



Addis Ababa University
Addis Ababa Institute of Technology
School of Electrical and Computer Engineering

**AN AUTOMATIC DIABETIC RETINOPATHY DETECTION
USING ARTIFICIAL NEURAL
NETWORK**

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LIST OF ABBREVIATIONS

DR	Diabetic Retinopathy
PDR	Prolific Diabetic Retinopathy
NPDR	Non proliferative Diabetic retinopathy
ANN	Artificial Neural Network
AAO	American Academy of Ophthalmology
MLT	Multi-Level Thresholding
OD	Optic Disk
CLAHE	Contrast limited Adaptive Histogram Equalization
RGB	Red Green Blue
HSI	Histogram Saturation Intensity
AHE	Adaptive Histogram Equalization
GLCM	Gray Level Co-occurrence Matrix
SOM	Self-Organizing maps

ABSTRACT

Diabetic retinopathy is a disease that affects the eye of a diabetic patient. Diabetics being the abnormal level of glucose in the human blood, it is a cause for several types of organ disorders in the body. One of them being the eye. Diabetic retinopathy is caused when the blood vessels in the eye start leaking blood in to the surface of the eye. Detection of diabetic retinopathy at different stages of the disease is an invaluable input for physicians in the medical field.

In this paper a research has been made for detection of diabetic retinopathy exudates by using an artificial neural network. The process of image detection starts from image pre-processing, next is image segmentation then feature selection and finally classification. In the image pre-processing a median filtering and adaptive histogram equalization is used. The image blood vessels and Optic disk are then segmented out using morphological analysis.

Accuracy of segmentation of the optic disk is 90%, 87% and 90 % for exudates containing images, normal images and all images that contain all features of diabetic retinopathy respectively.

The gray level co-occurrence matrix of the image is then calculated to evaluate the textual features. Fourteen features are then used to feed the artificial neural network. Two fundus image data sets (STARE 402 images, and DIABETRETDB1 with 130 images) were obtained from two medical universities have been used for the detection process. Using the proposed methodology, a detection performance of 84% sensitivity and 63% specificity is obtained. The implementation is done by using matlab 2015.

CHAPTER ONE - INTRODUCTION

1.1. Background

Diabetes is a disease characterized by abnormally high glucose levels in the blood. The high glucose level is caused by the inability of pancreases gland to secrete enough insulin or the inability of the body to process it correctly. When the blood sugar is unable to be maintained at a steady state it starts to damage blood vessels in the eye[1]. This change in the blood vessels cause a condition called Diabetic Retinopathy(DR). DR causes blindness among adults edged 20-74 years. During the first 20 years of the disease almost all patients with type 1 and above sixty percent of type 2 patients have DR.

Based on the visual effects of an eye fundus image, DR is characterized by Micro-aneurysms, hemorrhage, hard exudate, soft exudate and neovascularization (the different effects can be seen on Figure 1). There are several stages of DR that need to be identified and threated accordingly. The major two categories are proliferative DR (PDR) and non-proliferative DRs(NPDR). NPDR consist of the effects like micro-aneurysms(red small dots), hemorrhage, hard and soft exudate together or separately depending on the severity.PDR is the last stage of the condition in which in addition to the NPDR effects mentioned, another effect called neovascularization (growing of new blood vessels as a result of nourishing signal) is added [1].

Early detection of DR is vital because it can be used to slow down the progression of the disease. Treatments for DR are given by laser which can decrease the risk of blindness by up to 50 percent [1].

DIABETIC RETINOPATHY

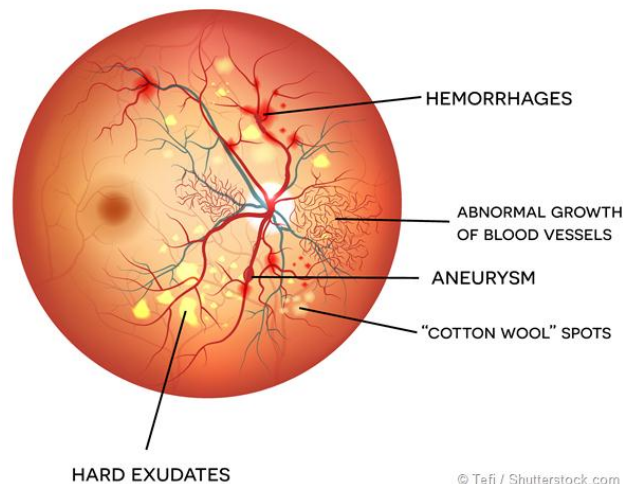


Figure 1 Features in DR[2]

Diagnosis of DR in medical centers is done by taking a retinal image from a diabetic patient. A fundus camera is used for the diagnosis. The physician is then going to examine the images to look for any of the above mentioned effects for the diagnosis. This process can be automated and facilitated by using image detection techniques. This can help avoid the work load of the physician and increase the accuracy of the diagnosis.

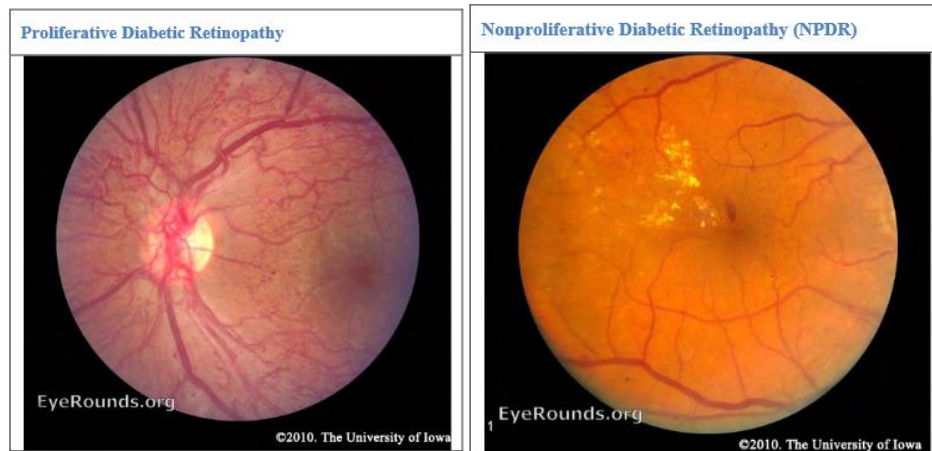


Figure 2 PDR and NPDR[3]

1.2. Problem Description

Automatic detection of DR from fundus images is a hot research topic because there is a challenging task in the process. By nature, an image taken off a diabetic patient's eye can have several effects at the same time, and can be seen at different places in variable amounts. i.e. an effect for example exudates does not have a known size or location for images of different patient or for the same patient taken at different period of time. This makes it a difficult task to segment out unwanted artifacts on the fundus image or even the effects that are seen on the image. Another challenge is the nature of the Optic Disk in the eye is very similar to the effect exudates. They both might have the same intensity and size that makes it difficult to segment either one of the two from the image.

Another problem in the process of the detection is the quality of the image from different patients. The images taken from the fundus camera are also taken on different calibration settings. This makes the pre-processing procedure not to be uniform for all images under consideration.

In this paper, since the above mentioned and several other reasons make different detection procedures to perform less (have unsatisfactory specificity and sensitivity values), a new approach to improve the detection performance is done. The new approach uses Artificial neural network for diabetic retinopathy detection.

Objective of Thesis

1.2.1. General Objective

- To develop a DR detection system using the advantages of intelligent algorithms like Artificial neural networks in different image processing steps.

1.2.2. Specific Objective

- To do a thorough literature review and understand DR and detection of DR.
- Understanding the implementation of intelligent algorithms and other image processing algorithms in their usage for detection of DR.
- To design a ANN DR image processing.
- To compare and validate the obtained results in the study with other intelligent and other image processing methods for detection of the DR
- Evaluating and presenting the quantified results obtained

1.3. Contribution of the thesis

The significance of doing this thesis is to address the challenges that are facing the problem of DR detection by the use of a new approach. The new approach is using Artificial neural network for the detection purpose. The proposed approach involves a texture feature extraction technique that is used to feed the Artificial Neural Network for classification and then detection of the presence of DR effects in the image.

1.4. Outline of the Thesis

The thesis is organized as follows. In the second Chapter, theoretical back ground of diabetic retinopathy and state of the art detection researches are explored.

Third Chapter, the standard image processing method has been followed for the proposed solution in this paper. The first step is image pre-processing, then segmentation, feature extraction then classification. In this Chapter, the methods/algorithms followed in each of the steps in the paper are detailed.

Fourth Chapter, which is the designSection of the research contains the overall algorithm that is used to do a fundus image DR detection. This is starting from the image preprocessing, then image segmentation then feature extraction and finally neural network selection.

The fifth Chapter presents the experimental results, including the data sets used that led to the results. Discussion on the results shows how the results are interpreted based on the datasets used and the methodology that was taken.

Sixth Chapter, consists of conclusions deduced from the research , the recommendation and the future work that will need to be done.

CHAPTER 2-DIABETIC RETINOPATHY DETECTION

2.1. Introduction

In this Chapter theoretical background of diabetic retinopathy detection for diagnosis is discussed. In the first Section deals with diabetic retinopathy, starting from structure of the human eye, then symptoms screening and treatments. In the second Section, fundus images are discussed, starting from how the image is captured using the fundus camera then what features are gotten from the images that should be considered for the detection of DR effects. The Third Section is a literature review that summarizes state of the art detection methodologies that are in published in the automatic diabetic retinopathy detection research area.

2.2. Diabetic Retinopathy

2.2.1. Structure of the Eye

The eye consists of a retinal –lined fibro vascular sphere which contains he aqueous humor, the lens and the vitreous body as illustrated in the figure.

The retina is an essential component of the eye and serves the primary purpose of photoreception. All other structures of the eye are subsidiary and act to focus images on the retina, to regulate the amount of light entering the eye to provide nutrition, protection or motion. The retina may be considered as an outlying island of the central nervous system, to which it is connected by a tract of nerve fibers, the optic disk.

