

Computer Aided Diagnosis of Color Fundus Images using 2D Discrete Wavelet Transform and Neuro Fuzzy System

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ABSTRACT:One of the common vision threatening complications of diabetes is Diabetic Macular Edema (DME). It occurs when blood vessels in the patient's retina begin to leak into the macula region of eye. The leakages cause the macula to swell and thicken, developing gradually into blindness. To prevent diabetic patients from this, early detection of DME must be done. One of the screening methods is to carefully analyze the input fundus images. If the analyzing is performed manually it would be time consuming and inaccurate. Therefore various types of DME computer aided diagnosis have been developed. In this study, an attempt to devise such a computer aided diagnosis using 2D Discrete Wavelet Transform (DWT) based features and Adaptive Neuro-Fuzzy Inference System (ANFIS) is reported. The computational results show that ANFIS could give 92% overall accuracy which is 9% and 2% better than feed forward neural networks with 2 and 3 hidden layers respectively.

KEYWORDS:Discrete wavelet transform, Neuro-Fuzzy, Diabetic Macular Edema, retina, Hard exudates, fundus

I. INTRODUCTION

Diabetes in recent years has become a prevalent disease in the world[1] and it causes many complications. One of the complications of diabetes is Diabetic Retinopathy (DR). It is a common diabetic retinal disease due to the blood vessels in the retina changes from its original shape. At earlier stage, the DR patient may not notice any changes in his vision. However, in the long standing DR, it may worsen and cause vision loss[2]. According to [3] and [4], DR is a common cause of blindness among adults aged 20-74 years and its prevalence keeps rising. However, it can be prevented by proper initial treatment and consulting the ophthalmologist at an early stage. If a person has diabetes for long period, the chances of developing DR are higher.

Another complication of diabetes is DME. DME comes under DR category. It occurs when blood vessels in the retina begin to leak into the macula area, a very small area at the center part of the retina that responsible for the pinpoint vision, allowing to view objects (see Fig 1, normal retina). DME mostly occurs in long standing diabetic patients and can be screened by the existence of Hard Exudates (HE) in fundus images.

Figure 1 depicts normal retina and DME retina fundus image. In normal retina, there is no HE existing. While in DR retina, HE exist, indicated by small bright spots. The location of HE have been used to grade the risk of macular edema according to[5]. If HE present near the macula, the severity is moderate. If HE present inside the macula region, the severity is high. At the initial stage of this disease, the ability of vision starts to decrease. Patients should consult the problem in vision with ophthalmologists. In order to help ophthalmologists in diagnosing whether the patient is normal or abnormal, several CAD of color fundus images have been proposed. In this study we attempt to contribute CAD of color fundus images using 2D DWT and ANFIS approach. Our proposed CAD performed normal and abnormal (DME) retina classification and did not perform classification of DME severity.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 8, August 2015

