Diabetic Eye Disease Detection Using Machine Learning Techniques

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Abstract:- Diabetic Retinopathy (DR) is an eye disease that affects people that suffer from diabetes over prolonged periods of time. If not detected and diagnosed at the right time, it often leads to weakening of vision and can even lead to absolute loss of vision. The disease generally affects people who are aged between 35 to 50 years, but recent cases involving teenagers have also been reported widely. The process for diagnosing Diabetic Retinopathy is often difficult since very few visible symptoms appear in patients until it is too late for treatment and the point of no return is met. Current techniques that exist for detecting Diabetic Retinopathy are extremely time consuming and require a manual procedure to be carried out by lab technicians which involves inserting medical tools into the patient's eye. The proposed methodology is to utilize the neoteric branch of computer science i.e. Machine Learning techniques to assist in identifying and diagnosing the disease by analysing the images of the eye. As per the research study, the images will be preprocessed, and converted to the Gray Scale following which the extraction of relevant features using appropriate supervised learning techniques are carried out to obtain the final trained model.

Keywords:- *Diabetic Retinopathy, Diabetic eye disease, Microaneurysms, Exudates, Machine learning, Supervised learning Introduction.*

I. INTRODUCTION

The Department of Public Health in the United States estimates that about 29 million people suffer from diabetes in the United States [1]. Diabetic Retinopathy is an eye disease that affects people suffering from diabetes over prolonged periods. Weakening and loss of vision due to Diabetic Retinopathy can be avoided if it is detected at the right time, however this is a very challenging task since the disease displays very few symptoms before it is too late for diagnosis and providing treatment. Current techniques that exist for detecting Diabetic Retinopathy are extremely time consuming and require a manual procedure to be carried out by the lab technicians which involves examining the eye of the patient with the help of lab tests which involve inserting medical tools into the eye.

Symptoms that help identify and detect Diabetic Retinopathy are lacerations and other deformations that are caused by the disease [2]. Even though this procedure is very accurate at identifying the disease, it is extremely inefficient since it requires a lot of manual work and no automation currently exist for it. Also, many times the medical tools as well as equipment and the expertise required for carrying out the procedure is lacking in regions of the world where a large number of people have diabetes and where the need of such a system for detection is most needed. Since the current lifestyle of people around the world would only lead to a greater number of people across the world with diabetes, there is an ever increasing need for automation in this procedure and the current system will soon not be able to cope up with the increasing demands in the respective field.

The process consists of recognizing very minute details, such as microaneurysms, to some broader and more visible details, such as *exudates*. Also, the position of these physically observable deformities are important to carry out the procedure for detecting the disease.

Microaneurysms are the first symptoms that are observable and are visible in the images as red dots that typically vary from 25 to 100 micrometres in diameter [3]. Exudate on the other hand is a fluid that constitutes of proteins, cells and other solid entities and leaks out of from blood vessels into the surrounding tissues [4]. Exudate seeps from areas of inflammation, cuts and infections and is also commonly referred to as pus. In people suffering with diabetic retinopathy, exudates form in the retina of the eye as shown below [5].

Fig 1:- Sample Image (Thin Arrows: Exudates; Triangle: Microaneurysms; Thick arrow: Retinal haemorrhage)

II. LITERATURE SURVEY

The challenge with detecting and diagnosing Diabetic Retinopathy is that the patient is unaware that they are affected by the disease until the disease has developed to an extent that treatment will prove to be ineffective. Automation of this procedure for detecting and identifying the disease has great potential in reducing the cost of the procedure as well as saving time and reducing the amount of manual labor required. Techniques that involve analysing the images with the help of computer systems can help to a great extent in identifying the symptoms precisely as well as in determining the damage that has already been caused by the disease. Correct diagnosis of the disease on time reduces the probability for total loss of vision by 50% in the patient [6]. Since there are almost millions of patients each year that undergo the procedure for determining the presence of the disease, doctors and lab technicians are finding it extremely difficult to cope up with the ever increasing demand for their skill and expertise. This is especially the case in rural areas where majority of people do not have access to good healthcare facilities as well as the shortage of doctors and other experts in these regions [7]. Therefore, automating the process for detecting the disease can assist the doctors and other experts in the field and can also help to limit the damage that is caused by this disease.

Processing the images of the eye with the help of computer systems help in quick detection of the disease as well as provides convenience to the patient since the need for inserting medical tools into the eye does not exist anymore.