The retina is within two coats of tissue which contribute protection and nourishment. On the outside of the sphere, corresponding to the dura mater, a layer composed of dense fibrous tissue serves as a protective envelope, the fibrous tunic. The posterior part of the fibrous tunic, the sclera, is white and opaque. Although it retains its protective function, the anterior portion, the cornea is clear and transparent.

Immediately internal to the sclera, and between it and the retina, lies the uvea, a vascular tunic. The primary function of the uvea is to provide nutrients to the eye. Choroid is the posterior portion of the uvea; it consists entirely of blood vessels. A second portion of the uvea called ciliary body, lies just anterior to the choroid and posterior to the corneoscleral margin and provides nutrients by forming intraocular fluid, the aqueous humor. In addition, the ciliary body contains muscles which provide a supporting and focusing mechanism for the lens. The most anterior portion of the uveal tract, the iris, is deflected into the interior of the eye. The iris acts as a diaphragm with a central rounded opening, the pupil, which dilates to allow more light to the retina in dim lighting. The iris also has some degree of nutritive function, since it acts to help regulate the fluid flow in the eye.

The lens, the focusing mechanism of the eye, is located immediately behind the iris and is supported from the ciliary body by a suspensory ligament, the zonule. The space between the iris and the lens is called the posterior chamber. The anterior chamber consists of the space between the iris and the cornea. Behind the lens is the vitreous, a gel-like, transparent body which occupies the space between the lens and the retina[3].

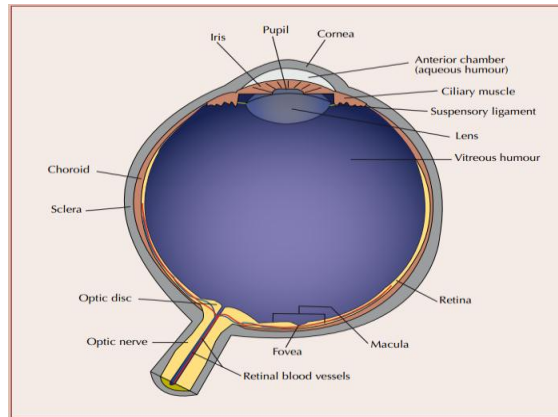


Figure 3: Schematic Diagram of the Human Eye [3]

The central retinal artery exists out of the optic nerve, and its branches arch temporally both above and below the macula (the sensitive region of the retina responsible for central vision).

Although the exact pathophysiology of diabetic microvascular disease is unknown, hyperglycemia is thought to cause basement membrane thickening which contribute to leaky, incompetent blood vessels[4].

2.2.2. DR Symptoms Screening, Examination and Treatment

The difficult thing with DR is that no early stage symptoms can be seen with the patient, until late in the course of the disease when treatment may be ineffective. The late symptoms also differ depending on the cause. Bleeding into the vitreous can cause sudden loss of vision[4]

Screening is recommended to diabetic patients because no symptoms are experienced until the advanced stages of the disease. If the disease is recognized early, vision threatening side-effects can often be prevented with appropriate treatments. DR screening for diabetes type 1 patents should start right after diagnosis of the disease (because most of them already have developed DR) and for type 2 patients it should start between 3 to 5 years after diagnosis of the diseases (according to the [5]).

Primary treatments of NPDR are tight control of blood pressure and blood glucose level. Then a laser therapy is used to treat micro aneurysms. Similar laser treatments of NPDR are used to treat PDR except that the aim here is to tame the growth of new problematic vessels. The basic treatment is called pan retinal photocoagulation (PRP) which is a procedure including treatment with thousands of laser burns to destroy portion of the retina by saving the macula. Several other treatments including surgery are described in [4] for interested readers.

2.3.Fundus Image

2.3.1. Fundus Camera

The retina can be photographed directly as patient sits at the fundus camera with their chin in a chin rest and their forehead against the bar. The pupil is used as both the entrance and exit for the fundus camera's illuminating and imaging light rays. A flash is fired as the photographer presses the shutter release to create a fundus photograph. To generate the illuminating light rays, light generated from either viewing lamp or the electronic flash is projected through a set of filters and onto a round mirror. This mirror reflects the light up into a series of lenses which focus the light. A mask on the upper most lens shapes the light into a doughnut. This shaped light is reflected onto a round mirror with a central aperture, it then exits the camera to enter to the cornea of the eye through the objective lens. An imaging light ray is received from the cornea through the central, un-illuminated portion of the doughnut shape. Then it passed through the center of the previous mirror through a correction device and compensation lenses then back to the single lens reflex camera system[6].

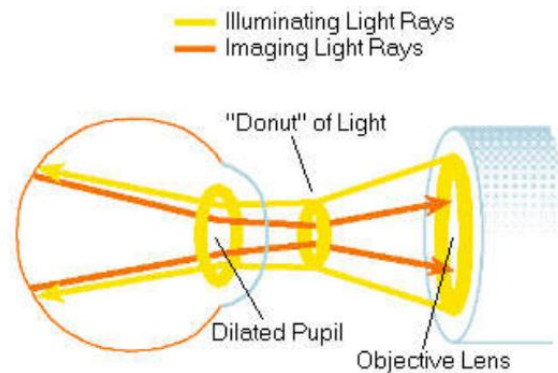


Figure 4: operation of a fundus photography[6]

2.2.2 Structure of the Features in the fundus image

Most of the features in the fundus image indicating DR should be studied and detected in a detection algorithm. The features include micro-aneurysms (red small dots), hemorrhage, hard exudate, soft exudate and neovascularization. The features are shown in the image of figure 1

Micro-aneurysms (red small dots)

Micro-aneurysms are the earliest clinical sign of diabetic retinopathy and occur secondary to capillary wall outpouching due to pericyte loss. They appear as small red dots in the superficial retinal layers and there is fibrin and red blood cell accumulation in the micro-aneurysm lumen.

Hemorrhage

Dot and blot hemorrhages occur as micro aneurysms rupture in the deeper layers of the retina, such as the inner nuclear and outer plexiform layers. These appear similar to

micro aneurysms if they are small; fluorescein angiography may be needed to distinguish between the two.

Flame-shaped hemorrhages are splinter hemorrhages that occur in the more superficial nerve fiber layer.

Soft Exudate

Soft exudates appear as white feather like spots with blurred borders. They are swellings of the retinal nerve fiber layer because of microvascular diseases.

Hard Exudate

Hard Exudate and retinal edema are caused by the breakdown of blood-retina barrier, allowing leakage of serum proteins, lipids, and protein from the vessels.

Neovascularization

This is an abnormal growth of new blood vessels on the inner surface of the retina. The growth of the blood vessels is initiated to attempt to compensate for the lack of oxygen supply. The new blood vessels are abnormal as they bleed in to the vitreous cavity. As a result, vision can be obscured.

2.3. Literature Review

2.3.1 Detection of DR using non-artificial intelligent methods

The research in the area of DR detection involves prescreening, segmentation of the optic disc and blood vessel and classification stages. In the following reviewed papers these steps have been described.

In the research [7], Image pre-processing is done by taking green channel of the image, then a morphological analysis is done to increase the image contrast. For optimum threshold value selection for segmentation of the blood vessels a harmony search algorithm based kapur MLT(Multi level Treshholding) has been used. The segmented image is then given to a feature extractor to extract features such as energy and entropy to do the context based searching for image retrieval.

In the research [8], after acquiring the image several image preprocessing procedures have been conducted. These are removal of the OD, median filtering Non-uniform Luminosity correction, mapping of the image using an intensity rate then finally image intensity enhancement. In the detection and segmentation stage texture analysis is used to describe the region of the image by quantifying its texture content. Then adaptive threshold and median filtering is applied, that changes the image to a binary form. Several morphological operators are conducted afterwards to correctly identify the lesions on the image. Finally, the boundaries of the lesions are identified by a use of a matlab function which then is used to calculate the area of the region. A comparison of the lesion area size and the total image size is done as a percentage to help the physician in severity of the disease.

In the research[9], the existence of hard exudates is applied to classify the moderate and severe grading of Non-Proliferative Diabetic Retinopathy (NPDR). In pre-processing stage input the retinal fundus image, resizing and selection of green channel is done by using morphological enhancement, which enable to intensify the difference between the bright and darker areas without affecting the area sizes of different components. Then the optic disc and retinal boundary are eliminated via Hough Transform and the adaptive morphological approach, for the segmentation process use K-means clustering , the feature vector of the segmented exudates is classified using three different classifiers to get comparison of results(i.e. soft margin Support Vector Machine, Multilayer Perceptron, and Radial Basis Function Network)and The classification of retinal images of NPDR results high accuracy (89.29%, 91.07%, and 85.71% respectively). As a result, it automates the segmentation of hard exudates and obtain a more accurate and faster evaluation process.

In the research [10], a detection method of drusen and exudates from different retinal fundus images have been proposed. Several feature extraction methods have been implemented for a dataset of over 400 fundus images from different data sources (STARE, DRIVE, DRIDB, HEI-MED, MESSIDOR and HRF). The features used are LBP(Local Binary Patterns), SURF(Speeded Up Robust Features) and HOG(Histogram of Oriented Gradients). A dictionary is built from these feature extracts and a histogram of individual extracts is developed. The classification is done by using SVM(Support Vector Machine). Evaluation is done based on

the use of the individual features and a combination of the features. The mean accuracy of individual feature extraction was found to be 97.2%, while the accuracy of the combination of the feature extracts was 99.77%.

A research in [11], showed that Optic disk segmentation proposed an automated technique based on mathematical morphological operations. Here, dilation and erosion to remove OD and enhance the appearance of binary images. the technique was tested used was MESSIDOR database The proposed technique was tested on 400 images of the publicly available MESSIDOR database. Their experimental result showed that the accuracy is 73%.

2.3.2 Detection of DR using ANN

In the research done by [12] normalization and contrast enhancement of original image has been done as a pre-processing stage, the echo state neural network is trained to find the threshold value for exudates segmentation. Evaluation is done by comparing the performance against contextual clustering technique. The proposed solution brought a 90% sensitivity for exudates segmentation. But the data set that is used is only 30. Other measurements have also not been presented.

