A Survey Paper on Quantification of Retinal Tissue Damage

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Abstract: Retina is the outer lining of the human eye where image formation takes place. Any threat to the retina causes severe eye defects and may lead to complete blindness. During a defect the retina gets distorted. To measure the severity of a disease we need to determine different retinal tissue damages. These damages must be quantified to make useful predictions. Here we attempt to quantify retinal tissue damage through various image processing techniques. To verify our estimate we applied machine learning algorithms to create a classifier for the detection of diabetic retinopathy and macular edema disease.

Diabetic retinopathy & Macular Edema are diseases prone to diabetic people. They cause progressive damage to the retina of the eye. DR is the leading cause of blindness in the working-age population of the developed world. It is estimated to affect over 93 million people. Diabetic Retinopathy is an active research area. A lot of research has been done in the last few years. Computer scientists and medical researchers have developed many algorithms for the automatic detection of eye diseases, though accuracy has never been very great. Researchers have been trying new features and new algorithms to improve further.

Diabetic Retinopathy (DR) is a complication caused by diabetes that affects the human eye. It is caused by the mutilation of the blood vessels of the light-sensitive tissue at the back of the human retina. It's the most recurrent cause of blindness in the working-age group of people and is highly likely when diabetes is poorly controlled. Although, methods to detect Diabetic Retinopathy exist, they involve manual examination of the retinal image by an Ophthalmologist. The Proposed approach of DR detection aims to detect the complication in an automated manner using Deep Learning.

1. Introduction
An inspection of the retina is performed in order to study it. We use optical coherence tomography or fundus photography to capture retinal pictures (OCT). OCT is one of the recent developments in medical imaging. OCT data is three-dimensional profile of the retina's many layers. There are studies using OCT data that concentrate on figuring out how the thickness of various retinal layers changes over time. Fundus photography is the practise of taking pictures of the back of the eye. Fundus photography uses specialised fundus cameras, which combine a microscope with a flash-enabled camera. Ophthalmologists analyse fundus images looking for specific flaws and patterns in picture to detect diseases. This system has a lot of issues. The world lacks highly skilled ophthalmologists. People are forced to wait a long period before beginning their drugs as a result. Sometimes, this makes the situation worse. Another significant drawback is the lack of consensus among medical professionals regarding a single fundus profile. To analyse the retina, we started with fundus images. Our approach uses powerful image processing methods to analyse these flaws. From the fundus image, we extract features based on recognised patterns and flaws. A classifier is created using these features. Based on what it has learned, the classifier makes a determination. Research into diabetic retinopathy is ongoing. In the recent years, a lot of study has been conducted. Although accuracy has never been extremely high, medical researchers and computer scientists have created numerous techniques for the autonomous identification of eye problems. To further improve, researchers have been experimenting with additional features and algorithms. This method's specificity is excellent, with 99.99% and 98.23% for PPV values, respectively. First, we went over each of the key ideas on which we based our work in great detail. To date, we have outlined the techniques for extracting features from blood vessels, microaneurysms, exudates, and haemorrhages in the section that follows.

1.1 Radon Transformation
Reconstructing pictures from medical CT scans involves using the Radon transform, an integral transform. We measure the projections as an integral of f along the z axis for every r, as shown in the figure. The position of the x, y, and (r, z) coordinate axes in relation to each other. The z axis runs parallel to the X-ray beam's direction. We make the assumption that the source and detectors use parallel beam geometry for this analysis. The X-rays are degrees anticlockwise from the y axis for a specified [0, 180°]. Every r at the specified is used to measure the line integral along z. We rotate the (x, y) coordinates to express them in terms of r and z as we can only access the image as a function of x and y. Also keep in mind that, theoretically, just projections for [0, 180°] are needed. Whichever way along the z-axis we start our integration from is irrelevant.
1.2 OCT Image Analysis:

OCT creates an illustration of optical scattering from interior tissue microstructures in two dimensions using interferometry with low coherence. OCT can identify signals reflected at a distance of 10% of the incident optical power and has the lateral and longitudinal spatial resolutions of a select few micrometres. Since its initial description 15 years ago, optical coherence tomography (OCT) has advanced to become one of the most important diagnostic tools for glaucoma and retinal illnesses, two ophthalmic subspecialties. At least two characteristics of the OCT results are to blame for the technology’s widespread use: first, the results are understandable to non-specialists, where minute retinal abnormalities are visibly obvious and gross; second, the results are repeatable and extremely quantitative in the hands of the expert.

