AN ADAPTIVE THRESHOLD BASED DETECTION AND SEGMENTATION OF RETINAL LESIONS IN FUNDUS IMAGES

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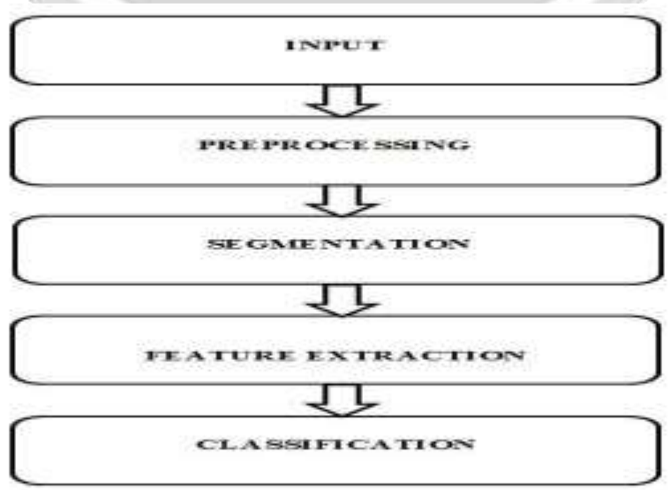
ABSTRACT

Obtaining the entire segmentation map of retinal lesions is that the initiative towards an automatic diagnosis tool for retinopathy that's interpretable in its decision-making. However, the bottom truth lesion detection in fundus images is more important factor. during this paper, we propose a completely unique approach for training adaptive threshold based architecture with supervised learning. The architecture is simultaneously trained for 2 tasks: **detection** *and* **segmentation** *of retinal lesions. additionally , we analyses the various geometrical features of processed images like area, density, contrast, skewness for performing the segmentation of retinal lesions. Our complete system produces both detection and segmentation of retinal lesions in images with better classification results.*

1. INTRODUCTION

The term digital image refers to processing of a two dimensional picture by a IP system. in an exceedingly broader context, it implies digital processing of any two dimensional data. a picture given within the variability of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in hardware. For display, the image is stored in an exceedingly rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display.

2. SYSTEM DESIGN:



3. MODULES:

1. INPUT
2. PREPROCESSING THE INPUT IMAGE
3. TO SEGMENT THE AFFECTED AREA
4. EXTRACT THE FEATURES
5. CLASSIFICATION

3.1 MODULE DESCRIPTIONS:

1. INPUT IMAGE:

Read and Display an input Image. Read an image into the workspace, using the imread command. In image processing, it is defined as the action of retrieving an image from some source, usually a hardware-based source for processing. It is the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed.

2. PREPROCESSING.

Pre-processing is a common name for operations with images at the lowest level of abstraction both input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Image pre-processing methods use the considerable redundancy in images. Neighboring pixels corresponding to one object in real images have essentially the same or similar brightness value. Thus distorted pixel can often be restored as an average value of neighboring pixels.

2.1 RESIZING THE INPUT IMAGE:

All the input images are resized into same dimensions. If the specified size does not produce the same aspect ratio as the input image, the output image will be distorted.

2.2 CONVERTING COLOUR FORMAT:

For many applications of image processing, color information doesn't help us. If you get into the business of attempting to distinguish colors from one another, then one reason for converting RGB image to BLACK AND WHITE or GRAYSCALE formats in image.

3. SEGMENTATION

Image segmentation is a commonly used technique in digital image processing and analysis to partition an image into multiple parts or regions, often based on the characteristics of the pixels in the image. In computer vision, Image Segmentation is the process of subdividing a digital image into multiple segments (sets of pixels, also known as super pixels. Segmentation is a process of grouping together pixels that have similar attributes. Image Segmentation is the process of partitioning an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous Pixels in a region are similar according to some homogeneity criteria such as color, intensity or texture so as to locate and identify objects and boundaries (lines,curves,etc) in an image. Segmentation accuracy determines the eventual success or failure of computerized analysis procedure.

3.1 COLOUR SPACE CONVERSIONS:

Color space conversion is the translation of the representation of a color from one basis to another. This typically occurs in the context of converting an image that is represented in one color space to another color space, the goal being to make the translated image look as similar as possible to the original.

3.2 MORPHOLOGICAL OPERATIONS:

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size.

Some segmentation techniques is,

A) ADAPTIVE THRESHOLDING

4. FEATURE EXTRACTION

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

a) Shape features
b) Geometrical features
c) Texture features

A) SHAPE FEATURES:

Visual features of objects are called the shape characteristics or visual features. For example, circular object or triangular objects or other shapes, perimeter boundary of the object, the diameter of the border and so on. The visual features showed intuitively are all belongs to shape features.

