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The Diabetic Retinopathy Detection Using Machine learning

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Abstract
According to the International Diabetes Federation, there are currently over 470 million individuals diagnosed with diabetes globally, and by 2050, that number might rise to 700 million. There are two types of it: Type 1 and Type 2. Type 1 diabetes is chronic and incurable, however Type 2 diabetes can be cured if caught early. Identification of anomalies in retinal pictures is tough and complex in the medical sector since these signs of diabetes that affect the eyes appear to be very modest. Therefore, a non-invasive technique to uncover these abnormalities was required.
After reviewing a number of research projects and developments, we attempt to highlight and explain the various methodologies used, their benefits and limitations, the general goal of the results, and the significance of a DR detection system. The survey also highlights the significance of early detection and the need to eliminate the factors that obstruct timely discovery.

Keywords
Diabetic Retinopathy (DR), Non-Invasive, Digital Image Processing

I. Introduction
About 470 million people worldwide are diagnosed with diabetes. During the period spanning 2000-2016, a 5% increase in deaths related to diabetes was observed, with 1.6 million deaths each year. Diabetes can be considered a major public health problem in India. Its symptoms are indistinct, one can grow thirstier or become hungrier than usual, or we might not figure out why we're more tired than usual. The meteoric rise in urbanization and industrialization, along with our lifestyle choices provides an ideal scenario for the prevalence of diabetes and its associated complications.

Fig. 1: Normal Image Fundus Diabetic Retinopathy Image

It has been noted that there are variances in the ratio of ophthalmology-trained medical professionals to patients, which makes it difficult to diagnose and treat diabetic retinopathy. This is owing to the steady and gradual increase of diabetes around the world. As a result, problems with screening time, greater prices, decreased device sensitivity and specificity, etc., needed to be addressed. As a result, the introduction of automated detection systems based on standalone algorithms was suggested. The screening and diagnosis of DR are important study areas, and many researchers are working to advance these fields. Methodologies for image processing have made it simple and advantageous to examine acquired images, including their traits, behaviours, and processing.

Additionally, the development of new image processing techniques, classification algorithms, and neural networks has helped computer-aided detection systems perform quickly and has been recognised as a reliable option for applying analysis on retinal pictures. The aforementioned system models would seek to determine the necessity of referral for additional treatment and ongoing eye care. We won't be too far off from being able to apply these techniques on our cell phones given the speed at which technology is developing. To identify DR, extensive study has been done and numerous methods/processes have been developed. The implementation of automated screening systems and the outcomes obtained are characteristics of success and a potential failure. The effectiveness and complexity of the existing algorithms for the identification of DR employing the various image processing processes and their associated methodologies can yet be improved. Here, we want to provide you a general overview of how to create an application that can identify anomalies caused by DR in the retina of the eye.

II. Existing System
The author of the research paper [1] employs feature extraction to locate and extract the details that are specific to the image. Speeded-Up Robust Features (SURF) detects blob features. It is a kind of detector algorithm that draws attention to particular locations on images that have been transformed into a coordinate system. The MSER (maximally stable extremal region) is used for matching. Extremal pixels are those that are either more or less intense than the pixels on the MSER's outer perimeter. Comparing the extracted image and the categorized image to their counterparts in the input image, observations are made.

The procedure for removing blood vessels and optical disc detection are both thoroughly detailed in this research paper [2]. They act as a starting point for identifying further traits. Candidate area selection, Sobel edge detection, and Estimation are the three steps in the detection process here. The Kirsch method is used to detect the blood vessels by edge detection. This technique convolutions the image with eight template impulse response arrays to calculate the gradient. After enhancement, a reference point or threshold is set up to determine if a pixel is an edge pixel or not.

For the purpose of detecting diabetic retinopathy, the authors of the research [3] employ morphological operations. To reduce false positive exudates, the blood vessels and optical disc are first retrieved and removed. This is essential for the removal of lesions. Here, the use of procedures like erosion and dilation for the removal and detection of blood vessels is also noted. The structuring element causes a proper circular dilation of the optic disc's fragmented parts. In order to locate the circle in the image that corresponds to the optical disc, the circular Hough transform is used.

In the paper [5], feature extraction is done in three phases. Initially, feature extraction is done because it's crucial to distinguish between different stages of diabetic retinopathy, and for this to happen, the binary image's total sum of white pixels must be defined as 1. The concept of mean is then introduced to equalize both photos when they are compared to one another and lessen the likelihood that the images will be of different resolutions or sizes. The classification of disease, which draws a conclusion because an exudate is noticeable in NPDR, considers the entire area of exudates seen in the image.