Working:

OCT uses reflected light imaging as its foundation. However, it rotates depth as opposed to a simple camera image, which only has transverse dimensions (left/right, up/down). The depth resolution is on the order of 0.4 thousandths of an inch or 0.01 millimetres. Similar to tissue slices under a microscope, this gives cross-sectional views of internal tissue features (tomography). OCT has been defined as a technique for non-invasive tissue "biopsy" as a result. By monitoring their optical reflections, this method enables non-invasive cross-sectional imaging of internal biological tissue structures. With the help of segmentation algorithms, OCT has been used to assess the volume, overall thickness, and structural changes of the retina’s distinct cellular layers. Understanding the vitreoretinal connections and the internal architecture of the retinal structure has become important in the assessment and management of retinal illnesses. By using OCT less frequently, insensitive tests like perimetry and subjective disc grading have also been reduced, which has helped the identification and management of retinal disorders. Regions with early pathological signs are distinguished from normal regions by differences in thickness, and in pathological eyes, differences in the optical characteristics and texture descriptors of normal and abnormal retinal tissue may also reveal more details about the progression of the disease. The suitability of texture to categorise tissues in OCT images has been demonstrated in earlier investigations. The assessment of anatomic alterations and cellular dysfunction in the neurosensory retina represents a possible advancement in the clinical application of OCT to eye illnesses. According to our first findings, in addition to the structural information, the fractal dimension of the intraretinal layers may help distinguish between healthy eyes and MDR eyes, which are characterised by early-stage neurodegeneration.
1.3 Fractal Dimension

At every scale, fractals are self-similar structures. Fractals are usually nowhere differentiable as mathematical equations. the investigation of continuous, nondifferentiable functions by Karl Weierstrass, Bernhard Riemann, and Bernard Bolzano in the nineteenth century, as well as introduction of term “fractal” in the twentieth century, are just few examples of the Describes the formal trail of published works that has been used to trace the mathematical roots of the idea of fractals over the years, beginning in the 17th century with notions of recursion. Mathematician Benoît Mandelbrot coined the term “fractal” for the first time in 1975. Mandelbrot utilised it to relate geometric patterns in nature to the notion of theoretical fractional dimensions. He took the word “broken” or “fractus,” which is Latin for “fractured.”. There is some debate among experts regarding the proper definition of the term “fractal” Mandelbrot's own summary was as follows: "beautiful, incredibly difficult, and getting worse That is a fractal. "Considering \( N=r^D \), we take the log of both sides to get \( \log(N) = D \log(r) \). When determining \( D, D = \log(N)/\log(r) \). Felix Hausdorff, a German mathematician, is honoured by having his name attached to this generalised treatment of dimension. It has demonstrated utility in defining natural objects and assessing the trajectories of dynamic systems.

\[
FD = (5-B)/2
\]

By averaging the fractal dimension measurements over all A-scans in each macular region of each intraretinal layer, the mean value of the fractal dimension was determined. The assessment of anatomic alterations and cellular dysfunction in the neurosensory retina represents a possible advancement in the clinical application of OCT to eye illnesses. According to our first findings, in addition to the structural information, the fractal dimension of the intraretinal layers may help distinguish between healthy eyes and MDR eyes, which are characterised by early-stage neurodegeneration.

Figure 3: Fractal Dimension for \( n = 1, 2, \) and 3
Box Counting Method:
Cutting it and reducing the squares to half the side length of each square, To create the original square, four of these smaller pieces are needed. Now splitting it into smaller squares, each with a quarter of the side length, it will be taking 16 of such squares to make the original square. The total number of pieces of “s” size needed to completely cover the original square can be calculated using the calculation shown above: N(s) = (1/s). Follow step 2N(s) for a cube equals (1/s) 3. In the cases above, the factors 1, 2, and 3 are essential to how we consider the relevant dimension.N(s) = (1/s)D, where D is dimension which need not be the same 12-bit integer as before, is a generalisation of this that is feasible. In other words, the dimension can be calculated by comparing the slope of log(N(s)) versus log(1/s) represents dimension; if the dimension is a fractional (fractal) dimension, not an integer. We get log(1/s) = log(N(s)) if we take the logarithms of both sides.