The primary goal of the automated system in detecting the disease is to accurately identify patients who have progressed to threshold disease in a reliable manner so that quick and effective treatment can be provided to them. As shown in fig. 2 [8], current techniques for detecting the disease are manual and time consuming.

Fig 2:- Manual Screening of the Eye

III. PROPOSED SYSTEM

The system that is proposed in this research paper employs supervised machine learning techniques in order to classify an images of the eye that is given as input into two categories: “Positive” and “Negative”. The positive category indicates the presence of the disease and the negative category indicates its absence.

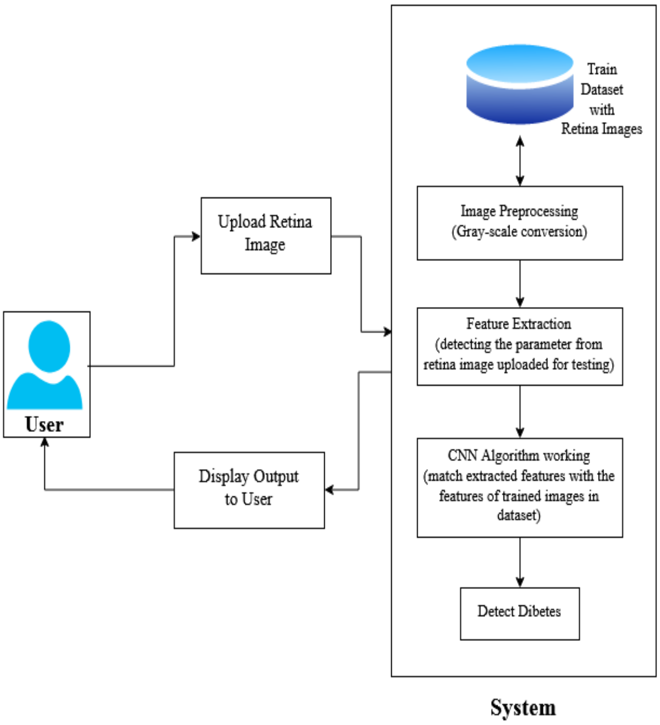

Fig 3:- Proposed Methodology

The system is first trained on the images from the training dataset which are labelled with their respective categories. Prior to training, the required preprocessing steps such as RGB to Gray conversion are carried out. After achieving accuracy above a specific threshold, the system is used to classify new incoming images of the patient’s eye.

A. Image Pre-processing

In this step, the image is converted from the RGB to Gray scale is subsequently used as an input for extracting the features. The Gray scale involves different shades where the darkest shade that is possible on the scale is black whereas the lightest possible shade is white. A black shade on the scale signifies the absolute absence of any kind of light whereas the white shade signifies the absolute reflection or transmission of light across all the visible wavelengths [9]. The RGB to gray scale conversion is shown in fig.4 and fig.5 below [10].

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Fig 4:- Colored image

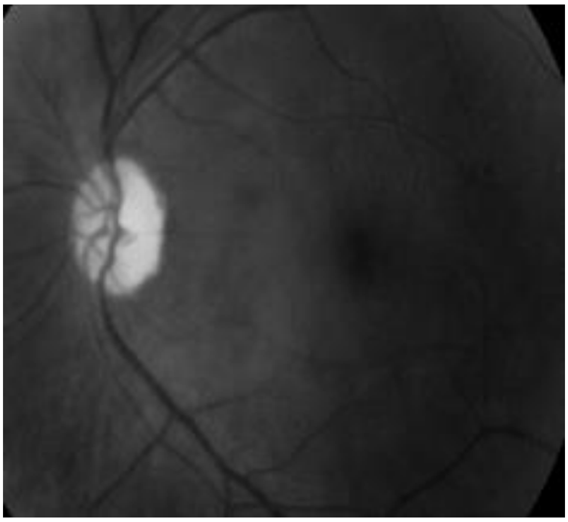
Fig 5:- Gray Scale Image

The blood vessels that are present in the original images are mostly unclear, and the size of each image in the dataset is different from each other, therefore it is essential to preprocess images so that they are brought to the same size and the visibility of the blood vessels and various other features that assist in detecting the disease are improved. Before we proceed to extract the features, the images are first rescaled to the same size.

B. Pooling

Pooling is a technique that is used to convert the input matrix $M_{in} \times N_{in}$ into a smaller $M_{out} \times N_{out}$ output matrix.