The research by [13], a data set of DIAREDB1 is used for the research. The preprocessing procedure involved conversion of RGB to HSI color space, Median filtering and CLAHE. The optic disk is removed using Hough transform. Classification is used using a neural network of input and hidden neuron size of eight. Feature extraction method used is seven Hu moment invariants. The proposed approach gained a performance of 95% sensitivity, 96.65% specificity and 95.15% accuracy. The algorithms and interpretation of the data in this research is not clearly presented in this paper.

In the research by [14] a preprocessing stage involving luminosity and contrast normalization. Then segmentation is performed using local and global adaptive histogram thresholding methods. Feature extraction was done by the use of 18 visually distinctive features which include color and shape features, such as mean RGB values in the region, standard deviation of RGB values, mean values outside segmented region and so on. A comparison of different neural network based classification was implemented namely for MLP (Multi-Layer Perceptron), RBF (Radial Basis Function) and SVM. By changing parameters of each network (e.g. number of neurons). Around 90% sensitivity, specificity and accuracy is achieved for each classifier.

In the research by [15], exudates segmentation is first done by first segmenting out the blood vessels and optic disc from the fundus images. The features extracted for the are four of the harlik Grey Level Co-occurrence Matrix (GLCM) features from the segmented image are then used for training and testing three different classifiers Support Vector Machine (SVM), Scaled Conjugate Gradient Back Propagation Network (SCG-BPN) and Generalized Regression Neural Network (GRN). From their experimental results have shown the performance of SVM classifier

is greater than the rest of the classifiers.They have used the DIARETDB1 data for their experiment.

In this research a new approach using texture feature analysis and artificial neural networks will be taken to achieve DR exudates segmentation and detection. By using morphological analysis segmenting out the OD will help in identifying the valid regions of the fundus image for further possessing thus minimizing the error in identifying an OD as exudates/dursen. Also the use of ANN for the classification is vital in the sense of the type of the image that is being processed (i.e. fundus image). This is because, representing /classifying differently featured fundus images is a difficult one, but the use of feature extraction techniques makes it possible to properly represent fundus images at different stages of the disease.

CHAPTER3- METHODOLOGY

3.1 Introduction

The standard image processing method has been followed for the proposed solution in this paper. The first step is image pre-processing, then segmentation, feature extraction then classification. In this Chapter, the methods/algorithms followed in each of the steps in the paper are detailed.

3.2 Image Preprocessing

3.2.1 Histogram equalization

When the raw images are first retrieved they have different contrast values. **Histogram equalization** is a technique used to enhance the contrast of an image by adjusting its intensity.

Let I be a given image represented as m_r and m_c matrix of integer pixel intensities ranging from 0 to $L-1$. L is the number of possible intensity values (usually 256). Let p be the normalized histogram of I with a bin for each possible intensity. So

$$p_n = \frac{\text{Number of pixels with intensity } n}{\text{Total number of pixels}} \quad n = 0, 1, \dots, L - 1 \quad (1)$$

The histogram equalized image h will be defined by

$$h_{i,j} = \text{floor}(L - 1 \sum_{n=0}^{I_{i,j}} p_n) \quad (2)$$

In this case floor takes the floor integer value.

A histogram equalization uses the same transformation derived from the histogram to transform all pixels. This works well when the distribution of pixel values is similar throughout the image[16].

For this paper the use of only histogram equalization is not enough, because it cannot be applied in the case of fundus image; it contains regions that are significantly lighter (lesions) or darker (blood vessels) than most of the image. These two regions do not get enhanced as a result of an ordinary histogram equalization. The solution to this is an **adaptive histogram equalization (AHE)**. AHE improves on this by transforming each pixel with a transformation function derived from a neighborhood region. Each pixel is transformed based on the histogram of a square surrounding the pixel.

Transforming based on a histogram of a surrounding square brings up over amplification of certain regions relative to the whole image. To combat this problem a **contrast limited adaptive histogram equalization (CLAHE)** is used. CLAHE has a contrast limiting property. The contrast limiting procedure is applied at every neighborhood from which a transformation is performed. CLAHE avoids over amplification of noise as a result of AHE[16]. CLAHE is used in

the implementation in this paper, for the reasons mentioned in the above paragraphs. A math lab function is used for the implementation.

3.2.2 Median filtering

As part of the pre-processing median filtering has been implemented for the removal of unnecessary features (noise). Media filtering is a nonlinear digital filtering technique, usually used to remove noise from an image or signal. The idea of a median filtering is to run through the signal entry by entry, replacing each entry with the median of the neighboring entries. Before replacing the values with median value we the pixel values are sorted in ascending order. The median x can be defined as the following:

$$y[m, n] = \text{median}\{x[i, j], (i, j) \in w\} \quad (3)$$

where w is the neighborhood defined by user, centered around locaion $[m, n]$ in the image.

Median filtering for our research is proved to be important in removing the noise that happens from the raw fundus images. The noise mainly comes from a calibration and signal noise that is induced because of the different fundus cameras that are used to take the different images.

3.3 Image Segmentation

3.3.1. Segmentation of Blood Vessels

In this research segmentation of blood vessels is done by the use of morphological image processing as proposed by [17]. Mathematical morphology is a theory and technique for the analysis and processing of geometrical structures. It is called morphology because it deals with shape and form of objects. It is mathematical because it is based on mathematical theories such as the set theory, integral geometry and lattice algebra. Several morphological operations are available but only knowing the use of these operations is not good enough to be able to use it in image processing problem solving. Additional guidelines and expert knowledge on the way to combine and use these sequence operations (sequences of elementary transformations) is required[17].

3.3.1.1. Morphological Image Processing

Morphological image processing is a process involving a set of non-linear operations based on shape or morphology in an image. A **structuring element** which has pre-defined binary shape is used for doing the operations on the image. The analysis is then based on whether this shape hits or misses the shapes in the image[16]. In binary morphology an image is viewed as a subset of an Euclidean space \mathbf{R}^d or the integer grid \mathbf{Z}^d , for some dimension d . Based on that the following two structuring elements are examples: where B is the structuring element.

- Let $E = \mathbf{R}^2$; B is an open disk of radius r , centered at the origin.
- Let $E = \mathbf{Z}^2$; B is a 3×3 square, that is, $B = \{(-1, -1), (-1, 0), (-1, 1), (0, 0), (0, 1), (1, -1), (1, 0), (1, 1)\}$

Morphological operations

The two basic operations are erosion and dilation; the rest of the operations are derived from these two operations.

Erosion: the erosion of a binary image can be defined as follows.

$$A \ominus B = \{z \in E | B_z \subseteq A\}, \quad (4)$$

Where B_z is the translation of B by the vector x, i.e. $B_z = \{b + z | b \in B\}, \forall z \in E$.

When a structuring element B has a center (e.g. B is a disk or a square), and this center is located on the origin of E, then the erosion of A by B can be understood as the locus of points reached by the center of B when B moves inside A.

Dilation: the dilation of A by a structuring element B can be defined as follows.

$$A \oplus B = \{z \in E | (B^s)_z \cap A \neq \emptyset\}, \quad (5)$$

where B^s denotes the symmetric of B, that is, $B^s = \{x \in E | -x \in B\}$.

Opening: opening is defined as the erosion of an image followed by dilation of the resulting image.

$$A \circ B = (A \ominus B) \oplus B. \quad (6)$$

Closing: closing is defined as the dilation of an image followed by erosion of the resulting image.

$$A \bullet B = (A \oplus B) \ominus B. \quad (7)$$

Top-hat Transforms: top-hat transform is an operation that extracts small elements from given images. The two types of top-hat transforms are white top-hat transform and black top-hat transform. The former is the difference of an input image and its opening by a structuring element. The latter is the difference of the closing and the input image.

White top-hat transform

$$T_w(f) = f - f \circ b \quad (8)$$

Black top-hat transform

$$T_b(f) = f \bullet b - f \quad (9)$$

Opening-by reconstruction: because in an opening operation erosion removes small objects then dilation restores the shape of the remaining object, the restoration operation is not very accurate, it depends on the structuring element and the shape of the restoring objects. An opening by reconstruction restores the objects in a much better accuracy after erosion is applied.

It is termed as the reconstruction by *geodesic* dilation [16] of n erosions of F by B with respect to F .

$$O_R^{(n)}(F) = R_F^D[(F \ominus nB)] \quad (10)$$

Where $(F \ominus nB)$ denotes a marker image in morphological reconstruction by dilation.

$R_F^D[(F \ominus nB)] = D_F^{(k)}[(F \ominus nB)]$ D denotes geodesic dilation with k iterator until stability such that $D_F^{(k)}[(F \ominus nB)] = D_F^{(k-1)}[(F \ominus nB)]$, since $D_F^{(1)}[(F \ominus nB)] = [(F \ominus nB) \oplus B] \cap F$ the marker image is limited the growth region by mask image, the dilation operation on marker image will not expand beyond mask image so that the marker image is subset of mask image $(F \ominus nB) \subseteq F$.

The following image shows an erosion, dilation, opening and closing operations that is performed on a binary image.

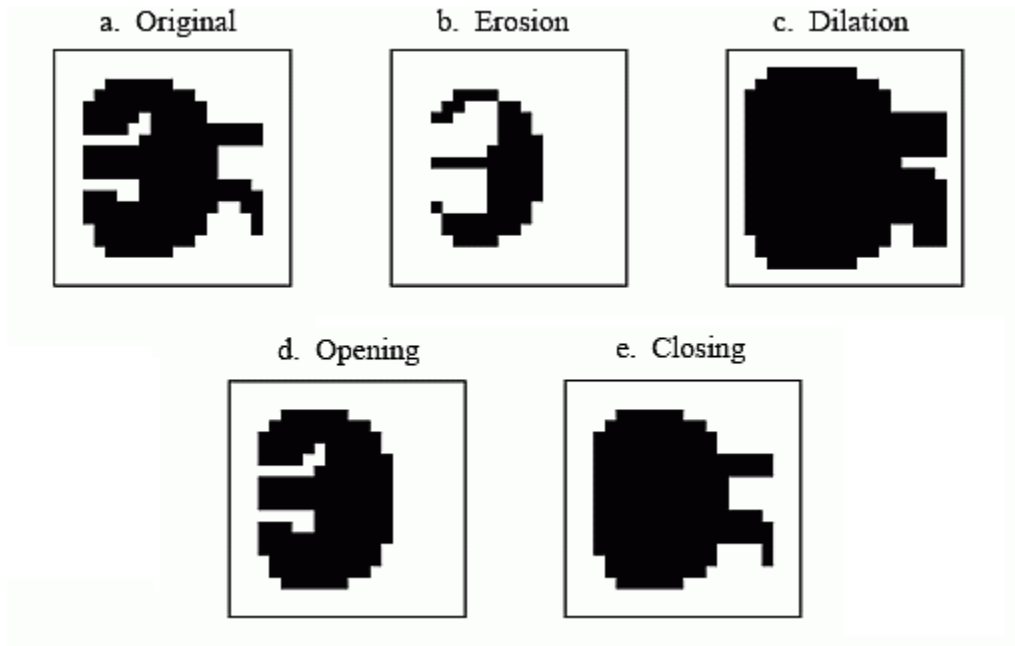


Figure 5: The four morphological operations performed on an image [18].

