Comparison of Computational Intelligent Technique for Detecting Age-Related Macular Degeneration

R. Priya
Associate Professor
Computer Science & Engineering Department,
Annamalai University,
Chidambaram, Tamil Nadu, India

P. Aruna, Ph.D.
Professor
Computer Science & Engineering Department,
Annamalai University,
Chidambaram, Tamil Nadu, India

D. Thenmozhi
M.E Final year
Computer Science & Engineering Department,
Annamalai University,
Chidambaram, Tamil Nadu, India

ABSTRACT
Age-related macular degeneration is an eye disease, which leads to loss of eye in the elderly, due to degeneration of macula in retina. The disease comes within the one of the two types namely, 1) Dry ARMD and 2) Wet ARMD. The purpose of this paper is to diagnose the disease ARMD and classify the types it belongs to. The extent of the disease spread can be identified by extracting the features of the retina. Detection of the disease is done using Probabilistic Neural Network (PNN) classifier. The accuracy of the proposed system is 78%.

General Terms
Probabilistic Neural Network classifier, macular disease.

Keywords
Macula, Retina, Probabilistic Neural Network, Accuracy, Sensitivity, Specificity.

1. INTRODUCTION
Age-related macular degeneration (ARMD) is a macular disease that causes a disorder in the retina, that is the light-sensitive inner lining in the back of the eye. The macula is a small, central portion of the retina which is necessary for sharp and helps to recognize all objects clearly. When the macula degenerates, it does not lead to total blindness because the remaining and undamaged parts of the retina around the macula continue to provide "side" vision. ARMD can be classified into two types as follows:
1) Dry ARMD- Dry macular degeneration is more common and is characterized by the thinning of the retina and drusen, small yellowish- white deposits that form within the retina. The dry form of the macular degeneration is usually mild. The disease is reported to occur in 30% of the population of 75 years and above.
2) Wet ARMD- Wet macular degeneration can happen more quickly and be more serious. It occurs when vessels under the retinal layer hemorrhage and cause the retinal cells to die creating blind spots or distorted vision in the central vision. This disease is reported to occur in 4-5% of the individuals over 70 years.
In [1], D.Jayanthi et. al automatically detected and segmented retinal diseases with the help of a neural network based classifier. In [2], Ziyang Liang et. al presented a method of detecting drusen in retinal fundus images. The method first determines the location of the macula, which is used as a landmark for a clinical drusen grading overlay. In [3] one of the difficulties in detecting and locating drusen is that their aspect (shape, texture, color, extent) varies significantly, and because of this it is often difficult to build a classifier. To address this difficulty, D.E. Freund et. al used a two pronged approach based on (a) multiscale analysis and (b) kernel based anomaly detection. In [4] MohdHanafi Ahmad Hijazi et. al aimed at histogram approach for screening in age-related macular degeneration. In [5] Adam Hoover and Michael Goldbaum aimed at locating optic nerve using fuzzy convergence of blood vessels. In [6] R.Priya and Dr.P.Aruna aimed to assist in the early detection of Age-related macular degeneration, by detecting changes in blood vessel and patterns in the retina.

2. PROPOSED SYSTEM
Figure 1 illustrates the block diagram of the proposed system for diagnosis of ARMD. In this paper, an automated approach for classification of the disease ARMD using fundus images is presented.

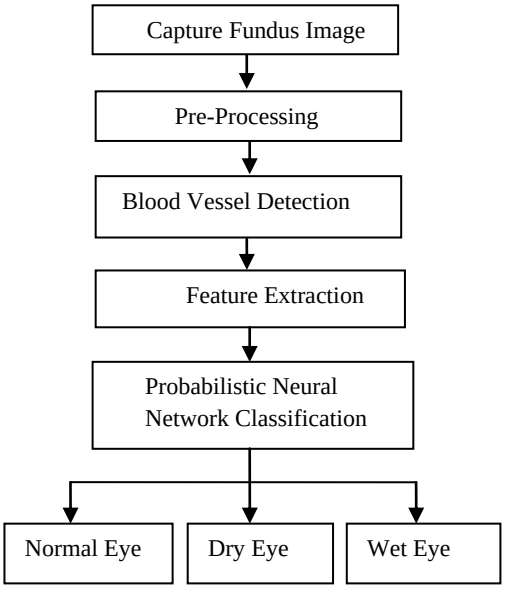


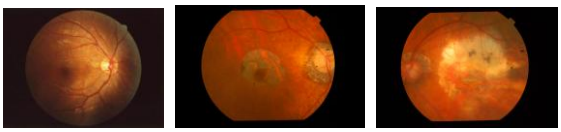
Figure 1: Block diagram of the proposed system for the diagnosis of ARMD