The Gabor filter is used by the author of this research work [7] to carry out automatic detection and classification. This will be utilized for texture detection and has the potential to be used for image retrieval. When used, this procedure operates in the Fourier domain. Multiple tests revealed that large blood arteries with anomalies only occurred and were visible at high frequency or smaller scales in the finer scale output generated from the filters. They thus hardly ever showed up in the output of lowpass filters.

The authors of the research paper [8] suggest a novel method to enhance the prognosis. The severity and treatment strategy for treating DR depend on the detection of Retinal vessels and Microaneurysms. As the sensitivity is easily optimized using evolutionary algorithms, they discover that the matched filter (MF) technique is more effective than theSobel operator or Morphological operator in this case. A top-hat alteration of the image is taken into consideration for the microaneurysm detection method. Real-time detection and ground truth retinal images provided by clinical specialists are used to train the algorithm to distinguish between the original and altered images.

The authors of the research article [9] provide an effective method for localizing characteristics and lesions. Geometric properties and correlations are employed to separate the intensities of overlapping features. Here, it is noticed that an original restriction for locating ocular discs (OD) is based on the intersection of retinal blood vessels to approximation its position, and further localized utilizing colour features. The Hough Transform is used to triangulate the data and create an intersection map.

III. Problem Statement

Early diagnosis and treatment of diabetic retinopathy (DR) can be aided by the identification of the condition's first signs. The current methods of DR detection are generally manual, expensive, and possibly time-consuming, necessitating the assistance of professional employees. Although some experimental research have made advances, they have not yet been implemented on a wide basis.

Here, we put the same little model into practise to find certain abnormalities in the impacted retinal pictures.

IV. Methodology

Machine learning, which is a subfield of artificial intelligence (AI), includes deep learning. Figure 2 provides a graphical representation of this relationship.

The main objective of AI is to develop a set of algorithms and methods that can be used to issues that people intuitively and almost automatically solve but that are otherwise exceedingly difficult for computers to handle. Interpreting and comprehending the contents of an image is a fantastic example of this category of AI challenges; whereas a human can perform this task with little to no effort, robots have found it to be incredibly challenging.

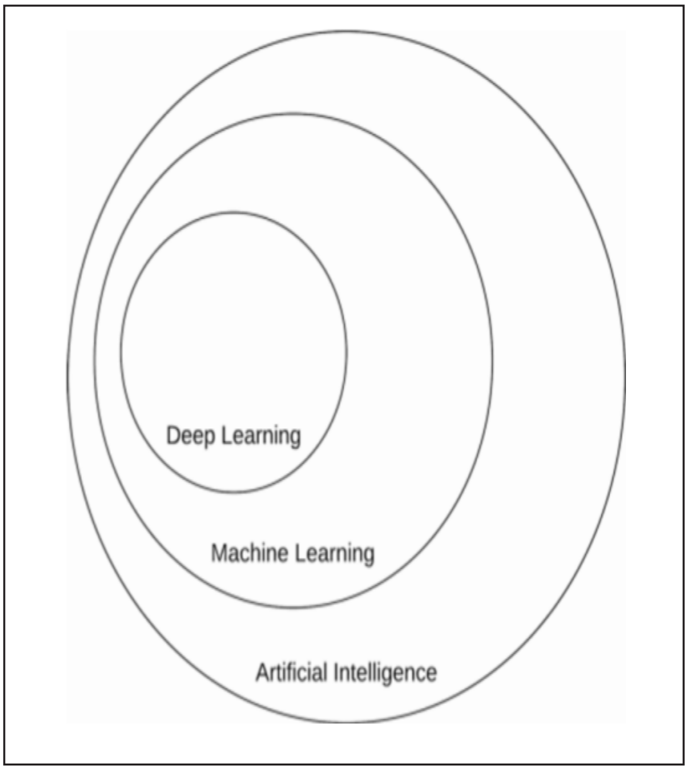

Fig 2: A Venn diagram describing deep learning as a subfield of machine learning which a subfield of artificial intelligence is in turn.

A. Image Acquisition:

The obtained image is in digital form hence requires scaling followed by color conversion i.e., either RGB to grey or vice versa. These are obtained from the public open-source or privately owned data repositories. Some of them have been mentioned in Table 1.

B. Image Processing:

This comprises extracting or enhancing the specific features of the image based on the requirement, reducing the effects that degrade the image, keeping the resolution to an acceptable level, etc.

C. Background Subtraction:

Here, we detect blood vessels and optical disks to eliminate them. It is the crucial step to simplify the process of identification of the exudates and microaneurysms.

D. Lesion Detection:

Microaneurysms and Hard exudates are symptoms usually observed in the mild and moderate non- proliferative stages of retinopathy. The hard exudates are the yellow flecks of lipid residues which are clear lesions. Microaneurysms appear as tiny red dots. The top-hat morphological procedure is utilized here.

E. Classification:

Assigning a label to the output image, indicating whether the image is healthy or not, based on descriptors.