The algorithm used in this research for blood vessel segmentation is shown below.

Algorithm:

Function Detect_Blood_Vessel

BEGIN

g=EXTRACT(greenchannel);

h=ADAP_HIST_EQ(g);

se:= DISK STRUCTURING ELEMENT SIZE 5;

opIm:=OPEN_IMAGE(h,se);

topHatIm:=TOP_HAT_TRNS(opIm,se);

binIM:=BINARIZE_IMAGE(topHatIm);

fillIm:=OPEN_BY_RECONSTRUCTION(BINim);

extract:=DILATE_RECONSTRUCT(film);

END

Where,

EXTRACT: a function that separates a green channel on the image.

ADAP_HIST_EQ: a function that does *CLACHE*

OPEN_IMAGE: a function that performs an opening operation on an image

TOP_HAT_TRNS: a function that performs a top hat transform operation on an image.

BINARIZE_IMAGE: a function that converts a gray scale image in to a binary image

OPEN_BY_RECONSTRUCTION: a function that performs an open by reconstruction transform operation on an image.

DILATE_RECONSTRUCT: a function that performs a dilation by reconstruction transform operation on an image.

The following shows the result of a segmentation process for an eye fundus image.

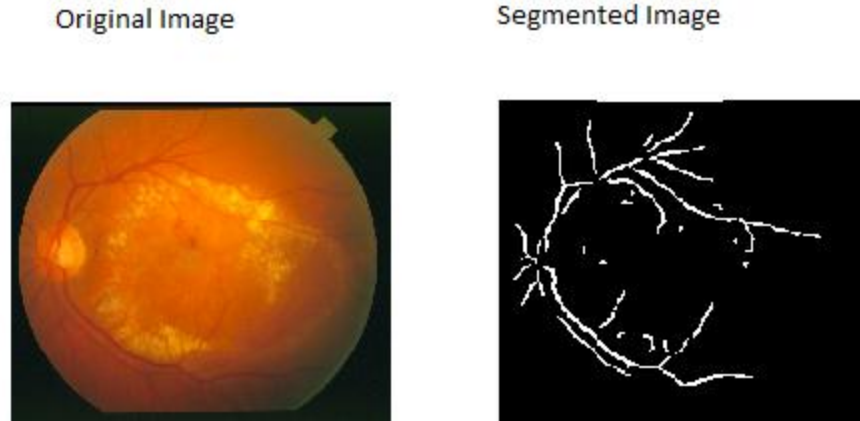
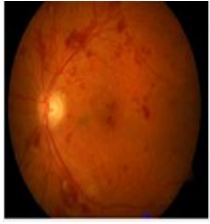


Figure 6: Blood Vessel Segmentation

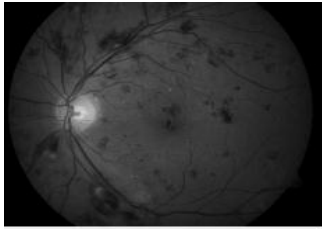
3.3.2. Segmentation of Optic Disk using Morphological Analysis

Morphological analysis is taken for removal of the blood vessels from the fundus image are taken to take out the optic disk:

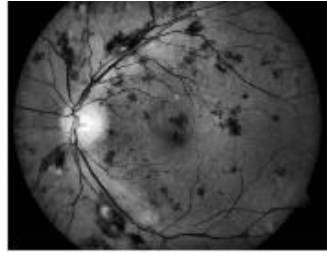
First the image's green channel is extracted out, this is because the features pertaining to the detection of DR are found in this channel and it is found with experimentation and previous researches[1][12]. Contrast enhancement is performed on the image for increasing the intensities of the image pixels, especially those pixels that the OD is present in. The image is then binarized using an optimal threshold value that is obtained by experiment. The closing operation afterwards increases the sizes of features that are found in the image, which also will increase the area covered by the OD, this makes it easy to later extract the OD from the rest. The next step is to identify the number of connected components in the image. Then removal of small components is performed by setting the smallest connected pixel number, this is also found by experiment. Then the number of connected components is calculated again, this time to calculate the biggest component to remove the rest of the connected components.



a. Original image



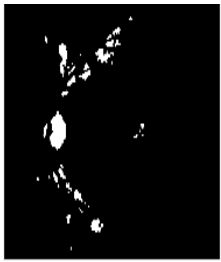
b. Green channel extracted



c. Histogram equalized image, contrast enhancement



d. Binarized at an optimal threshold



e. Image closing



f. Removal of pixels that are smaller than a threshold value



g. Selection of biggest connected component



h. image closing, increasing the size of the optic disk

Figure 7 Segmentation of optic disk

Algorithm:

Function OD

BEGIN

g=EXTRACT(greenchannel);

h=ADAP_HIST_EQ(g);

se:= DISK STRUCTURING ELEMENT SIZE 5;

binIM:=BINARIZE_IMAGE(closedIM);

closedIM:=CLOSE_IMAGE(binIM,se);

filIm:=CALCULATE_NUMBER_CONNECTED(closedIM);

For all in filIm

If(NumPixel<1500)

RemovedIM= REMOVE_COMPONENT(closedIM, filIm);

END

END

filIm:=CALCULATE_NUMBER_CONNECTED(RemovedIM);

biggestComp=CALCULATE_BIGGEST_COMP(filIm);

OD= RemovedIM(biggestComp);

END

Where,

EXTRACT: a function that separates a green channel on the image.

ADAP_HIST_EQ: a function that does *CLACHE*

CLOSE_IMAGE: a function that performs an closing operation on an image

CALCULATE_NUMBER_CONNECTED: a function that calculates the number and size of connected components on an image.

BINARIZE_IMAGE: a function that converts a gray scale image in to a binary image

CALCULATE_BIGGEST_COMP:a function that calculates the maximum number and size of connected components on an image.

REMOVE_COMPONENT : a function that removes a connected component from a list of connected components by taking index as an input.

The following shows the result of a segmentation process for an eye fundus image.

3.4 Feature Extraction

Feature extraction is a process of finding a simplified representation of an image, to be used for classification. Feeding an entire image value to a classifier is not an efficient method for classification, instead finding a way to minimize the amount of data to be used as an input to the neural network classifier is a more reasonable approach[1][14]. There are several ways to do a feature extraction on an image, to be inclusive in properly identifying a fundus color images aTextural feature extraction categories have been implemented in this research.

3.4.1 Textural Feature Extraction

Textural features based on gray- tone(level) co-occurrence matrix(GLCM) has been developed for the extraction purpose [19]. GLCM is a matrix that represents a gray tone value for an image

GLCM

If we assume an image to be analyzed is rectangular and has N_x resolution cells in the horizontal direction and N_y resolution cells in the vertical direction. And taking a quantized set of gray tone N_g levels.

Let $L_x = \{1, 2, \dots, N_x\}$, *horizontal spatial domain.*

Let $L_y = \{1, 2, \dots, N_y\}$, *vertical spatial domain.*

Let $G = \{1, 2, \dots, N_g\}$, *set of N_g quantized gray tones.*

The set $L_y \times L_x$ is the set of resolution cells of the image ordered by their row-column designations. The image I can be represented as a function which assigns some gray tone in G to each resolution cell in the image [19]. This assignment of gray tone is based on a measurement from angular nearest-neighbor gray-tone spatial-dependence matrices. Nearest neighbor resolution cells on an image are cells of size eight as shown in the image below, excluding the once on the periphery of the image.

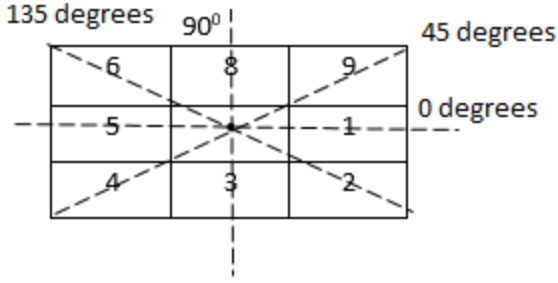


Figure 8: Image cells of size 3x3 pixel size.

The texture context information of an image is contained in the overall spatial relationship which the gray tones in the image I have to one another. Precisely the texture information is adequately specified by the matrix of relative frequencies P_{ij} with which two neighboring resolution cells separated by distance d occur on the image, one with gray tone I and the other with gray tone j . Such matrices are functions of the angle between the two cells and the distance between them. For angles quantized to 45° intervals the unnormalized frequencies are defined by the following expressions:

$$P(i, j, d, 0^\circ) = \#\{(k, l), (m, n) \in (L_y \times L_x) \times (L_y \times L_x) | k - m = 0, |l - n| = d, I(k, l) = i, I(m, n) = j\}$$

$$P(i, j, d, 45^\circ) = \#\{(k, l), (m, n) \in (L_y \times L_x) \times (L_y \times L_x) | k - m = d, l - n = -d \text{ or } (k - m = -d, l - n = d), I(k, l) = i, I(m, n) = j\}$$

$$P(i, j, d, 90^\circ) = \#\{(k, l), (m, n) \in (L_y \times L_x) \times (L_y \times L_x) | k - m| = d, l - n = 0, I(k, l) = i, I(m, n) = j\}$$

$$P(i, j, d, 135^\circ) = \#\{(k, l), (m, n) \in (L_y \times L_x) \times (L_y \times L_x) | k - m = d, l - n = d \text{ or } (k - m = -d, l - n = -d), I(k, l) = i, I(m, n) = j\}$$

Where # denotes the number of elements in the set.

