing: Images are pre-processed using feature extraction, RGB to Grayscale conversion, filtering, noise removal, high and low intensity region identification, image scaling.

The data is trained using neural networks. Output of the neural networks determines whether the patient has diabetic retinopathy or not. If he does then he'll be suggested to visit ophthalmologist.

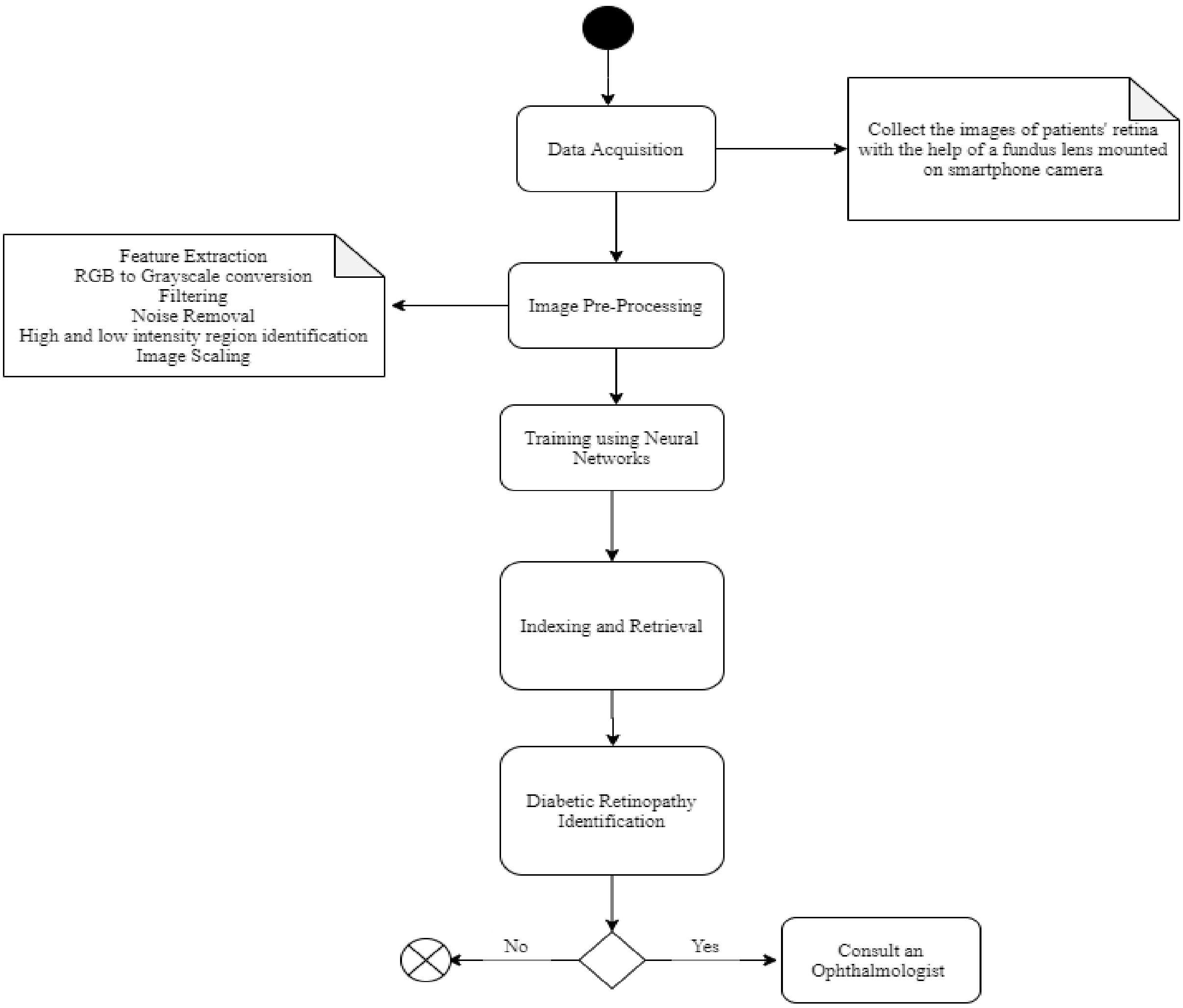


Figure 26:Activity Diagram

3.7 Benefits of Proposed Solution

The proposed solution has the following advantages over the conventional methods of retinal imaging for retinopathy detection:

- One time cost of system
- Ease of operation as anyone can use it
- Faster diagnosis and report generation
- Portable
- Additional conditions and complications can also be predicted
- Helps to take measures for other diabetes-related complications as well
- Low maintenance
- Cost effective
- Convenient as it can be accessed from anywhere

4. Feasibility Study of Proposed Solution

4.1 Technical Feasibility

Our project suggests a novel, cheaper and convenient approach to capture high definition retinal images and detect the likeliness of DR. In this method, we offer to mount an external lens on a smartphone camera, which can then be used by anyone as per their needs. This lens can take live images of subjects who need to undergo diagnosis. The images taken will then have various image processing and machine learning algorithms applied on it. We will also be predicting the possibility and likeness of other diabetes related complications. It is based on technologies such as Natural Language Processing, Machine Learning and Deep Learning where significant research is already been done. We aim to use existing algorithms as well as generate our own algorithm if need be.

4.2 Operational Feasibility

The proposed solution will be of great help to organisations as well as medical camps.
The lens can take live images of subjects who need to undergo diagnosis which will help in faster diagnosis and it can also be used by anyone. It is portable and also helps to predict additional conditions and complications. It helps to take measures for other diabetes-related complications as well. Low maintenance as well as cost effective . These challenges may require rigorous research about Deep Learning and Machine Learning techniques to come up with the ideal solution. Our system can run on web as well as mobile platforms.

4.3 Economic Feasibility

The proposed solution will have low maintenance costs. It includes the cost incurred for sophisticated fundus cameras and operating technicians. The development cost includes only the internet connection charges. The application is available to user free of cost on all the platforms . Overall, this product will be cost efficient.

5.Conclusion

The proposed system significantly reduces the workload of experts. The presented system is accurate, efficient, low cost, portable and user friendly so that the screening camps can be easily conducted throughout the entire region including rural places. For automatic classification of Diabetic Retinopathy (DR) images at the screening camp site, a hybrid features are extracted from various regions and data processing tools are utilized . The proposed system gives better results for image level DR classification. In future, the system can be improved for automated screening and to reduce false positive ratios. Also the DR stages can be found using number of lesions present in the retinal fundus image.

After studying and analyzing different algorithms similar to our project we conclude that it is possible to implement this project.

And from technical, operational and economic feasibilities we can conclude that the system is affordable and possible to implement.

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