V. Methodology

One of the major reasons of road accidents in real world has solution now. The system is one step towards safeguarding precious lives by avoiding accidents in real world. Proposed system is based on DLIB & SOLVE PNP Models.

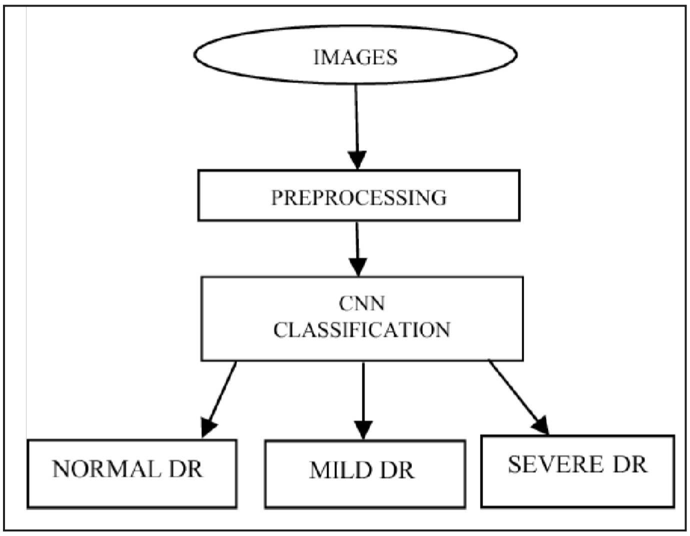

Fig. 2: Flow of the proposed system

A. Data collection

Compile a sizable dataset of retinal pictures, including both images with and without diabetic retinopathy. The existence and degree of retinopathy should be noted on these images.

B. Data preprocessing

Enhance the properties of the photos and eliminate any noise or artefacts that can obstruct the detection procedure. Resizing, normalization, and contrast correction are frequent preprocessing techniques.

C. Data augmentation

Enhance the dataset by subjecting the photos to various transformations, including rotation, scaling, flipping, and cropping. This increases the diversity of the data and strengthens the generalization abilities of the model.

D. Model selection

Select a deep learning architecture like convolutional neural networks (CNNs) that is suited for the task. CNNs are frequently employed for image-related applications because of their efficiency in capturing spatial data.

E. Model training

Create training and validation sets from the dataset. Utilize the training set to train the deep learning model while adjusting its settings to reduce the difference in expected and actual labels. To avoid overfitting, keep an eye on the model's performance on the validation set.

F. Model evaluation

Use a different test set that wasn't utilized for training or validation to assess the trained model. To evaluate the model's effectiveness in diagnosing diabetic retinopathy, compute pertinent assessment metrics including accuracy, precision, recall, and F1 score.

G. Optimisation and fine-tuning

If the initial model performance is unsatisfactory, think about optimizing the model by modifying the architecture, including transfer learning from trained models, or adjusting the model's hyperparameters. Repeat this procedure as necessary to attain the desired results.

H. Deployment

The model can be used to categorise retinal images for the identification of diabetic retinopathy once it satisfies the appropriate performance criteria. For simple access and usability, make sure the model is integrated with the appropriate user interface or application.

The quality and diversity of the dataset, as well as the skill in choosing and optimizing the deep learning model, are critical components in making the process successful. Working with medical data also necessitates getting ethical permission and following data privacy laws.

VI. Implementation

Pre-processing techniques are used in the given proposed methodology, as shown in Fig. 2, to obtain input images from the given data set. After that, morphological operations are carried out to identify exudates and microaneurysms. Finally, a multiclass SVM and KNN classifier are applied to determine the degree of irregularity. The input photos for the approach are collected from MESSIDOR and Diabeticret DB1.