The co-occurrence matrix filled with the values of P is the number of times the gray tones(levels) have been neighbors in the image. For example $P(1,0)$ at 0° with $d=1$ is counting the number of times the gray level 0 has been a neighbor for gray level 1 horizontally at 0° (in that order).

For the image shown in the (fig 8) the quantized gray level is 4 i.e. $G = \{0,1,2,3\}$, and the calculated gray-tone spatial dependence matrix for the image ($P(i, j, 1, 0^\circ)$) is given in the table next to it.

4 X 4 image			
1	0	1	2
3	2	1	0
0	0	0	2
2	1	1	3

P(i,j)	0 deg.	1	2	3
0	2	1	1	0
1	1	0	1	1
2	0	2	0	0
3	0	1	0	0

Figure 9: Example image and its spatial –dependence matrix

In this research fourteen of the harlik features have been selected for the feature extraction purpose. The features are extracted from the gray tone spatial dependence matrices in [19], the following are three of the features that represent homogeneity (Angular Second Moment), contrast and correlation in an image.

$$f_1 = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \left(\frac{P(i,j)}{R} \right)^2 \quad (11)$$

$$f_1 = \sum_{i=1}^{N_g-1} n^2 \left\{ \sum_{|i-j|=n} \left(\frac{P(i,j)}{R} \right) \right\} \quad (12)$$

$$f_1 = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} [ijP(i,j)/R] - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (13)$$

Where $\mu_x, \mu_y, \sigma_x, \sigma_y$ are the means and standard deviations of the marginal distributions and R is the normalizing constant.

Algorithm

Function Texture_Feature_Extraction

Begin

Repeat

convImg=rgb2gray(Segmented_Image);

glcmImg=graycomatrix (convImg);

x= texture_features(glcm);

Until Input_Images are complete;

End

Where,

rgb2gray: is a matlab built in function that converts a color image (rgb image) to a gray scale image.

graycomatrix: is a matlab built in function that calculates glcm of a gray scale image.

texture_features: is a function that calculates harlik features by using a glcm of a gray scale image.

3.5 Data Preparation For Classification

The next step in the process of fundus image DR classification is preparation and presentation of the textural features ready for the classifier network.

The above texture feature extractions will produce a set of features that are represented by numbers for each image.

The training and testing data along with the ground truth value that is used in this research, have been put in the dataset that is used DIRTDB1 and STARE. To properly represent this input and target values the following algorithm has been used.

Target data (ground truth value) is available from DIRTDB1 in a file with a single line containing 5 fields and target data of the STARE data set is put on a text file that has numbers for each feature of DR.

For example, we can have in a file “redsmalldots hemorrhages hardexudates softexudates neovascularization” if one or more of these values is missing in the image, they will be replaced with n/a.

Algorithm:

Function Data_Preparation(input:testname, output:x,TTD)

Begin

//prepare input data

Repeat for I in {"_File"}

Image= Read_File(concatenate(I,"_File"));

textureValue=calculateHaralik(image);

x=append(textureValue);

Until all texture features calculated complete;

//prepare target data

Repeat i=1

Set TD=zeros(2, size_Input);

Read target_file;

Read line (Values);

If (in Values \exists testname)

TD(1,i)=1;

else

TD(2,i)=1;

End if;

Until i= number_target_files;

End

Where,

testname: is one of the names in {exudates, hemorrhage, hard exudates, microaneurysms, neovascularization} in our case it is exudates.

Read_File : is a matlab inbuilt function that reads lines of a file

Concatenate: is a matlab inbuilt function that concatenates two strings

Append: Is a matlab inbuilt function that appends a value to a vector variable.

x: the input vector to the neural network

TD: is Target Data vector.

size_Input: the input size of the neural network (it is the size of the fundus images that is used for the training or the testing purpose)

3.6 Classification Using ANN

3.6.1 ANN Types

Neural networks are also based on a biological background. There are several types of neural networks but the major categories of these networks is either a supervised or unsupervised neural network. Supervised Neural Nets are nets that need a target output. i.e. the network is designed to learn the model by forcing it to match the target output. The network is trained until the desired minimum error is obtained when comparing the network output and the target value. Unsupervised neural nets do not need supervision (i.e. no need of providing target output). Supervised types of networks are suitable for systems that do approximations of equations, classification where target values are provided and so on. The need to have target values for supervised networks makes it limited in applications for most of the problems in the real world that can be solved with such networks because either the getting target values is difficult or preparing (tagging in the case of image classification) is a difficult task. Meanwhile non supervised neural networks are suitable for solving classification problems but they require a larger amount of training data when compared with the supervised network to get to a desired minimum error of the solution.

3.6.1.1. Supervised

Multi-layer Feed Forward Networks

Multi-layer neural networks are ordered in to layers. The first layer is the input layer the second is the hidden layers the third is the output layer. The hidden layers in between the input and output layers can be as many as required by the application [20].

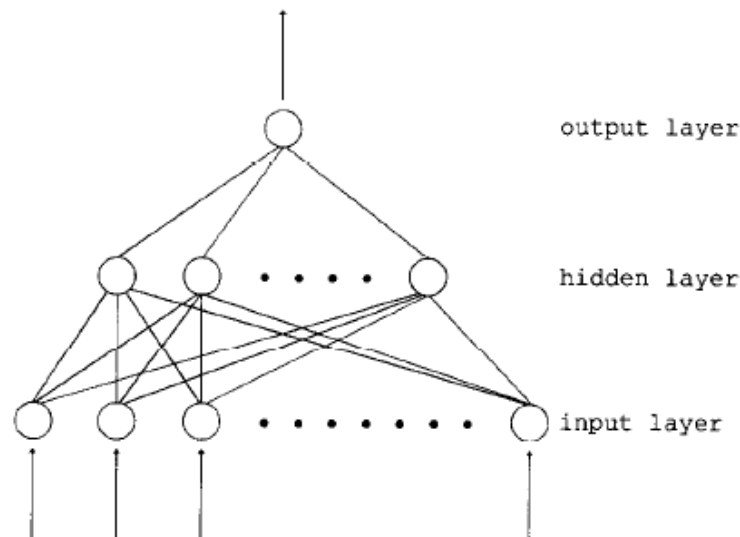


Figure 10 : Typical feed-forward neural network composed of three Layers [20].

For the formal description of the neurons we can use the so-called mapping function r , that assigns for each neuron i a subset $T(i) \subset V$ which consists of all ancestors of the given neuron. A subset $T'(i) \subset V$ than consists of all predecessors of the given neuron i . Each neuron in a particular layer is connected with all neurons in the next layer. The connection between the i th and j th neuron is characterised by the weight coefficient w_{ij} and the i th neuron by the threshold coefficient rY_i (Fig. 10). The weight coefficient reflects the degree of importance of the given connection in the neural network. The output of each neuron is found by :

$$x_i = f(\varepsilon_i) \quad (14)$$

$$\varepsilon_i = \vartheta_i + \sum \omega_{ij}x_j \quad (15)$$

where ε_i is the potential of the i th neuron and function $f(\varepsilon_i)$ is the so-called transfer function (the summation is carried out over all neurons j that carry out the signal to the i th neuron).

The usual transfer function f is the following.

$$f(\varepsilon) = \frac{1}{1+\exp(-\varepsilon)} \quad (16)$$

The supervised adaptation process varies the threshold coefficients ϑ_i and weight coefficients w_{ij} to minimise the sum of the squared differences between the computed and required output values. This is accomplished by minimization of the objective function E :

$$E = \sum_o \frac{1}{2} (x_o - y_o)^2 \quad (17)$$

where x_o , and y_o , are vectors composed of the computed and required activities of the output neurons and summation runs over all output neurons o .

3.6.2 ANN Learning Algorithm

The conjugate gradient learning algorithms that was used in this research.

3.6.2.2. Conjugate Gradient

Let an arbitrary feed forward neural network be given, in which the weights are expressed in vector notation. And the weight vector is a weight vector in the real Euclidean space R^N where N is the number of weights and basis in the network. The weight vector can be defined as the following:

$$w = (\dots, w_{ij}^l, w_{i+1}^j, \dots, w_{Nj}^l, \theta_j^{l+1}, w_{ij+1}^l, w_{i+1+j+1}^j, \dots) \quad (18)$$

Where w_{ij}^l is the weight from unit number i in later number l to unit number j in layer number $l+1$, N is the number of units in layer 1, and θ_j^{l+1} is the bias for unit number j in layer number

l+1. The global error function $E(w)$ can be assumed to be attached to the neural network, can be the standard least square function that is shown above.

The strategy used in conjugate gradient algorithm to minimize the error function E is shown in the following pseudo algorithm.

Algorithm[21]

1. Choose initial weight vector w_1 and set K (conjugate gradient plane) = 1
2. Determine a search direction P_k and step size a_k so that $E(w_k + a_k P_k) < E(w_k)$
3. Update vector $w_{k+1} = w_k + a_k P_k$
4. If $E(w_k) \neq 0$ the set $k=k+1$ and go to 2 else return w_{k+1} as the desired minimum.

Determining the next current point in this iterative process involves two independent steps. First search direction has to be determined. i.e. in what direction in weight space do we want to go in the search for a new current point. Once the search direction has been found we have to decide how far to go in the specified search direction, i.e. a step size has to be determined.

3.6.3 Training and Testing the Network

For training several types of networks, that are mentioned above are experimented for this research. No configuration or external setup have been done the networks themselves, when the network receives the input values it will know how many input and output neurons will be used. Other configurations such as number of hidden layers and number of neurons in those hidden layers are kept constant.

In the testing, the test image data value is obtained after segmentation and calculating the texture features.