B) GEOMETRICAL FEATURES:

Geometric features are features of objects constructed by a set of geometric elements like points, lines, curves or surfaces. These features can be corner features, edge features, Blobs, Ridges, salient point's image texture and so on, which can be detected by feature detection methods.

C) TEXTURE FEATURES:

An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image .Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.

Some feature extraction methods are,

i) GLCM (Grey level co-occurrence matrix)

ii) REGION PROPERTIES

5. CLASSIFICATION:

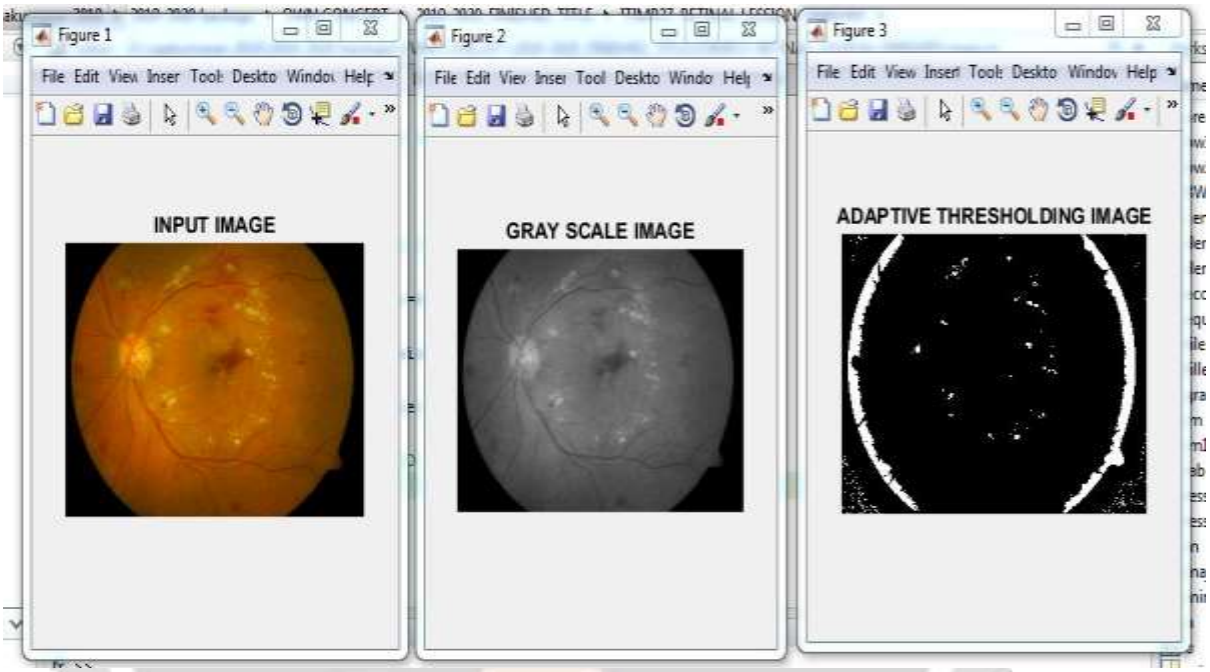
Image classification refers to the task of extracting information classes from a multiband raster image. The resulting raster from image classification can be used to create thematic maps. The recommended way to perform classification and multivariate analysis is through the Image Classification toolbar. There are many classification algorithms are available and some classification algorithm that are given below,

A) SVM (SUPPORT VECTOR MACHINE CLASSIFICATION)

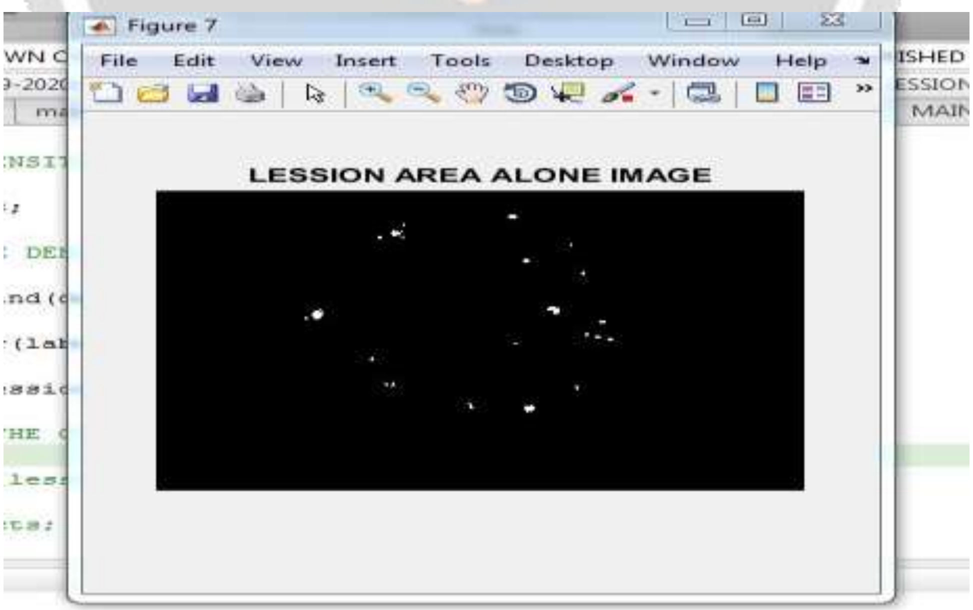
4.RESULTS AND DISCUSSION:

RESULT AND SCREENSHOTS: FOR LESSION IMAGES

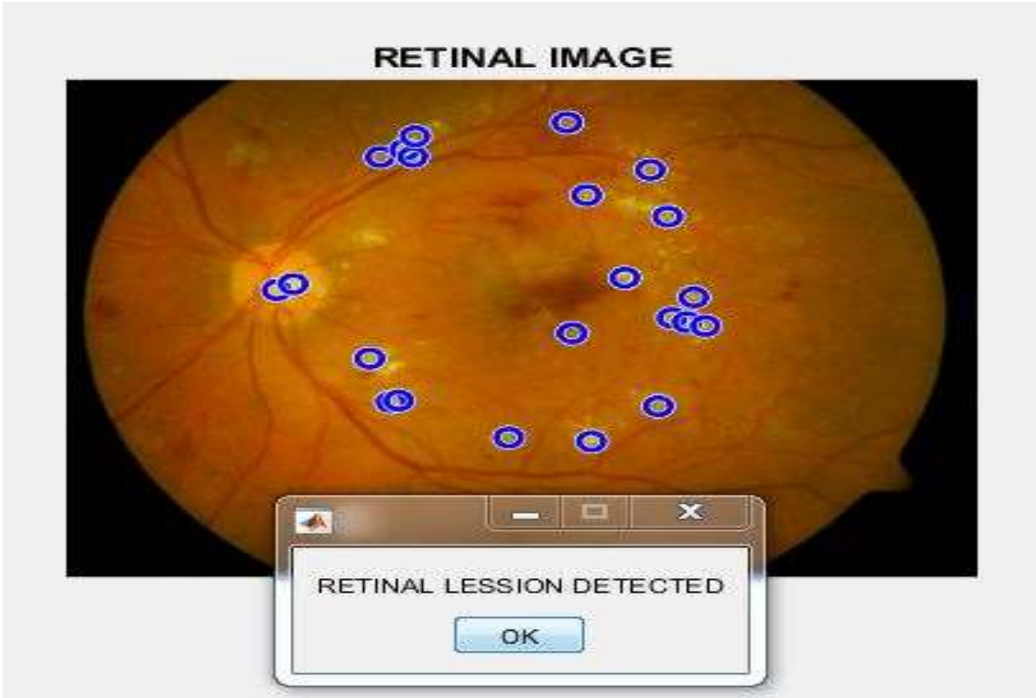
1.INPUT& GRAYSCALE &ADAPTIVTHRESHOLD IMAGES



2.LESSION SEGMENTED IMAGE:

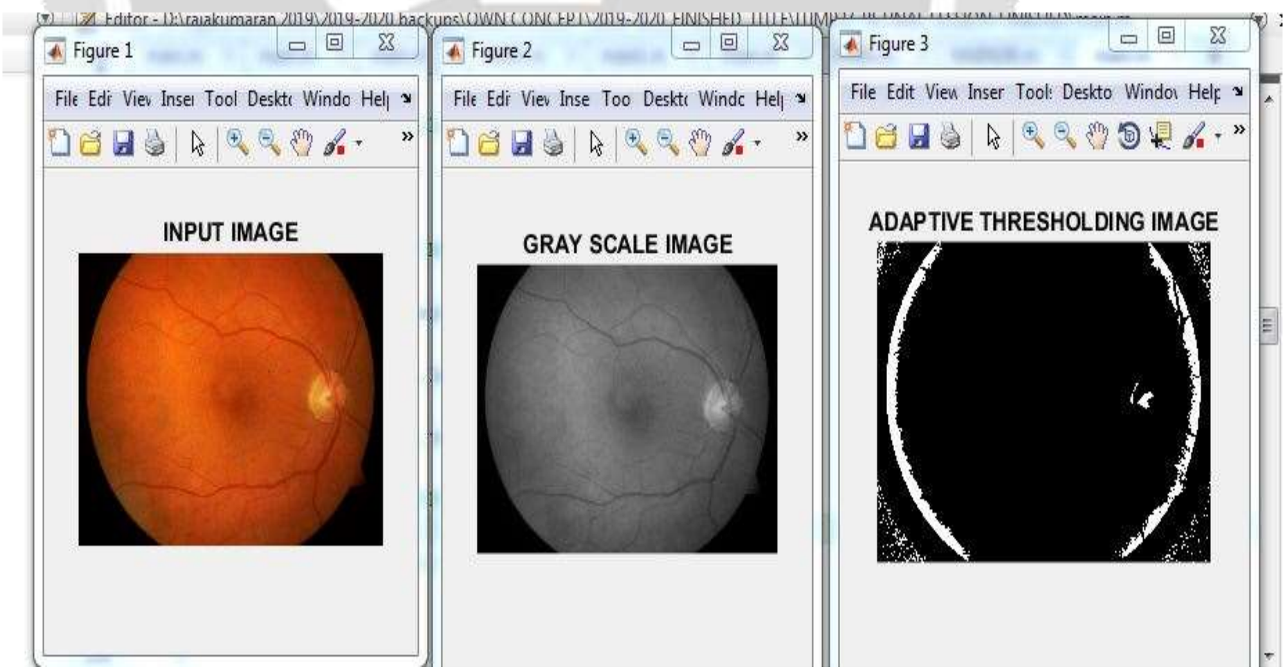


3.FINAL OUTPUT IMAGE:



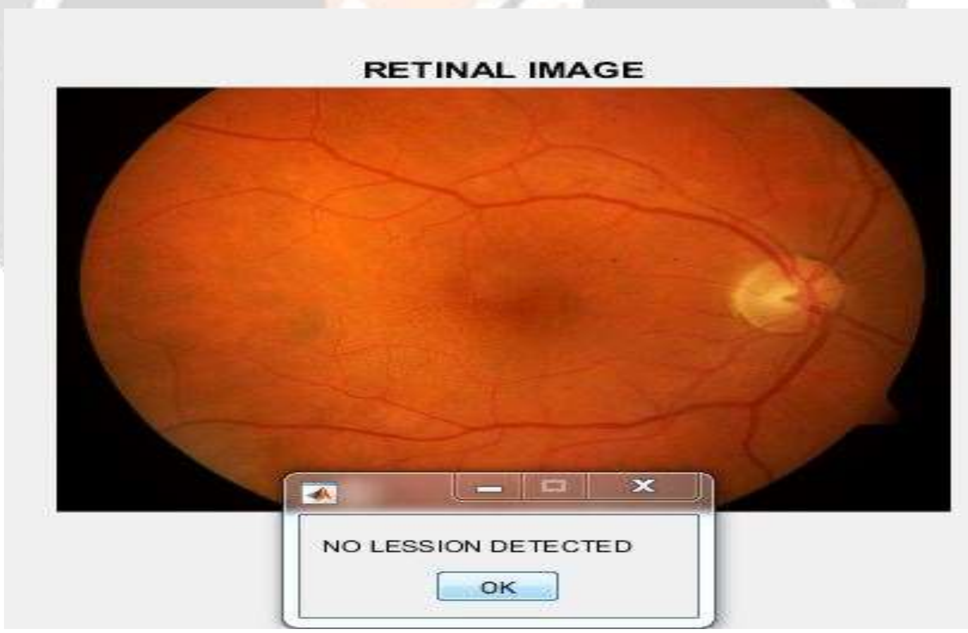
FOR HEALTHY RETINAL IMAGES:

1.INPUT& GRAYSCALE &ADAPTIVTHRESHOLD IMAGES



2.LESSION SEGMENTED IMAGE:

3.FINAL OUTPUT IMAGE:



5. CONCLUSIONS:

The proposed approach provides a fully trainable model for segmentation of retinal lesions in retinal images and proposes a novel methodology of adaptive thresholding based method for exploiting image-level labels to improve segmentation performance. The fast execution time makes the model suitable for clinical deployment. Consequently, future work will assess how it can acceleratethe process of labelling data by a clinician, by providing lesion pre-annotations. Subsequent research will also focus on classifying the individual segmented lesions. This will serve two purposes: 1) building a detailed atlas of the retinal lesions, and 2) providing an automatic diagnosis established using a set of rules based on the detected lesions. Both of these developments will contribute to a computer-aided diagnosis system that is transparent in its decision-making.

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