C. Classification algorithms

➢ Convolutional Neural Network (CNN)

Each neuron that is a part of the neural network is affected by only its receptive field. It is impractical to use feed forward neural networks to classify images since an extremely large number of neurons would be required due to the large input size of the images where each and every pixel is represented as a different variable that is used for processing. For example, a neural network that processes a small image of size 50 x 50 has 2,500 corresponding values for each neuron in the second layer. The convolutional neural network is able to tackle this problem by reducing the number of parameters that are considered for further processing thereby allowing to construct a deeper network with fewer parameters.

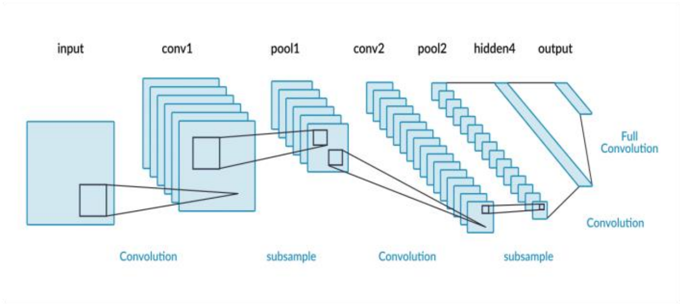

Fig 6:- CNN

As shown in fig.6 [11], CNN consists of multiple convolutional and pooling layers. The connected layers of the network will serve as a classifier on top of the extracted features and will assign probabilities for the objects in the image being what the algorithm predicts them to be.

➢ *Support Vector Machine (SVM)*

SVM is used to determine the optimal hyperplane that is able to linearly separate the data points into two components while maximizing the distance and margins of the hyperplane from data points in each category. In two dimension, the hyperplane is represented in the form of a straight line whereas it is represented as a plane in the three dimension. SVM is widely used to classify data that is linearly separable since it cannot accurately classify non-linear data due to the lack of flexibility in SVM to bend the hyperplane. Once the training data is proved to be sufficiently linear, SVM can be used to implement the system for classification into the "Positive" and "Negative" categories.

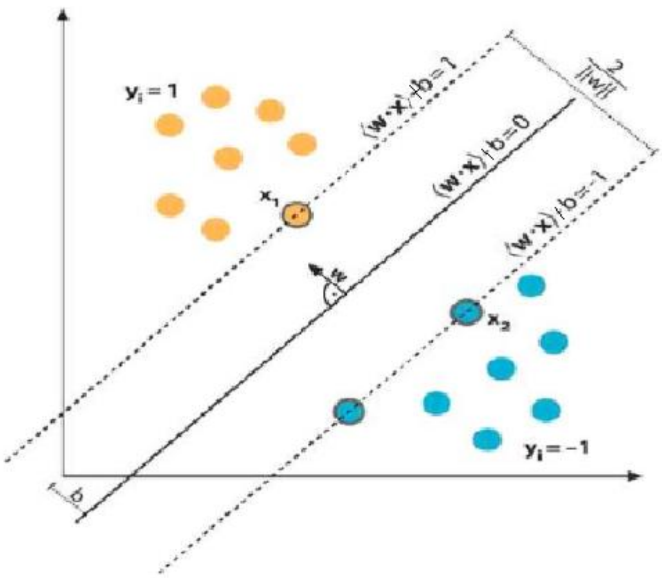

Fig 7:- SVM

From the above figure [12], SVM problem can be formulated as:

$$w.x_i + b \geq 1 \qquad for\ y_i = +1 \qquad ....(1)$$
$$w.x_i + b \leq -1 \qquad for\ y_i = -1 \qquad ....(2)$$
combining above two equation, it can be written as
$$y_i(w.x_i + b) - 1 \geq 0 \qquad for\ y_i = +1, -1$$

Here y_i =+1 represents the positive class (having eye disease) and y_i = -1 represents the negative class (not having eye disease).

D. Performance Analysis

- *Accuracy:* Accuracy is a metric that is used to represent the number of predictions that are correct out of the total number of predictions that are made.

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}}$$

- *Sensitivity*: Sensitivity is used to measure the accuracy of the predictions of diabetic diseased eye that are made by the model.

$$Sensitivity = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- *Specificity:* Specificity is used to measure the accuracy of the predictions of normal eye that are made by the model.

$$Specificity = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Here, TP- True Positives; FP- False Positives; TN- True Negatives; FN- False Negatives.

IV. CONCLUSION

In the proposed work, a non-invasive procedure has been presented to identify and diagnose diabetic eye disease with the help of supervised Machine Learning techniques.

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