Algorithm

Function Train_Network(input: networktype,output:network)

Begin

Setdemorandstream(constantvalue)//this keeps the initial weights of the network constant.

network= networktype_net(x,TTD);

End

Algorithm

Function Test_Netwok(input:testname)

Begin

testY=Net(testX)//the value of testY is going to be 1 or 2. i.e containing or not containing DR

Repeat for i=1

If (testX=1)

Write file(result_file_image i, "n/a n/a"+testname+"n/a n/a")

End if

Until i=size(testY);

End

3.7 Evaluation Methodology

The evaluation that is need to validate the output of this research work has been done by the method proposed in [22]. There is an evaluation tool available that takes an input of directory names of ground truth and actual value (the one obtained from the proposed solution). What the evaluation algorithm does is count the number of **true positives and negatives**(i.e. the number of fundus images that are correctly identified as defective in a particular feature (exudates for our case) and correctly identified as non-defective in a particular feature(exudates for our case), number of **false positives and negatives**(i.e. the number of fundus images that are incorrectly identified as defective in a particular feature (exudates for our case) and incorrectly identified as non-defective in a particular feature(exudates for our case)respectively.

Algorithm

Function EVALUATE(input: testname, testnameposition output: sensitivity ,specificity)

//e.g for testnameposition redsmalldots=1..hardexudates=3 and soon.

Begin

Truepositive=0;

Falsenegative=0;

Falsepositive=0;

Repeat i=1

groundinfo=read(groundtruthfile(i));

testedinfo=read(result_file(i));

if(groundinfo(testnameposition)=testname && testinfo(testnameposition)=testname)

trupositive=trupositive+1;

else if(groundinfo(testnameposition)=testname && testinfo(testnameposition)='n/a')

falsenegative=falsenegative+1;

else if(groundinfo(testnameposition)='n/a' && testinfo(testnameposition)=testname)

falsepositive=falsepositive+1;

else if (groundinfo(testnameposition)='n/a' && testinfo(testnameposition)='n/a')

truenegative=truenegative+1;

Until ground/test files complete;

Sensitivity=truepositive/(truepositive+falsenegative);

Specificity=truenegative/(truenegative+falsepositive);

End

Where,

groundinfo = a vector that holds the values in the ground truth value files.

testedinfo = a vector that holds the values in the tested file.

Sensitivity = a measure of the percent of true positive values that are correctly identified.

Specificity = a measure of the percent of true negative values that are correctly identified.

CHAPTER 4-DESIGN

4.1 Introduction

The design Section of the research contains the overall algorithm that is used to do a fundus image DR detection. This is starting from the image preprocessing, then image segmentation then feature extraction and finally neural network selection.

4.2. Image Pre-processing

Unmasking and cropping of the row image needs to be done as part of the pre-processing.

Although there are several ways to do image pre-processing for equalizing the image contrast, which are mentioned in the methodology, CLAHE was used for the preprocessing, for the reasons mentioned in the methodology Section. The different type of Histogram equalization techniques for image processing are presented in the methodology are HE and AHE.

For this paper the use of only histogram equalization is not enough, because it cannot be applied in the case of fundus image; it contains regions that are significantly lighter(lesions) or darker (blood vessels) than most of the image. These two regions do not get enhanced as a result of an ordinary histogram equalization. The solution to this an **adaptive histogram equalization(AHE)**. AHE improves on this by transforming each pixel with a transformation function derived form a neighborhood region. Each pixel is transformed based on the histogram of a square surrounding the pixel.

Transforming based on a histogram of a surrounding square brings up over amplification of certain regions relative to the whole image. To combat this problem a **contrast limited adaptive histogram equalization (CLAHE)** is used. CLAHE has a contrast limiting property. So therefore, we have used CLAHE in this research for equalizing image histogram (for contrast enhancement) of fundus images taken from the image dataset.

As part of the image processing median filtering is used to remove noise caused by the difference in camera calibration and light intensity when taking the fundus image. The Gaussian median filtering is used for the purpose of the fundus image filtering.

4.3. Image Segmentation

The image segmentation technique that is used in this thesis research for the segmentation of the blood vessels is morphological operation. The step taken is show in design diagramshown below in Section 4.4.

4.4. Feature Extraction Selection

Through experiment the maximum sensitivity and specificity of detection is obtained when using the 14 Haralik textural features.

4.5. Neural Network Selection

The neural network selected for this research is supervised feed forward network with a gradient decent learning algorithm. Of all the neural networks that have been tried and experimented, both supervised and unsupervised, the selected one is the supervised feed forward network.

4.6. Proposed Neural Network Based DR Detection System

The following is the overall design of the proposed detection system, as explained in the previous Sections of this Chapter.

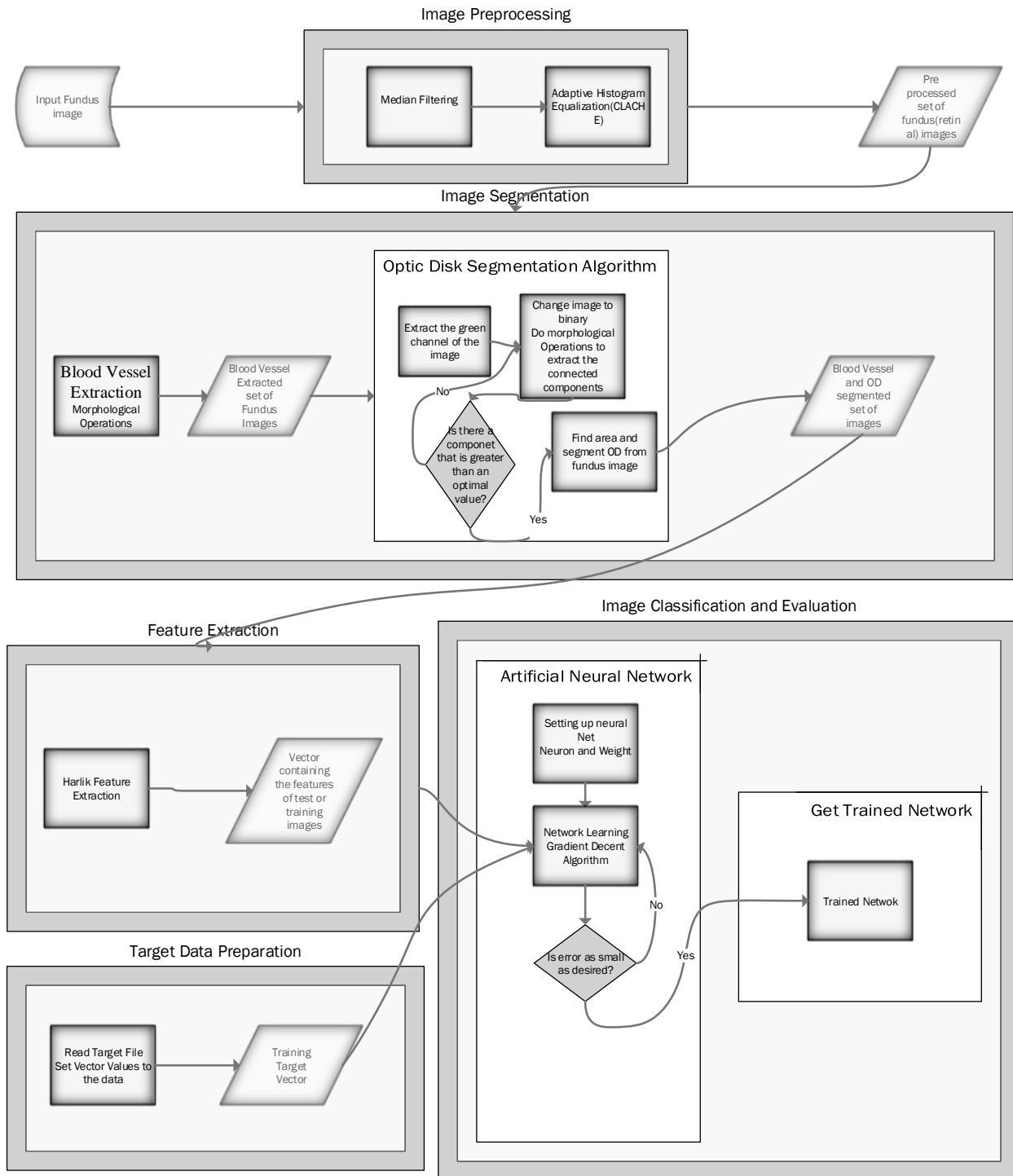


Figure 11: Design of the proposed detection system(Training Stage)