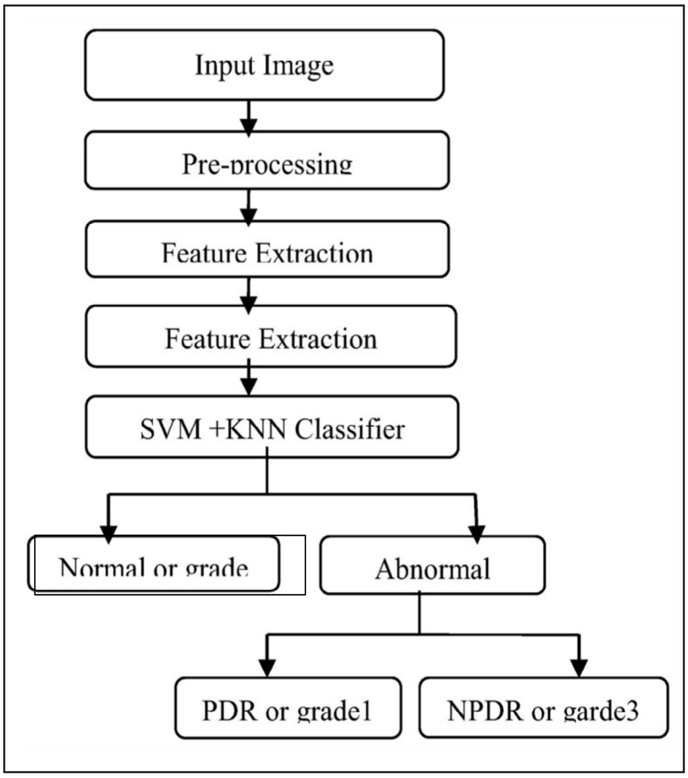

Fig. 3: Implementation of proposed system

The pre-processing stage is used to prepare the input image, which is 2240 x 1488 pixels in size. The segmentation method is then applied. During the preprocessing stage, issues with blurring, clarity, and size are fixed in the image. This stage involves image resizing, followed by colour space conversion issues, image restoration, and image enhancement. The input colour fundus image is turned into a hsi model during colour space conversion. Hue Saturation and Intensity, or HSI. It is the best tool for image processing because in this colour model space, the intensity component is divorced from colour, which contains information (hue and saturation) in colour images. All futures are taken from fundus photos that are grey in colour for processing purposes. The intensity (adjustment problem) of a grey image is more suited than that of a colour image. It's trans and the saturation component is given by,

$$h' = \begin{cases} undefine \ if \ c = 0 \\ \frac{Green-Blue}{c} mod \ 6 \ if \ M = R \\ \frac{Blue-Red}{c} + 2 \quad if \ \ M = R \\ \frac{Red-Green}{c} + \ 4 \quad if \ M = B \end{cases}$$

$$h = 60^{\circ} * h'$$

S = 1-3/[(Red +Green +Blue)*min(Red, Green, Blue)] Finally intensity component is given by:
I = II [3*(Red + Green+ Blue)]

Using a hybrid median filter, the transformed images are subsequently filtered to remove noise like pepper and salt that appeared during image acquisition. The hybrid median filter improves edge comer prevention, reduces noise caused by thick and narrow feature boundaries, and smooths the image quality. The CLACHE acronym stands for contrast limited adaptive histogram equalisation, which is carried out after contrast enhancement filtering to boost image quality. The image and histogram equalisation after preprocessing are shown in the figure below.

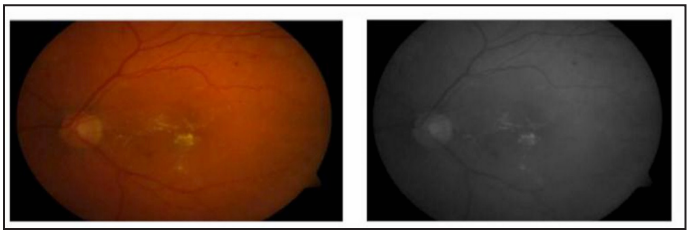

Fig. 4: Original Fundus Image on left, HSI model image on right

A. Deep Learning

Our classifier uses a training set to "learn" the characteristics of each category by generating predictions on the input data and then correcting itself when predictions are incorrect. We can assess the classifier's performance on a testing set after it has been trained.

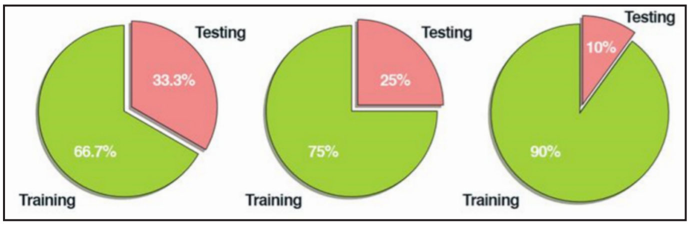

Fig. 5: Example of common training & testing dataset splits

It is crucial that the training set and the testing set are distinct from one another and do not overlap! Your classifier will have an unfair advantage if your testing set is included in your training data because it has previously seen the testing instances and "learned" from them. Instead, you must completely maintain this testing set apart from your training procedure and just utilise it to assess your network.

For training and testing sets, typical split sizes are 66:6%33:3%, 75%=25%, and 90%=10%, respectively.

VII. Conclusion

Both exudates and micro-aneurysms are found using the suggested approach. To prevent ophthalmologists from treating spurious problems, optical discs and blood vessels are removed for exudate detection. Morphological operations like closure are carried out for the purpose of detecting exudates. Operators for erosion and dilation are used. Count the number of micro-aneurysms that appeared in the image during micro-aneurysm detection so that we can determine the system's grade. Once features have been determined, they are sent into the SVM and KNN classifiers. SVM classifiers are superior to KNN classifiers. Inferring the disease grade as normal, moderate, and severe straight from the retrieved feature.

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