1.4 Methodology

The project's methodology can be supervised as follows:

Figure 4: High-Level Design
2. Study of FUNDUS images

According to the Ministry of Health and the World Health Organization, diabetes is expected to impact 69 crore people in India and 34.7 crore people worldwide. Uncontrolled diabetes is associated with diabetic retinopathy (DR), an eye disease. In India, between 40% and 45% of diabetics are suffering from the disease. The most common cause of blindness in persons of working age in developed countries is diabetic retinopathy. 93 million people are thought to be affected. The progression of vision damage can be stopped or postponed if DR is detected early enough. This can be challenging, though, because the illness typically involves little signs before it is too late for successful treatment.

Currently, a competent professional must perform a thorough manual inspection of digital colour fundus photographs of the retina in order to diagnose DR. Human reviewers generally submit their reviews in a day or two, but the delayed results cause missing follow-up, incorrect communication, and delayed treatment. Additionally, India lacks essential infrastructure and services necessary for eye health as well as nearly 1,27,000 ophthalmologists.

By looking for lesions connected to the vascular anomalies brought on by the disease, clinicians can recognise DR. Although this strategy works, it has substantial resource requirements. Where there is a high prevalence of diabetes among the local population and DR detection is most necessary, there is frequently a dearth of the necessary knowledge and tools. The infrastructure needed to stop DR-related blindness will get even more inadequate as the number of people with diabetes rises. Long-running programmes have made significant strides towards a complete and automated DR screening system by utilising picture categorization, pattern recognition, and machine learning. Routine retinal testing for DR may help to optimise laser therapy even at the time of type 2 diabetes diagnosis. Annual retinal examinations and the early detection of DR can dramatically reduce a diabetic's risk of visual loss. The requirement for image processing technologies that offer quick, accurate, and repeatable examination of key anatomical components in retinal Fundus pictures grew as CAD systems advanced. Any automatic retina analysis system must initially segment these retinal anatomical structures.

2.1 Steps of feature segmentation:
Morphological processing, thresholding, edge detection, and adaptive histogram equalisation are some of the procedures involved in segmenting retinal images. The subsections that follow will provide more details on these steps.

I. Morphological Processing: The study of shape is called morphology. The study of the mathematical concept for describing shapes using sets is known as mathematical morphology. Using the fundamental processes of erosion and dilation, mathematical morphology is utilised in image processing to examine the link between a picture and a certain structural feature. Here, the main mechanisms used include dilatation, erosion, opening, and closing. These procedures combine two groups of pixels in an original way. Usually, the structuring kernel is split into two sets, of which one holds the processed picture. The opening and the closing are two crucial transitions. Evidently, dilatation results in the growth of an image object while erosion results in its decrease. The structural element (SE) that is utilised to examine the input image is a crucial component of the dilation and erosion operations. A matrix that just contains 0s and 1s and may take on any shape or size is referred to as a structuring element. Structured elements in Figure 2 are depicted as diamond, disc, and octagon shapes. An image's shape is typically smoothed out by opening. Closing tends to eliminate minor holes and fill in contour gaps while narrowing smooth parts of curves. In order to construct mechanisms for edge recognition, noise removal, background removal, and detecting specific forms in images, algorithms combining the aforementioned procedures are used. We shall
sum up the morphological methods used in this study. Let B be a binary structuring element and f(x, y) be a finite-support grayscale image function defined on grid Z2.

\[
\text{Opening: } f \ominus B = (f \ast B) \ominus (B). \\
\text{Closing: } f \circ B = (f \ominus B) \circ (B). \\
\text{Dilation: } (f \oplus B)(x, y) = \max \{f(x-s, y-t) : (s, t) \in B\}. \\
\text{Erosion: } (f \ominus B)(x, y) = \min \{f(x+s, y+t) : (s, t) \in B\}.
\]

It suffices to know that in actual image processing, a finite set P can be used to apply morphology if:
1. We can arrange some of its components.
2. There are maximum and minimum values for each non-empty subset of P.

**Figure 6:** An illustration of the opening and closing of morphological procedures on the original image II.

**II. Thresholding:** Thresholding can help an image focus on the important elements by removing extraneous features. Fundus images of blood vessels are converted to binary pixels by eliminating any grey level information. Blood vessels must be distinguished from the surrounding information. Thresholding can reveal elements that were previously concealed. In the image region, hidden by equal grey levels, it is pretty helpful. It is crucial to choose the right threshold value since a little number may make some objects smaller or less frequent, whilst a big value may contain more background information. Due to the ease with which binary values can be found in images, thresholding enables us to turn an image's characteristics into numerical data that can subsequently be applied to numerous machine learning approaches. This presents a technique for numerically converting fundus pictures. Different thresholding algorithms exist, including OTSU, adaptive, etc.