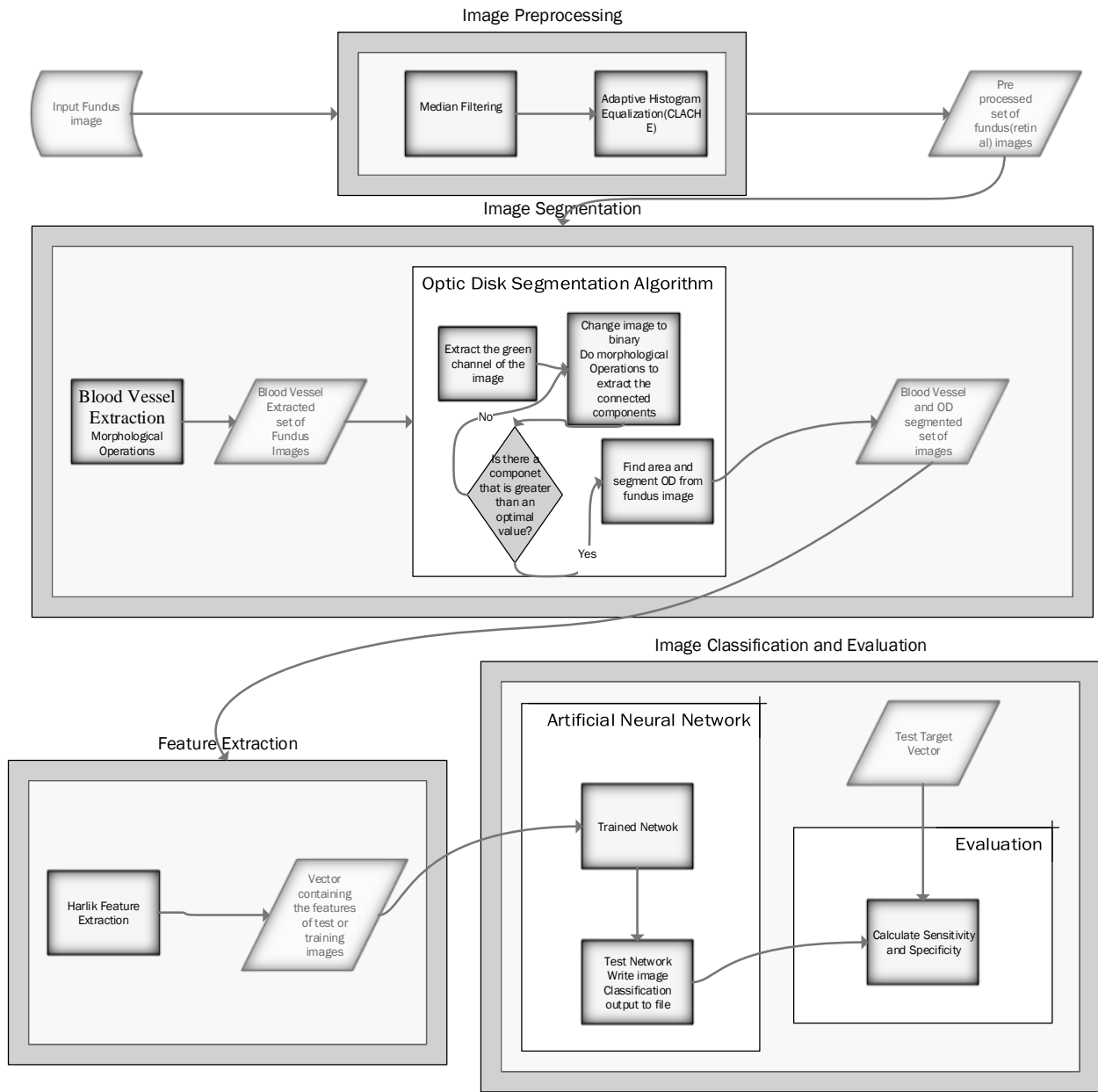


Figure 12: Design of the proposed detection system (Testing Stage)

CHAPTER 5-RESULTS AND DISCUSSION

5.1 Introduction

In this Chapter the experimental results are presented, including the data sets used that led to the results. Discussion on the results shows how the results are interpreted based on the datasets used and the methodology that was taken. Finally, the research work is compared against previous works in the area.

5.2 Data Sets

The data used in the research are mainly from two sources. The first is the Diabetic Retinopathy Database(DIARETDB1), and the second one is the STARE database.

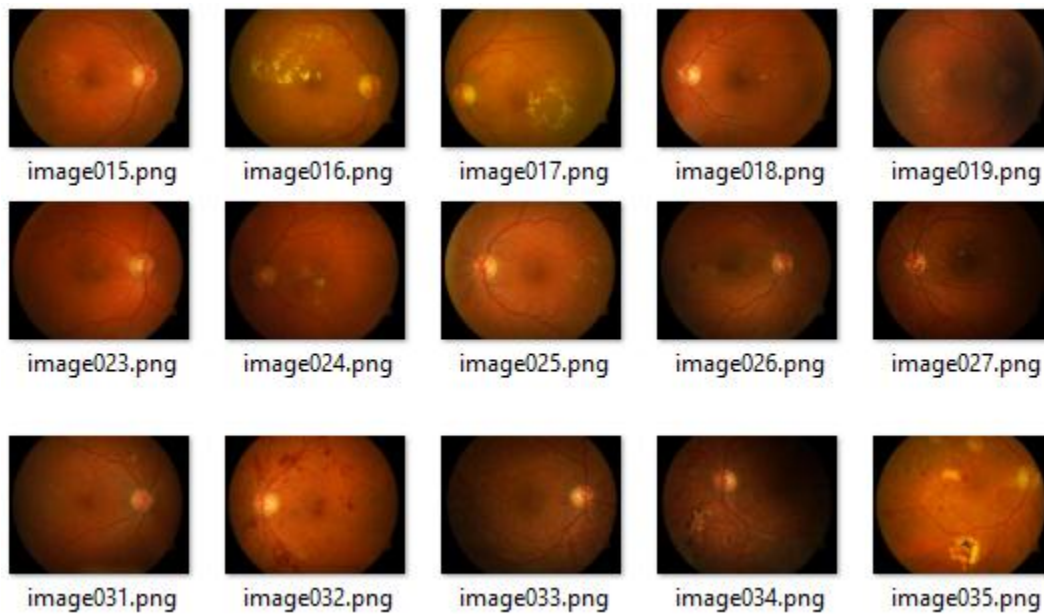


Figure 13: Sample of DIARETDB1 Data Set

The DIARETDB0 contains 130 color fundus images. In which 110 have signs of diabetic retinopathy and 20 are normal images. The images were taken at Kupio university hospital in Finland. Each images have ground truth values that is based on expert-selected findings related to the diabetic retinopathy and normal structures.

The STARE database contains 402 color fundus images. Of which 342 have signs of DR and 40 are normal images. SATARE is a data base of fundus images that is available for researches relating to a Diabetic retinopathy. The images are also presented with ground truth values that are selected based on expert selected findings.

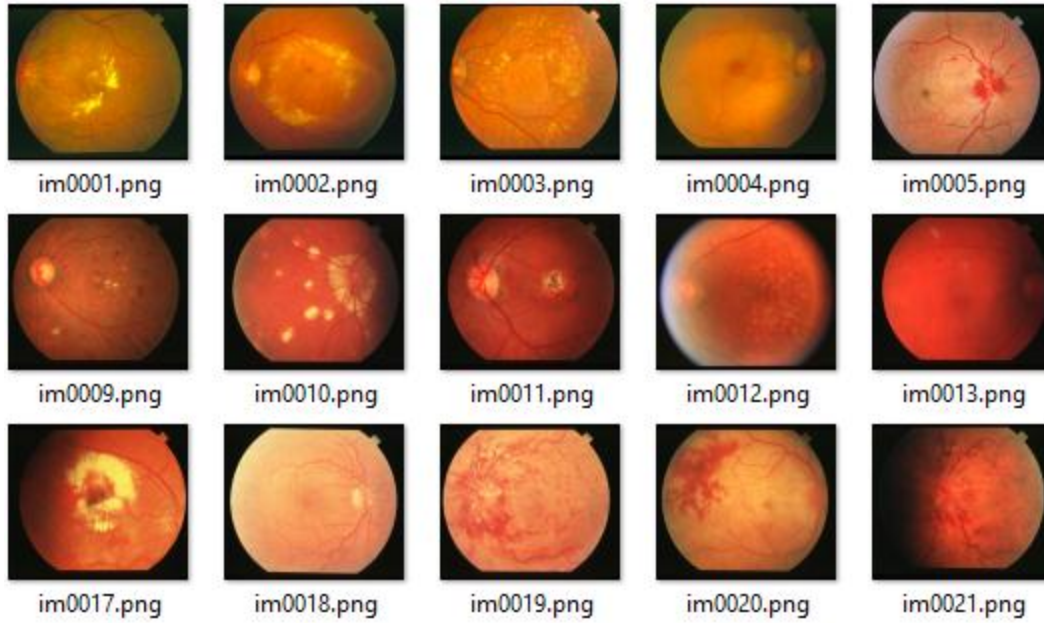


Figure 14 samples of the STARE Data Set

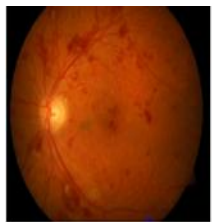
A person with a medical education(M.D.) and specialization to ophthalmology is considered as an expert.

5.3 Results and Evaluation

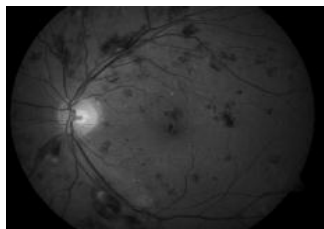
5.3.1. Image Segmentation

Segmentation of the Optic Disk:

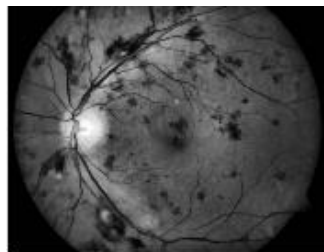
The following image show one of optic disk segmentation procedures that were taken on all funds images.



a. Original image



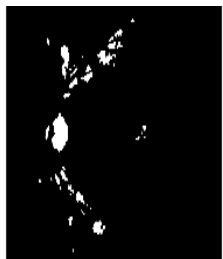
b. Green channel extracted



c. Histogram equalized image, contrast enhancement



d. Binarized at an optimal threshold



e. Image opening



f. Image Closing



g. Selection of pixels that are smaller in size



h. image closing, increasing the size of the optic disk

Figure 15 Result of image segmentation.