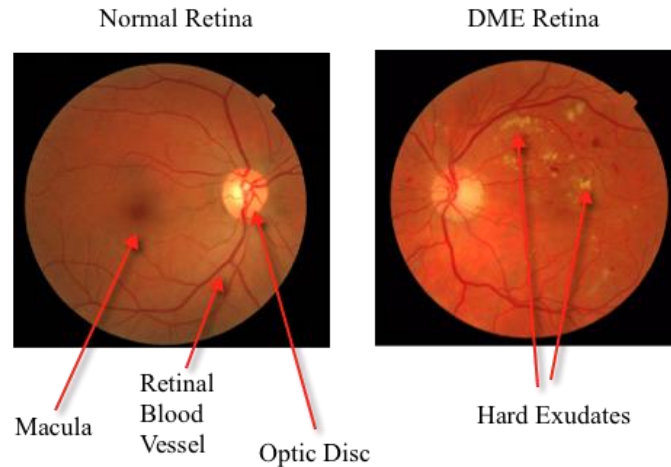


Fig. 1. Normal Retina vs DME Retina Image

II. RELATED WORK

Many researchers have used various datasets to build DME CAD systems of color fundus images. Various image pre-processing techniques and classifiers were also used. Vasanthi and Banu[1] have proposed Adaptive Neuro-Fuzzy Inference System (ANFIS) and Extreme Learning Machine (ELM) to classify whether the fundus images are in normal, mild, moderate, or severe stage of DME. The features of area and Gray-Level Co-Occurrence Matrix components(contrast, correlation, homogeneity, and energy) were used. Green channel separation from RGB (red, green, blue), filtering, image enhancement, and morphological operation were performed as pre-processing steps. The result of performances were evaluated in terms of the parameters such as sensitivity, specificity and accuracy whose values are 100%, 90% and 96.49% for ANFIS classifier and 94.28%, 100% and 96.49% for ELM classifier respectively. Unfortunately, there is no clear statement about the used dataset.

Another technique done by Angurajsiva et al [6]is much similar with the technique done by Vasanthi et al [1] in term of used features and classification method. However, they used different pre-processing steps. Angurajsiva et al performed pre-processing with RGB to gray conversion, image enhancement, and morphological operation. Upon pre-processing, optic disc removal and image segmentation were performed before extracting features.

The design strategies for classification of abnormalities in retinal images were proposed by Waghmare et al. [7]. They proposed RGB to gray, because gray scale image gives better visualization compared to the other, intensity equalization, and histogram equalization for pre-processing step. For classifier, they proposed ANFIS.

Another work that was done by Ramya et al [8]used MESSIDOR database for normal and DME retina classification, as well as classification of category 1 (moderate) and category 2 (severe). The objective and used dataset are similar to our work. However, the step of pre-processing and classification are different. Green channel separation from RGB images, localization of OD and macula, and motion pattern estimation were the proposed steps of image pre-processing. The feature selection using radon transform method was used. Gaussian Data Description (Gaussian DD) and Principle Component Analysis Data Description (PCA DD) were proposed for classification method. Overall, the accuracy of Gaussian DD and PCA DD are 84% and 92% respectively.

International Journal of Innovative Research in Science, Engineering and Technology

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III. METHODOLOGY

In this study, MESSIDOR [5] was used as the dataset. In that dataset, there are 1200 eye fundus color numerical images of the posterior pole. They were acquired using a color video 3CCD camera on a Topcon TRC NW6 non-mydratricretinograph with a 45-degree field of view. The images were captured using 8 bits per color plane at 1440×960, 2240×1488 or 2304×1536 pixels. Among 1200 images, 800 images were acquired with pupil dilation (one drop of Tropicamide at 0.5%) and 400 without dilation.

The dataset has labels of DME stages. Among 1200 data, 226 data are DME with category 1 (moderate) and 2 (severe), while the rest is category 0 (normal). In order to balance the classification system, 452 images, containing 226 normal and 226 DME were used. From 452 data, 70% were used for data training, 15% were used for data validation, and the rest 15% for data testing, divided by using interleaved indices. Figure 2 illustrates the whole steps of DME CAD system from pre-processing, feature extractions, and ANFIS classification. Each subsections below describes them in detail.