**III. Edge Detection:** Edge detection is done using the Canny method. The suggested strategy employs the Canny algorithm to find edges since it works superior to alternative edge detection techniques because, to discriminate amongst strong and weak edges, it applies two criteria. With the aid of the Canny edge detection technology, the quantity of data that has to be processed may be greatly reduced while still acquiring useful structural information from diverse visual objects. It is extensively employed in numerous computer vision systems.

According to Canny, most vision systems can use edge detection if the necessary conditions are met. Therefore, a system for edge detection that meets these criteria can be used in a variety of contexts. The basic standards for edge detection consist of:
1. Edge detection with a low error rate should accurately identify every edge that can be seen in the image.
2. The operator's edge point detection should accurately localise the edge's centre.
3. False edges shouldn't be produced by picture noise, and if at all feasible, an edge in the image must only be marked once.

The Canny edge detection algorithm consists of five steps:
1. Use a Gaussian filter to smooth the image and get rid of the noise.
2. Find the intensity gradients in the image.
3. Non-maximum suppression should be used to completely eradicate incorrect edge detection reactions.
4. To find possible edges, use a double threshold.
5. Track edge using hysteresis: Suppress all additional weak and disconnected edges to complete the edge detection procedure.

**IV. Adaptive Histogram Equalization:** When the important data in a picture is represented by near contrast values, histogram equalisation frequently raises the overall contrast of several photos. The intensity on the histogram can be dispersed more evenly by making this modification. Areas that don't have local contrast could then get more contrast. The most frequent intensity levels are evenly distributed to achieve this via histogram equalisation. The technique has the drawback of being indiscriminate. It might make background noise stand out more while reducing the signal that can be used. A computer image processing method called adaptive histogram equalisation (AHE) is used to enhance local contrast in photographs. In contrast to conventional histogram equalisation, the adaptive technique computes a number of histograms, each of which matching to a distinct region of the picture, and then utilises them to disperse the luminance values of the image. Therefore, it is appropriate for enhancing both the local contrast and the delineation of edges in each area of an image. When utilising AHE, the noise in a region gets amplified higher if the intensity range of the region being processed is relatively narrow. Additionally, it may result in the appearance of certain artefacts in such areas. A variant of AHE known as CLAHE can be used to reduce the appearance of these artefacts and noise. The gradient of CDF function at a specific intensity level determines how much contrast is enhanced at that level. As a result, by restricting the CDF's gradient, contrast enhancement can be avoided. The peak of a histogram for a given bin location determines the gradient of CDF for that bin point. Therefore, by restricting the slope of CDF, we can manage how much contrast enhancement is done by putting a top limit on the histogram's height.
The main distinction between ordinary AHE and CLAHE is that the histogram must first be clipped before its CDF can be computed while the mapping function is carried out. The algorithm for this function is described in the following general terms:

1. Using the image's largest possible dimension as a guide, determine the grid size. 32-pixel squares serve as the smallest grid size.
2. If a default window size isn't provided, choose the grid size.
3. Find the grid points beginning at top left corner of the image. The amount of pixels amongst each grid point is fixed.
4. Calculate the histogram of the region surrounding each grid point, with the grid point at the centre and a region the size of the window.
5. Use the provided clipping level to trim the previously computed histogram before computing the CDF using the new histogram if a clipping level is provided.
6. Repeat the steps 6 to 8 for every pixel of the input image after figuring out the mappings per grid point.
7. From the eight grid points, identify the four that are closest to each pixel.
8. Find the mapping of the pixel at the four grid points by taking the pixel's intensity value and the cdfs of those places.
9. In order to get the mapping now at the currently chosen pixel position, interpolate between these values. Put this intensity in the output image by mapping it to the \([\text{min}:\text{max})\) range.

The excess must be divided among the other bins in order to clip the histogram, which might raise the magnitude of the clipped histogram. This is a difficult task. In order for the highest histogram level to match the clip level after redistribution, the level of clipping should be lower than the stated clip level. The CLAHE method equalises the histograms of each photo after dividing it into contextual portions. This makes hidden aspects of the image more obvious by balancing the distribution of the employed grey values.

