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Computer-Aided Diagnostic Tool for the Detection of Macular Disorder using Retinal OCT Images.

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Abstract— The Optical Coherence Tomography (OCT) is an emerging technology in which lot of research work is going on to simplify the diagnosis of eye diseases. The proposed work is aimed at developing a computer aided diagnostic tool for detection of macular disorders like Age Related Macular Degeneration (ARMD) and its severity from which the dosage level and frequency of the intravitreal Anti-Vascular endothelial growth factor agents like Ranibizumab and Bevacizumab given to treat ARMD. The Retinal 3D OCT images are preprocessed using various filters and based on the parameters (MSE, RMSE, PSNR,UIQI) observed, Shock Filter gave the most prominent result The Symptomatic Exudate-Associated Derangement(SEAD) region is then segmented by Active Contour method. The features extracted are Runlength features, intensity features and Co-occurrence matrix features. Extreme Learning Machine (ELM), Self-Adaptive Resource Allocation Network (SRAN) and Meta-Cognitive Neural Network (McNN) are trained to classify the severity of the disease based on these extracted features and overall efficiency of 80, 87 and 80 percent is achieved respectively.

Keywords—Optical Coherence Tomography (OCT), Symptomatic Exudate-Associated Derangement (SEAD), Segmentation, Features, classification.

I. Introduction

Optical Coherence Tomography (OCT) is a new type of optical imaging modality. OCT performs high-resolution, cross-sectional tomographic imaging technique. OCT enables the contactless, non-invasive imaging of both the anterior and the posterior eye. The OCT is the imaging technique which helps to visualize the layers of retina in 3D view and analyze it in 2D. . Since OCT retinal images have a 10 µm of resolution, it is used for the detection and monitoring of a variety of macular diseases including macular edema, macular holes, age-related macular degeneration and choroidal neo-vascularization. Hence OCT plays a vital role in diagnosis and monitoring of diseases such as Age related Macular Degeneration and Macular Edema.

ARMD is the major cause of vision loss for the people above the age of 50 and also it can affect the diabetic patients in the age group of 45 to 64 years. There are two types of macular degeneration that are referred as 'wet' and 'dry'. Only about 10% of all people with macular degeneration have the 'wet' type (all others are affected by the 'dry' type). 'Wet' macular degeneration is caused by the accommodation of fluid under the retina. This causes bleeding and scarring which automatically leads to vision loss. 'Dry' macular degeneration develops slowly, then over years, and there is no treatment for this till now.

Manual extraction of SEAD region and classification of severity level is tedious and time consuming for physicians. Many methods have been reported for the segmentation of SEAD region. Many recent works have been reported on semi-automated segmentation of SEAD which requires manual initialization. Intravitreal injection which causes a regression of vascularization in retinal layer and reabsorbs fluid in that layer is generally used for treatment of ARMD. Determining the frequency and dosage level of this injection to ARMD patients based on accumulation of fluid is a challenging task. Hence we propose a new tool to extract the SEAD region and to classify it based on severity so that dosage level of intravitreal injection could be determined.

II. Methodology

Fig.1 shows the flowchart of overall processing. Our work begins with the collection of Retinal OCT images from sankara nethralaya eye hospital nungambakkam. Preprocessing is done by filtering process the comparison of different filters were done namely median filter, weiner filter, anisotropic diffusion filter, shock filter and the filter coefficients are derived. According to the mean square error and universal image quality index the Shock Filter

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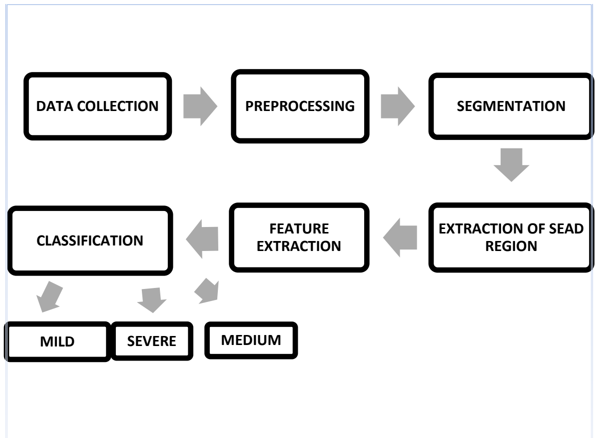