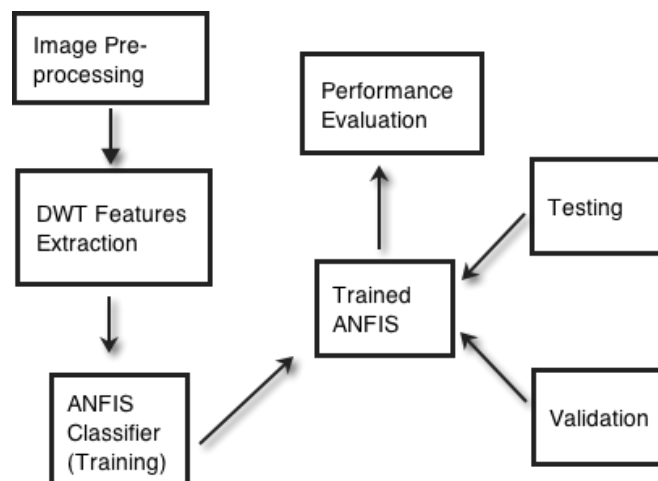


Fig. 2. Flowchart of the proposed Method

A. Pre-Processing

Figure 3 illustrates the pre-processing images for both normal and abnormal retina. First, the original images were uniformly resized into 1280×1920 pixels, because they have three various sizes. Upon resizing, they were cropped on the circular fundus, and then they were resized again into 1024×1024 pixels. Second, green channel was separated from RGB. This was needed to provide clear distinction between normal and abnormal images [1]. Third, image enhancement step was done with histogram equalization. The histogram equalization is very important to enhance the contrast of images, in order to suit the subsequent use.

B. Feature Extraction

To extract the features we used 2D Discrete Wavelet Transform technique. There are several wavelet families that are applicable in discrete analysis. They include orthogonal wavelets (Daubechies and Symlet) and B-spline bi-orthogonal wavelets [9]. In this work we chose Daubechies db5 type. The db5 type was chosen because based on our experiment db5 gives us faster and more accurate result than the other types. Upon applying DWT, we got 4 sub-bands: LL, LH, HL, and HH [10]. LL is the approximate image of the input image or low frequency sub-band. It can be used for further decomposition process. LH, HL, and HH are high frequency sub-bands. LH sub-band extracts the horizontal features of original image, HL sub-band gives vertical features, and HH sub-band gives diagonal features.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

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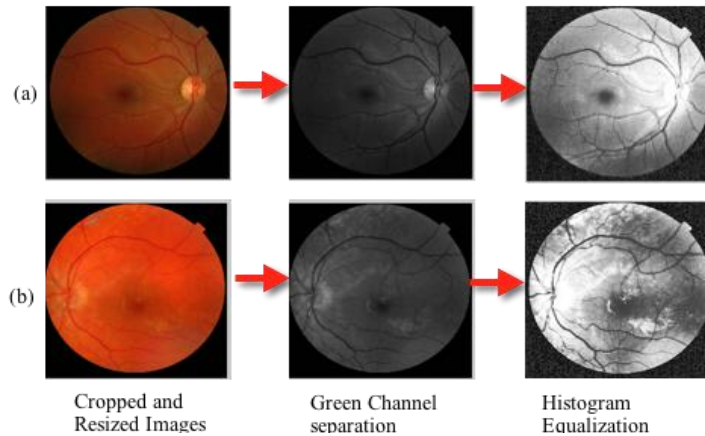


Fig. 3. Pre-processing Steps on Fundus Images (a) Normal Retina, (b) Abnormal Retina with DME

Assumed that each sub-band is represented by P matrix with $N \times N$ size, then we extracted the parameters of mean, variance, standard deviation, energy [10], and entropy with the following formulas, where $i = j = 1, 2, 3, \dots, N$.

$$Mean = \frac{1}{N \times N} \sum_{i=1}^N \sum_{j=1}^N P(i, j) \quad (1)$$

$$Variance = \frac{1}{N \times N} \sum_{i=1}^N \sum_{j=1}^N (P(i, j) - Mean)^2 \quad (2)$$

$$StandardDeviation = \sqrt{Variance} \quad (3)$$

$$Energy = \frac{1}{N^2 \times N^2} \sum_{i=1}^N \sum_{j=1}^N P(i, j)^2 \quad (4)$$