The features are being extracted from the enhanced images to diagnose the disease ARMD. After the extraction, Probabilistic Neural Network classifier is used to classify the type of disease and diagnose the disease**.** PNN classifier is used to analyze training data and to find an optimal way to

classify images. The main goal is to detect automatically and segment the disease age-related macular degeneration in retina without any human supervision and interaction. The proposed work of this paper consists of four modules, 1. Pre-Processing 2. Blood Vessel Detection 3. Feature Extraction 4. Classification of the disease using PNN.

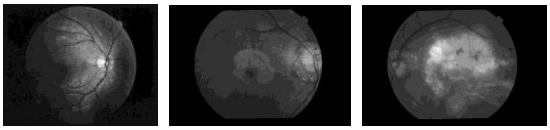
2.1 Pre-Processing

Pre-processing is the first step of the process. The input image taken will have lots of noise and so it is hard to extract the features of the image. The Green component is extracted from the original image. Then adaptive histogram is applied to increase the contrast of the green component image. The resultant image contains many noises, to remove it and to improve the quality of the image, anisotropic diffusion is used. Figure 2 shows the original eye images which is a combination of Normal, DMD and WMD. Figure 3 shows Green component extracted images.. Figure 4 shows the Adaptive Histogram Equalized images. Figure 5 shows the an-isotropic diffused images.



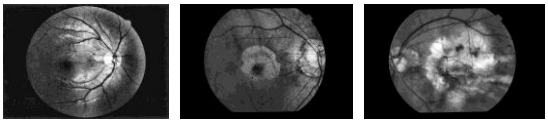
(a) (b) (c)

Figure 2: Input retinal image for (a) normal, (b) dry and (c) wet



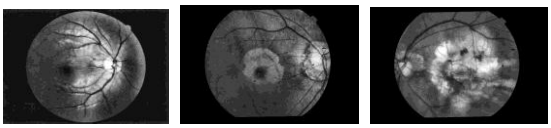
(a) (b) (c)

Figure 3: Green channel extracted image for (a) normal, (b) dry and (c) wet



(a) (b) (c)

Figure 4: Adaptive histogram equalized image for (a) normal, (b) dry and (c) wet



(a) (b) (c)

Figure 5: Anisotropic diffused image for (a) normal, (b) dry and (c) wet

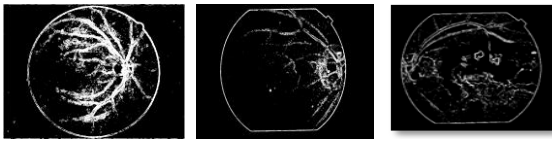
2.2 Blood Vessel Detection

2.2.1 Kirsch template

The image got in the previous process is taken for blood vessel detection using kirsch template. The Kirsch operator is made up of a number of templates. Each template focuses on the edge strength in one direction. This edge detector performs convolution with 8 masks calculating gradients. The Kirsch edge detection algorithm uses a 3×3 table of pixels to store a pixel and its neighbors while calculating the derivatives. The 3×3 table of pixels is called a convolution table, because it moves across the image in a convolution-style algorithm. The Kirsch edge detection algorithm identifies both the presence of an edge and the direction of the edge. Figure 7 shows the results of eye images after applying Kirsch template.

There are eight possible directions in the Kirsch Operator : North, Northeast, East, Southeast, South, Southwest, West, and Northwest. The direction is perpendicular to the edge. For a convolution table, calculating the presence and direction of an edge is done in three major steps :

1. Calculate the derivative for each of the eight directions.
2. Find the value and direction of the maximum derivative.
   Edge Max = Maximum of eight derivatives
   Dir Max = Direction of Edge Max
3. Check if the maximum derivative is above the threshold.



(a) (b) (c)

Figure 7: Kirsch operator image for (a) normal, (b) dry and (c) wet

2.3 Feature Extraction

Feature extraction can be done in two steps, 1) Features detecting the optic nerve, 2) Features detecting diseases.