2.2 Features of Fundus Images:
A. Detection of Blood Vessels:

Blood vessels are significant characteristics that aid in the evaluation of the retina. When an eye has a certain condition, blood vessels exhibit various symptoms. When diabetic retinopathy affects the eye, blood vessels swell. Due to obstructions close to the optic nerve, narrow blood vessels in non-proliferative diabetic retinopathy do not receive enough blood flow. They become disintegrated as a result, and fluid is released into the retina. This worsens with proliferative retinopathy. To counter it, the retina attempts to generate new blood vessels. Again, because of their frailty and confusion, these blood vessels occasionally bleed into the vitreous. Therefore, identifying blood vessels becomes crucial. To remove blood vessels, we used Alternate Sequential Filtering (ASF) in tandem with other approaches to image processing. Additionally, we made an effort to separate the image's red channel. But blood clots and haemorrhages made it challenging. Due to its higher contrast, we extracted the green channel of the image during our process. To increase contrast even more, we employ Contrast Limited Adaptive Histogram Equalization. The average intensity of each zone is superimposed over the original image when ASF is applied to it. We remove this image from the CLAHE output later. This gives us a picture that has had an optic disc and other things taken out of it, but there are still very weak hints of blood vessels. With the use of a threshold \(T\), we binarize this image and segment the blood vessels. The finished image also has some undesired components and noise. The image is eroded to reduce noise. By taking into account the fact that all blood arteries have a linear trend, undesirable features are eliminated.
B. Detection of Haemorrhages:
Blood vessel fragments that have leaked onto the retina are known as haemorrhages. Haemorrhages are an excellent sign of retinal injury. Haemorrhages appear as red blobs in a fundus picture. We observe minor as well as some quite significant signs of haemorrhages in proliferative diabetic retinopathy. We used the same process—up to a certain point—for the detection of blood vessels and haemorrhages. We do a xor operation on the current image and the image obtained after segmenting the blood vessels when we obtain the image (f). This provides us with an image that has minor noise elements and haemorrhages. We apply a median filter to the image to reduce noise. Haemorrhages as well as some tiny, broken blood vessels may be seen in the new image. To get rid of them, we collect all the contours and determine if they can roughly be represented by a polygon with sides bigger than 5.

![Figure 8: haemorrhages in the fundus picture (L) (R)](image)

C. Detection of Exudates:
Another crucial aspect of retinal examination is exudates. Bulges of yellow and white colour called exudates can be seen in the fundus. Exudates come in two varieties: hard exudates and soft exudates. Extracellular lipids from dysfunctional retinal capillaries make up hard exudates. The macular region is where hard exudates are most prevalent, and as the lipids consolidate and extend into the central macula, vision can be adversely compromised (fovea). The soft, cotton-like exudates represent infarcts in the nerve fibre layer.

Red and blue channels have been used to find exudates. We are aware that red and green make up the majority of the colour yellow. With threshold $T$ equal to $(\text{max(channel)} + \text{mean(channel)})/2$, we separately thresholded the red and green channels. The AND gate was used to combine these two binary channels, giving us all the pixels with the colour yellow. We can now see exudates and an optic disc in the image. We have developed an algorithm to eliminate the optic disc.

We create a window that is the right size and scans the image in steps. We compute the average window intensity for each scan. We receive the most at the optic disc since it is larger in size and has a higher intensity. We cover it with a dark glass to remove it. As a result, our image only contains exudates.

![Figure 9: segmental exudates of the fundus.](image)
D. Calculation of Fractal Dimension:
Fractal dimension is measured as a characteristic to classify the retina's texture. If a line were cut in half, we can reproduce the original line with just two bits. The line may be broken up into four segments, each of which must span the whole length of the line. In general, if we have a line segment of length "s," the formula \( N(s) = (1/s) \) tells us how many segments are required to completely encircle the starting line.

Using the following approach, we have retrieved the Hausdorff fractal dimension:
- The image's size should be increased by background pixels to a power of 2.
- To fit the image, adjust the box size 'e'.
- \( N(e) \), or the quantity of boxes with size "e" that contain at least one object pixel, is to be found.
- Repeat the previous step with \( e = e/2 \), if \( e > 1 \).
- Compute the values \( \log(N(e)) \times \log(1/e) \), then, in order to fit a line towards the points, utilise the least squares approach.

The Hausdorff fractal dimension \( D \) that was obtained is the line's gradient. Fundus images now have a fractal dimension that measures the degree of retinal roughness.