$$Entropy = \sum_{i=1}^N \sum_{j=1}^N -P(i, j) \times \log(P(i, j)) \quad (5)$$

Because there are five features in each sub-bands, we have 20 feature candidates in total. The next step is selecting the features. First, the correlated features, which are standard deviation and variance, were eliminated. The feature of variance was eliminated. Then 2, 3, and 4 features over remaining features in each sub-bands were chosen. However the accuracy results were not met the expectation. After performing several combination experiments, it was found that selecting features based on uniform parameters of each sub-bands resulting high accuracy in range of 86.3% and 92%. Table I represents the selected features and accuracy after ANFIS classification. Note that features number 1-5 represents LL, number 6-10 represents LH, number 11-15 represents HL, and number 16-20 represents HH. As the highest accuracy among those combinations of features was 92%, the selected features are attribute 3, 8, 13, and 18, or standard deviation of LL, LH, HL, and HH respectively.

TABLE 1. COMBINATION FEATURES AND ACCURACY

| No | Used Features | Accuracy | Description |
|----|---------------|----------|--------------------|
| 1 | 1, 6, 11, 16 | 86.3% | Mean |
| 2 | 3, 8, 13, 18 | 92% | Standard Deviation |
| 3 | 4, 9, 14, 19 | 88.7% | Energy |
| 4 | 5, 10, 15, 20 | 91.8% | Entropy |

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C. ANFIS Classifier

ANFIS needs data training to build fuzzy inference system (FIS). As stated, 70% of 452 data was selected as data training. Using data training with 4 inputs and 1 output, ANFIS constructs a FIS whose membership function parameters are tuned (adjusted) using Fuzzy C-Means (FCM) Clustering and Sugeno structure type. Figure 4 depicts structure of ANFIS, represents 4 input, two rules, and 1 output. The result of this step was FIS that would be validated and tested using data validation (15% of total data) and data test (15% of total data).

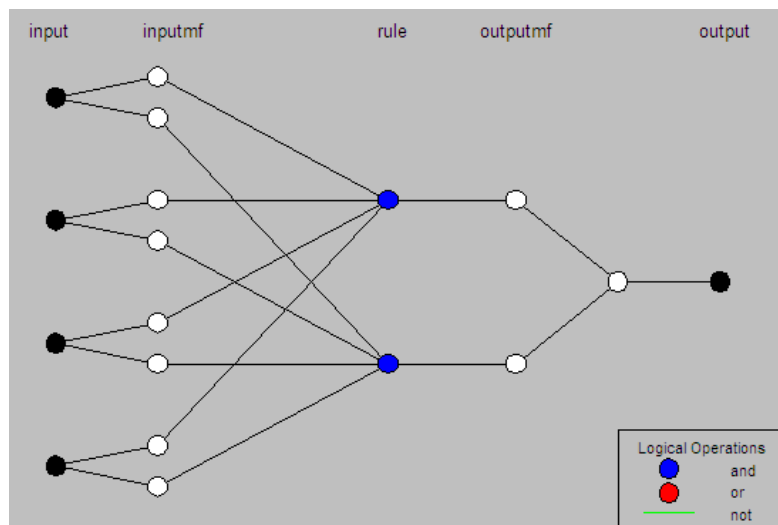


Fig. 4. Structure of ANFIS using Sugeno

The membership functions were built using Gaussian as illustrated in Fig 5. The used two rules are stated as follow.

- Rule 1: If (In1 is In1cluster1) and (In2 is In2cluster1) and (In3 is In3cluster1) and (In4 is In4cluster1) then (out1 is out1cluster1)
- Rule 2: If (In1 is In1cluster2) and (In2 is In2cluster2) and (In3 is In3cluster2) and (In4 is In4cluster2) then (out1 is out1cluster2)