2.3.1 Features Detecting the Optic Nerve

After applying the pre-processing techniques like histogram equalization and noise removal, we obtain a better contrast image with different objects having different textures. Each image is divided into large number of equal parts and local mean, standard deviation and variance are calculated. The characteristics of vessel structure are

1) Vessel density
2) Average vessel thickness

1) *Vessel Density, $\rho(x, y)$*

Vessel density is defined as the number of vessels existing in a unit area of the retina. Since the vasculature that feeds the retina enters the eye, the vessels tend to be most dense in this region.

$$\rho(x,y) = b_t(x,y) * w_v(x,y) \qquad (1)$$

Where, $b_t(x, y)$ is the skeletonzed image and $w_v(x, y)$ is the convolution window combinely as morphologically skeletonized window.

2) *Average Vessel Thickness, t(x, y)*

Vessels are also observed to be thickest near the optic nerve since most branching of both the arterial and venous structure does not take place until the tree is more distal from the optic nerve.

$$t(x,y) = \frac{b(x,y) * w_v(x,y)}{b_t(x,y) * w_v(x,y)} \qquad (2)$$

Where b(x, y) is the binary image and $w_v(x, y)$ is the convolution window combinely called as binary window. It can be divided by morphologically skeletonized window.

2.3.2 Features Detecting Disease

Both statistical and geometrical texture features is calculated in this paper and both describe texture in a form, which is suitable for pattern recognition. As a result each texture is described by a feature vector of properties, which represents a point in a multi dimensional feature space. Some of the features that are extracted for detecting diseases are given along with their formula:

2.3.2.1 Geometrical Texture Features

1) Area

The area of a circle is the space contained within the circumference and is measured in square units.

$$A = \Pi r^2$$

2) Radius

The Radius is the distance from the center of the circle to the circumference.

$$\text{Radius} = \frac{\sqrt{A}}{\Pi}$$

3) Diameter

The Diameter of a circle is the distance from one point of the circumference through the center to the opposite side of the circle. The diameter is twice the length of the radius.

$$d = 2 * \text{radius}$$

4) Perimeter

The perimeter of a circle is the circular line that marks the limits of a circle.

$$p = 2 * \Pi * \text{radius}$$

5) Centre angle

The angle subtended at the center of a circle by two given points on the circle.

$$ca = \frac{\text{perimeter}^2}{360}$$

6) Arc length

The distance along the curved line making up the arc.

$$\text{Arc} = \frac{(\text{Radius}) * (2 * \Pi * ca)}{360}$$

7) Mins of arc

A minute of arc or minute arc (MOA), is a unit of angular measurement equal to one sixtieth ($^1/_{60}$) of one degree ($^{\text{circle}}/_{21,600}$), or ($^{\pi}/_{10,800}$) radians.

Mins of arc= hour angle * 15

8) Volume

The amount o space that something contains or fill is volume.

$$V = 4 * (\Pi * r^3)$$

.

$$\frac{\qquad}{3}$$

2.3.2.2 Statistical Texture Features

1) Mean

The mean (also known as average), is obtained by dividing the sum of observed values by the number of observations, *n*.

$$m = \frac{x}{y}$$

where, x= sum of items

y= total no of items

2) Median

The median is the middle value of a set of data containing an odd number of values, or the average of the two middle values of a set of data with an even number of values.

3) Variance

The variance is a measure of how far each value in the data set is from the mean.

$$\delta = \frac{x}{y}$$

where, x=(sum-mean)

y= (sum-mean) ²

4) Standard Deviation

On average, how much each measurement deviates from the mean is called as standard deviation.

$$\sigma = \sqrt{\text{variance}}$$

5) Skewness

Skewness describes the shape of the data set's distribution. Skewness indicates how symmetrical the data set is.

$$\text{Skewness} = \frac{(\text{mean- median})}{\text{standard deviation}}$$

2.4 Classification of the Disease Using PNN

The below Figure8 represents the PNN architecture. Probabilistic neural network (PNN) is a feed forward neural network. PNN is a classifier that maps any input patterns into number of classification. In a PNN, the operations are organized into a multilayered feed forward network with four layers: Input layer, Hidden layer, Pattern layer/Summation layer, Output layer.

In the input layer, the number of neurons is equal to the number of input features.

In the pattern layer, the total number of neurons is the sum of the numbers of neurons used to represent the patterns for each category. Each category may contain many training patterns (training vectors) whose dimension is equal to the number of input factors, and taking a set of specific values of input factors. The training vectors are imported from sample data and hence they are not always necessarily representative of all existing patterns for that class.