E. Calculation of Homogeneity:
Homogeneity is another factor that is utilised to evaluate the texture of the retinal image produced by the Gray-Level Co-Occurrence Matrix (GLCM). The spatial arrangement of pixels is taken into account by the statistical method known as GLCM when analysing texture. It is created by calculating the frequency of pixel pairs in an image with specific values and arranged in a specific spatial relationship. This matrix can be used to obtain a number of statistics that provide details about the texture of an image. One such statistic that gauges how closely the distribution of GLCM components adheres to the diagonal is homogeneity. The inverse of contrast weights, homogeneity weights are determined as follows, with weights deviating from the diagonal falling exponentially further. The number "1" has been added to the denominator in order to avoid the value "0" being divided. Usually, the contrast reduces as homogeneity rises.

\[
H = \sum_{i} \sum_{j} \frac{1}{1+(i-j)^2} \ p_{d}(i,j)
\]

Where \((i,j)\) represents a likely pairing of the horizontal adjacent pixels i and j and \( p \) indicates the probability of a pairing of pixel values \((i,j)\) occurring in each picture.

F. Calculation of Entropy:
The texture of the input image can be described using entropy, a statistical measure of randomness. The entropy function treats images with more than two dimensions as multidimensional grayscale images rather than RGB images. The definition of entropy is:

\[
E = -\sum_{i} \sum_{j} ( p * \log_{2} p )
\]

where \( p \) represents the grayscale image's histogram values at various \((i, j)\).

The idea of entropy was first introduced through research on a study of heat engines' physics. It might be characterised as a way to gauge how chaotic a system is. A highly ordered structure, like a crystal or a living thing, has a low entropy because it is highly organised. The crystal melts and turns into liquid at a high enough temperature, a considerably less organised state. When an organism expires, it decomposes and is totally disrupted. Its entropy rises in both systems. Consider the range of states that a system can take to further express entropy. Such states are occupied by a limited number of low entropy systems while a big number of high entropy systems.

The several grey levels that a pixel could adopt within the context of an image are related to such states. For instance, eight-bit pixel has of these states. When both of these states are occupied, just as they are in the case of a picture that the past properly histogram equalised, the spread of states and the entropy of the image are both at their highest levels. However, if the picture has been thresholded leaving there are only two states occupied, and the entropy negligible. If every pixel in the image has the same number, the image's entropy is 0. In this progression, the image's information content rises as its entropy falls, using a full grayscale. We went from a high entropy image to a binary image with low entropy to a single-valued image with zero entropy.

G. Detection of Microaneurysm:
On fundus pictures, microaneurysms appear as tiny, black, rounded spots (between 15 and 60 mm). They are the initial indication of DR and are tiny bulges that form on fragile blood vessels. The pictures are in .tiff format and have been pre-processed to a standard size of 1488 x 2240.

The image's green channel is acquired because it offers a rich the microaneurysms in comparison to other places like the optic disc, exudates, etc. Adaptive histogram equalization has further increased image contrast. Before it uses the Canny method for edge detection to determine image's borders, It uses adaptive histogram equalisation to stretch the image's contrast. When the holes are filled in, the boundary can be seen, and when the morphological opening operation is performed, a structural element (SE) in the form of a six-radius disc is produced. The boundary-free image is subsequently created by taking away the boundary-containing photo from the edge detection photo. Once gaps or holes are filled, unwanted artifacts such as...
microaneurysms result. The above-mentioned technique allows for the detection of blood vessels, which are then removed from the image of microaneurysms and artefacts.

Figure 10: segmented microaneurysm with the fundus (L) (R)

3. CONCLUSIONS

Our image processing methods have proven remarkably reliable. The detection of blood vessels, microaneurysms, and exudates has been successful. Blood vessel extraction has been reported to produce superior results than the majority of other works. The creation and evaluation of a binary classifier system for a retinal abnormality caused by diabetic retinopathy. For diabetic patients, this approach offers an early warning of anomalies in diabetic retinopathy. Haemorrhage extraction is less accurate. The most significant factor is microaneurysms. We have discovered a positive link between fractal dimensions and entropy using the correlation matrix. This gives us the freedom to do so without significantly affecting accuracy. We tested our data using various models. Using 1200 data points from the MESSIDOR database, multiclass classification for macular edoema with Random Forests Classifier yields the highest accuracy.

4. REFERENCES