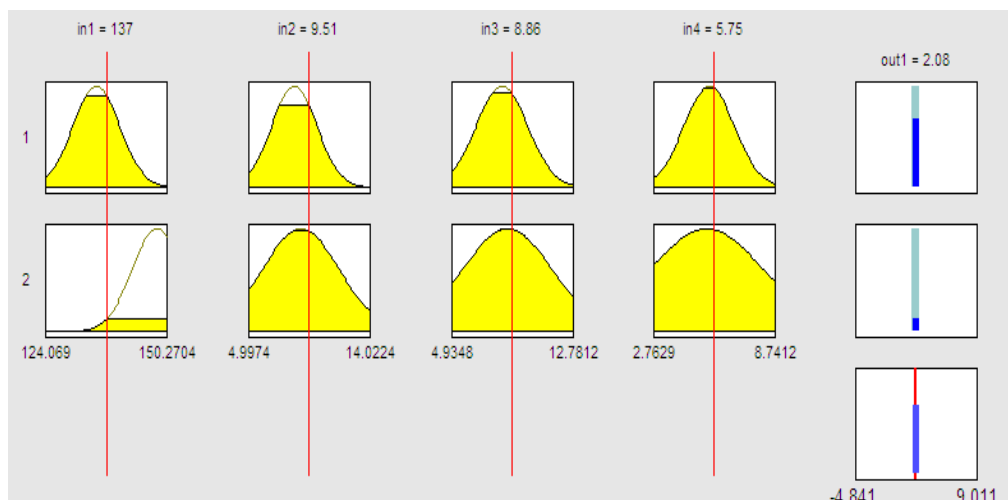


Fig. 5. Membership Function of FCM-Generated FIS

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D. Artificial Neural Network (ANN) Classifier

In order to compare the performance of ANFIS, we used the ANFIS parent's method called Artificial Neural Network (ANN) with feed forward network type. Using similar strategies in term of data training, data testing, and data validation, we classified the retina into normal or abnormal. We used cross validation or confusion matrix to measure the performance. Since ANFIS combines the ANN and Fuzzy Logic, we hypothesized that ANN performance was less accurate than ANFIS performance. In this work we used 2 and 3 hidden layers, as well as scaled conjugate gradient backpropagation for training function.

IV. RESULTS AND DISCUSSION

ANFIS and ANN classifiers were finally trained, validated, and tested to classify color fundus images as normal or DME. To measure the result, were evaluated in term of accuracy, sensitivity, and specificity % as follow.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100 \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \times 100 \quad (3)$$

Where,

- True Positive (TP) means the normal retinal image is detected as normal.
- True Negative (TN) means the abnormal retinal image is detected as abnormal.
- False Positive (FP) means the abnormal image is detected as normal.
- False Negative (FN) means the normal retinal image is detected as abnormal.

Table II represents the performance of ANFIS, 2 hidden-layers ANN, and 3 hidden-layers ANN. The accuracy, sensitivity, and specificity for 2 hidden-layers ANN classifier are 83.2%, 78.3%, and 88.1% respectively. While the accuracy, sensitivity, and specificity for 3 hidden-layers ANN classifiers are 90%, 94%, and 85.4%. In term of specificity, ANN with 2 hidden layers is the best among others. However, in term of sensitivity and overall accuracy, ANFIS is the best classifier.

TABLE II. PERFORMANCE MEASUREMENT RESULT OF ANFIS, 2 HIDDEN LAYERS ANN, AND 3 HIDDEN LAYERS ANN

| Parameters | ANFIS | 2 HL ANN | 3 HL ANN |
|-------------|-------|----------|----------|
| Accuracy | 92% | 83.2% | 90% |
| Sensitivity | 100% | 78.3% | 94% |
| Specificity | 84.1% | 88.1% | 85.4% |

Figure 6 illustrates the result of ANFIS classification towards data training, data validation, data testing, and overall result in detail. Towards data validation, accuracy, sensitivity, and specificity are 94.1%, 100%, and 88.2%. While towards data testing, accuracy, sensitivity, and specificity are 92.6%, 100%, and 85.3%. Overall the accuracy of ANFIS classifier is the best with 92% accuracy, 100% sensitivity, and 84% specificity.