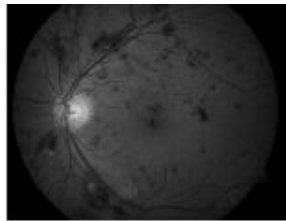
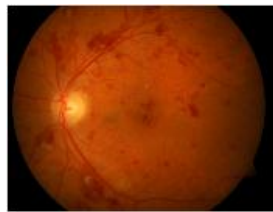
OD Detection Accuracy

Accuracy = Total Number of correctly identified OD/ total number of test data

Table 1: *OD Detection Accuracy*

	Number of tested images	Type of test data	Accuracy
1	81	Contains exudates	90%
2	22	Normal	87%
3	130	Containing all kinds of DR features	90%
4	198	STARE DB	80%
5	279	DIABETDB1 and STAREDB	83%

Segmentation of the blood vessels:



a. Original Image

b. Blood vessel segmentation

c. Binarizing at an optimal value

d. Morphological Operation 1

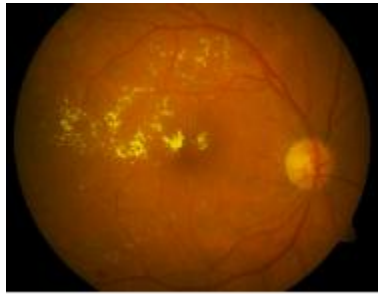


e. Morphological operation 2

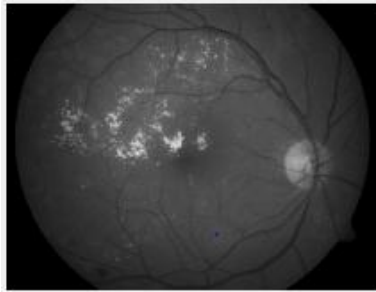
f. Morphological operation 3

Figure 16: Removal of Blood Vessels

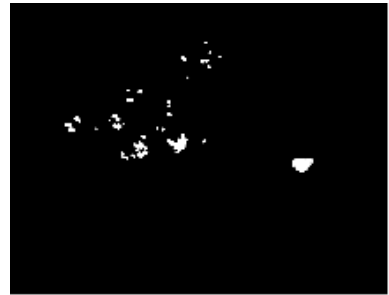
Segmentation of exudates



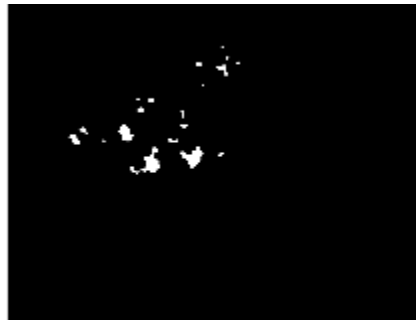
a. Original image



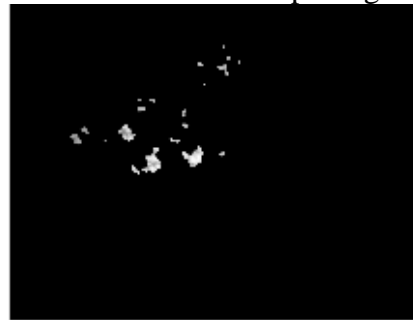
b. green channel extraction



c. After binarizing and Morphological operations



d. removal of OD



e. Gray scaled image that is sent to feature extractor

Figure 17 Segmentation of exudates

5.3.2. Features extraction:

GLCM features:

The fourteen haralik features. used which are then input to the neural network (feature vector) for some of the training and test images are shown below.

Table 2: Table Sample GLCM features

No	Feature Name	image054.png	image028.png	image016.png	image021.png	image002.png
1	Angular Second Moment (Energy) measure of contrast or local intensity variation	0.0100	0.0099	0.0098	0.0099	0.0099
2	Contrast	0.0024	0.0065	0.0289	0.0195	0.0161
3	Correlation (a measure of gray level linear dependence between the pixels at the specified positions)	0.0093	0.0097	0.0097	0.0098	0.0096
4	Variance(Sum of Squares)	0.1087	0.2139	0.5792	0.5242	0.2985
5	Inverse Difference Moment (Homogeneity)	0.0100	0.0100	0.0099	0.0100	0.0100
6	Sum Average	0.0606	0.0637	0.0720	0.0695	0.0652
7	Sum Variance	0.4323	0.8492	2.2879	2.0772	1.1779
8	Sum Entropy	0.0001	0.0003	0.0009	0.0007	0.0004
9	Entropy (Inhomogeneous scenes have low entropy, while a homogeneous scene has a high entropy)	0.0001	0.0005	0.0015	0.0011	0.0006
10	Difference Variance	0.0024	0.0065	0.0289	0.0195	0.0161
11	Difference Entropy	0.0000	0.0002	0.0005	0.0004	0.0002
12	Information Measure of	-0.0075	-0.0074	-0.0072	-0.0076	-0.0076

	Correlation I					
13	Information Measure of Correlation II	0.0011	0.0024	0.0039	0.0036	0.0027
14	Maximal Correlation Coefficient	0.0000	0.0000	0.0000	0.0000	0.0000

5.3.3. Classification and evaluation:

5.3.3.1. Using feed forward, conjugate gradient algorithm

The sensitivity and specificity presented in the following Sections are calculated using the evaluation algorithm that is presented in the methodology Section of this paper.

Table 3: Sensitivity and specificity using conjugate gradient algorithm

No	Size of training data	Size of testing data	Sensitivity of Exudates detection *100 %	Specificity of Exudates Detection *100 %
1	10	120	0.5522	0.6415
2	20	110	0.3333	0.8800
3	30	100	0.7679	0.3182
4	40	90	0.4444	0.7222
5	50	80	0.4783	0.5000
6	60	70	0.5610	0.5172
7	70	60	0.4054	0.6522
8	80	50	0.5313	0.7778
9	234	90	0.8481	0.6364

5.3.4. Comparison with other work

The segmentation results that were obtained by[11], using a dataset(MESSIDOR) of 400 images has a sensitivity of 73%, but the segmentation results that are obtained in this research with a dataset of also around 400 images from the STARE database and 120 DAIBETDR1 was around 80%. As shown with on the results the result with only the STAREDB of 234 images the result obtained is about 84%. The results obtained in our research have a much greater sensitivity values with an input datasets that is publicly available. Images from both the STARE and MESSIDOR are taken using the same camera (TopCon TRC NW6 Non Mydriatic fundus Camera)[23] thus, this makes the comparison a more reasonable one.

5.4. Discussion

5.4.1. Segmentation Results

The results shown on the optic disk segmentation are sufficient enough to further remove the exudates features from the image. An accuracy of 90% is obtained for all exudates containing images in the data set. Which means that 90% of the images that contain exudate will not falsely identify their optic disks as exudate lesions. Among the normal images, the accuracy is 87% because the normal images in the data set contain camera calibration(noise) effects.

Blood vessel segmentation procedures show that blood vessel segmentation is possible through morphological operations that are followed using the proposed methodology.

In addition, the OD segmentation performance using the proposed methodology has brought about an increasing performance compared to previous researches[11] ,showing a promising and robust segmentation methodology.

5.4.2. Feature Extraction Results

The features shown as a sample are the ones that have been used to construct the feature vector of the neural network.

5.4.3. Classification Results

On the conjugate gradient feed forward network performance.

In this network, first the training data's haralik features are fed to the network after the necessary preprocessing procedures have been performed. The evaluation after the network has been thought shows that there is a maximum of 84% sensitivity and 63% specificity when it is tested.

We can see that the larger the size of the training data the better the performance of the network.

Through experimentation it was found that the only learning algorithm that showed better sensitivity and specificity is the conjugate gradient algorithm. Other training algorithms such as resilient backpropagation and gradient descent were tested, but are not presented here.

CHAPTER 6-CONCLUSION, RECOMMENDATIONS AND FUTURE WORK

6.1 Conclusions

In this research a research has been made for detection of diabetic retinopathy exudates by using an artificial neural network. The process of image detection starts from image pre-processing, next is image segmentation then feature selection and finally classification. In the image pre-processing a median filtering and adaptive histogram equalization is used. The image blood vessels and Optic disk are then segmented out using morphological analysis.

Accuracy of segmentation of the optic disk is 90%, 87% and 90 % for exudates containing images, normal images and all images that contain all features of diabetic retinopathy respectively.

The gray level co-occurrence matrix of the image is then calculated to evaluate the textual features. Fourteen features are then used to feed the artificial neural network. The classification is performed by the artificial neural network, first by training with training data sets and target values. Once the network has trained to the required level it is feed with test data. Evaluation of this test data is then done by comparing the ground truth values of the test data against the results obtained from evaluating the test data to the trained neural network. Two fundus image data sets (STARE 402 images, and DIABETRETDDB1 with 130 images) were obtained from two medical universities have been used for the detection process. Using the proposed methodology, a detection performance of 84% sensitivity and 63% specificity is obtained. The implementation is done by using matlab 2015.

6.2 Recommendation

The following are the recommendations that are important for the ongoing research in this area.

- Appropriate pre-processing steps such as median filtering and segmentation of the OD and blood vessels, will lead to better performance of detection, as the fundus images are taken from different cameras with differing calibrations that lead to noises
- Feature vectors that are used as the input of the network represented the images sufficiently enough but adding more features to represent the image will undoubtedly increase the performance of the classification.
- Increasing the data set will enhance the performance of the neural network, this is concluded from the experimentation that was done, if more labeled data sets are found it will lead to better sensitivity and specificity of detection.

6.3 Future Work

The specificity and sensitivity of the detection process can further be enhanced by doing the following:

- Adding color based features
- Increasing the size of the data set
- Increasing the accuracy of segmentation of the artifacts such as the optic disk and the blood vessels.
- The time consumption of the algorithm proposed for training and detection is approximately 10 to 15 min, this time can be improved by apply parallel computing methods to the implementation.

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APPENDIX

This is the function that is used to call all the functions that are used in our work. The full code can be found at https://drive.google.com/open?id=1xWILdQDTzplx_-k7mAtwjomw7vmpIxFa.

```
function status=allinone(datasetNumber,traindatasetsize,testdatasetsize)

delete ResTest/*.res
delete GrounTruth/*.dot

%Calculate Haralick Features of both test and training datasets
TrainArray=calculate_Haralick_Dataset(strcat('traindatasets\traindata',datasetNumber),traindatasetsize);
TestArray=calculate_Haralick_Dataset(strcat('testdatasets\testdata',datasetNumber),testdatasetsize);

%prepare ground truth values for the network
T=gttrainexudate(datasetNumber,traindatasetsize);

%Train Network using the training data features and the target values
netWork=trainNetwork(TrainArray,T);

%test Network using the obtained network and test datasets:
testind=testNetworkExudate(netWork,TestArray,datasetNumber,testdatasetsize);

%copy ground truth data according to the testdataset to the 'GrounTruth/'
gttest(datasetNumber,testdatasetsize);

%Evaluate Result
evalFilePath='ResTest/';
groundtruthPath='GrounTruth/';
result=evaldiaretdb0(evalFilePath, groundtruthPath)

status=1;

end
```

DECLARATION

I, the undersigned, declare that this thesis work is my original work, has not been presented for a degree in this or any other universities, and all sources of materials used for the thesis work have been fully acknowledged.

Senait Getahun Koleche

Name

Signature

Place: Addis Ababa Institute of Technology, Addis Ababa University, Addis Ababa

This thesis has been submitted for examination with my approval as a university advisor.

Dr-Eng Getachew Alemu

Advisor's Name

Signature