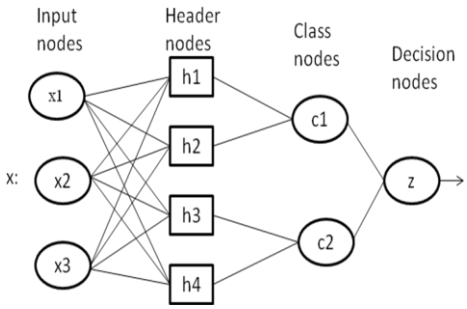


Figure 8: PNN Architecture

However, this is the advantage of PNN, in that it can generalize to allow recognition of a new pattern of a class. The activation function used in the pattern layer, is the Gauss kernel.

In the summation layer, the number of neurons is equal to the number of categories. The activation is simply a weighted sum function. The outgoing signals can be adjusted according to loss and prior probability value.

In the output layer, there is one neuron to represent the classification result. The output is thus obtained. This output corresponds to one of the three classes of the input images namely, normal, DMD and WMD separately.

3. EXPERIMENTAL RESULTS

The performance measure of PNN classification is shown in Table 1 and Table 2 shows the percentage of accuracy of the test data. The sensitivity and specificity of the proposed system are 67.75% and 95% respectively. The accuracy of the proposed system is 77.78%. Figure 9 shows the ROC curve for the system.

Table 1. Performance measure of PNN classification

True Positive	False Positive	True Negative	False Negative
23	1	19	11

Table 2. Percentage of accuracy

Sensitivity	Specificity	Accuracy
67.65%	95%	77.78%

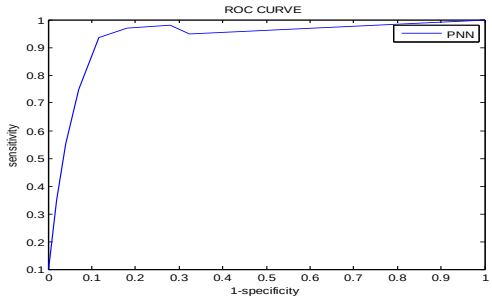


Figure 9. ROC curve

4. CONCLUSION

ARMD is a macular disease which leads to loss of eye in the elderly. As a result of Macular degeneration the central vision deteriorates, resulting in dark spots and cloudiness. The two different kinds of ARMD are identified as Dry ARMD and Wet ARMD. The input image is converted into green component and then adaptive histogram is applied to increase the contrast of the image. Next an-isotropic diffusion is used to remove the noise. Finally, blood vessel detection is done using kirsch template. The detected blood vessel's features are extracted both statistically and geometrically to differentiate the type of disease namely as, normal, dry and wet using Probabilistic Neural Network classifier. This method may be enhanced by taking some more features and by combining with other pattern classification models.

5. ACKNOWLEDGMENTS

The authors would like to thank Aravind Eye Hospital and Postgradute Institute of Opthalmology, Thavalakuppam Junction, Pondicherry for their help in obtaining the images used in this research.

REFERENCES

[1] D.Jayanthi, N.Devi, S.SwarnaParvathi, "Automatic Diagnosis of Retinal Diseases from Color Retinal Images", International Journal of Computer Science and Information Security, Vol.7, pp:1, 2010.

[2] Ziyang Liang, Damon W.K. Wong, Jiang Liu, Kap Luk Chan, Tien Yin Wong, " Towards automatic detection of age-related macular degeneration in retinal fundus images", 32nd Annual International Conference of the IEEE, pp:4100-4103, 2010

[3] D.E. Freund, N. Bressler, P. Burlina, "Automated Detection of Drusen in the Macula", ISBI, pp.61-64, 2009.

[4] MohdHanafi Ahmad Hijazi, Francs Coenen, YalinZheng, "A Histogram Approach for the Screening of Age-Related Macular Degeneration", Ophthalmology Research Unit.

[5] Adam Hoover and Michael Goldbaum, "Locating the Optic Nerve in a Retinal Image using the Fuzzy Convergence of the Blood Vessels", IEEE Transactions on Medical Imaging, Vol.22, 2003.

[6] R.Priya and Dr.P.Aruna**, "**Automated Diagnosis Of Age-Related Macular Degeneration From Color Retinal Fundus Images", International Conference on Electronics Computer Technology(ICECT), 2011.