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Vol. 4, Issue 8, August 2015

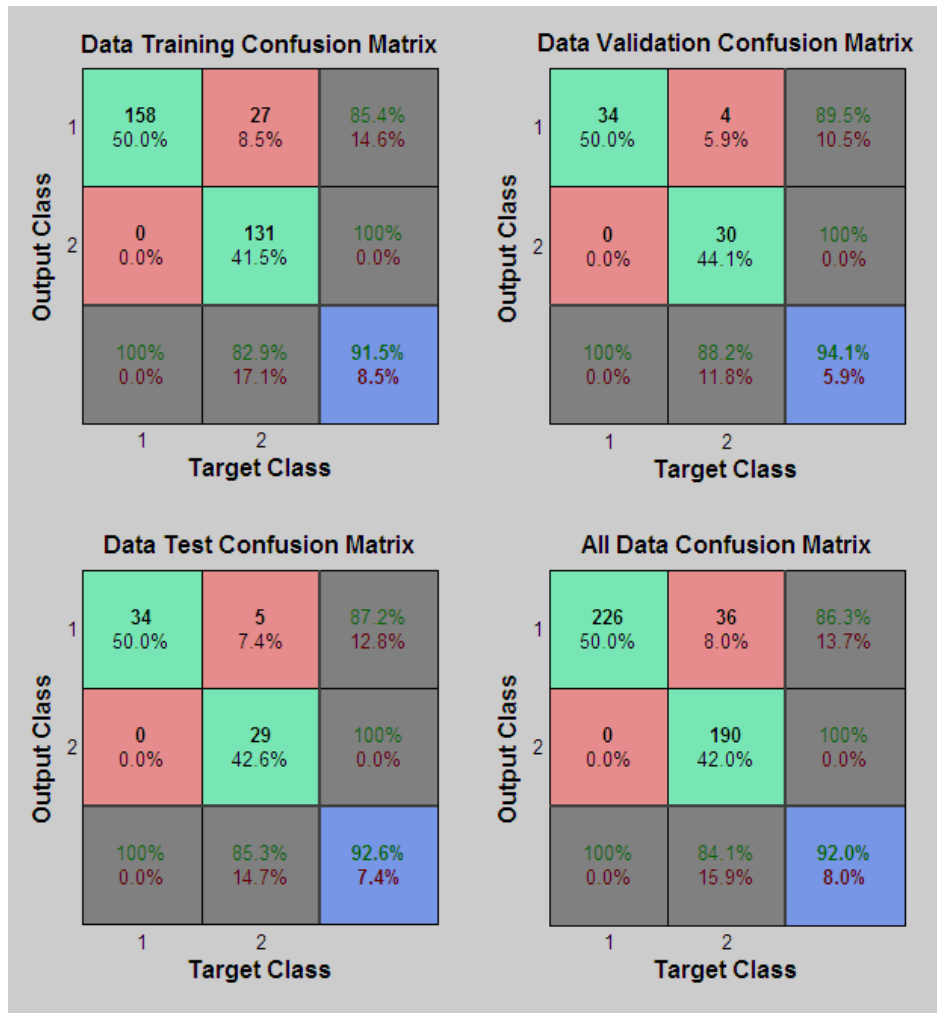


Fig. 6. ANFIS Performance with Confusion Matrix

V. CONCLUSION

In this paper we propose DME CAD of color fundus images using 2D DWT and ANFIS. By using MESSIDOR dataset, we have successfully trained the system to classify whether the fundus image is normal or abnormal with overall 92% accuracy. The results show that our proposed method is 9% and 2% better than 2-hidden layers ANN and 3-hidden layers respectively.

FUTURE WORKS

We recommend continuing this work in order to classify DME severity into moderate and severe. Detection and cropping of macula area can be considered to improve the accuracy.

ACKNOWLEDGMENT

The authors would like to thank Dr. Diaz D. Santika of Bina Nusantara University for his guidance.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 8, August 2015

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BIOGRAPHY



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