Fig.1 Flowchart of overall processing

is the best in reducing the speckle noise in oct images. Segmentation followed by the preprocessing is done by using two methods like marker-controlled watershed segmentation and active contour method. As marker-controlled watershed segmentation has oversegmentation problem which reduces some information in the image. So active contour method snake model is used mainly for edge preservation. Features like runlength feature, intensity feature, cooccurance matrix are extracted and parameters are calculated. The classifers like Extreme Learning machine (ELM), self-adaptive Resource allocation network (SRAN) and Meta-cognitive Neural Network (McNN) are used which are classified based on the severity of disease such as mild medium and severe. And the result is cross checked with the clinician's knowledge and verified.

III. *Preprocessing*

Preprocessing is done by comparing different types of filters and deriving the coefficients. Median filter can reduce the noise, but it leads to smoothening of image and blurring effect. Weiner filter gives a least mean square error but have reduces the sharpening of edges in an image. Anisotropic diffusion filer is used to reduce the speckle noise gradually present in OCT images. Shock filter provides us the most prominent effect by giving low mean square error value and high universal image quality index value.Fig.2 shows the output of shock filter.

IV. *Segmentation*

Active Contour Algorithm is used for segmentation. Active contours, or snakes, are computer-generated curves that move within images to find object boundaries. Our snake, which we call the gradient vector flow (GVF) snake, begins with the calculation of a field of forces, called the GVF forces, over the image domain. The GVF forces are used to drive the snake, modeled as a physical object having a resistance to both stretching and bending, towards the boundaries of the object. Fig.3 shows the working of active contour algorithm. The GVF forces are calculated by applying generalized diffusion equations to both components of the gradient of an image edge map. Since the GVF forces are derived from a diffusion operation, they tend to extend very far away from the object and this extends the capture range. The GVF snake is a new approach to active contours and surfaces. It focuses on the design of the external force first, and the implementation of the snake second. The computations are straightforward, and the result is always better than the traditional snake.

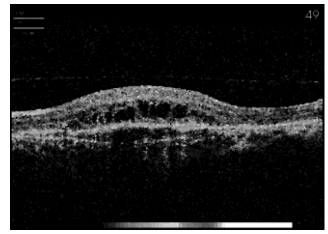
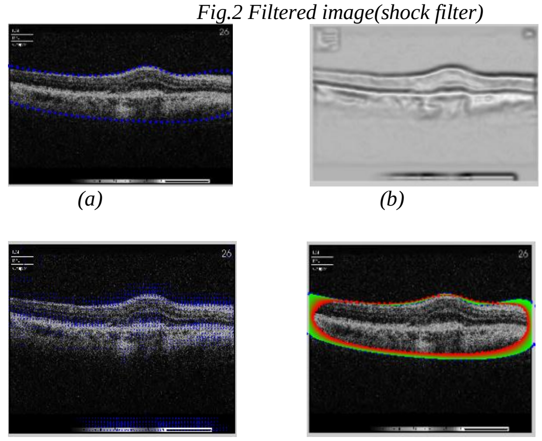


Fig.2 Filtered image(shock filter)



(a) *(b)* *(c)* *(d)*

Fig.3 Segmentation using Active contour
(a)Image with Initial Contour, (b)The External Energy, (c) The External Force Field, (d) Snake Movement.

IV. *Feature Extraction*

For giving the input to the classifier, the features are extracted from the segmented image. The features extracted are Intensity feature (mean, variance, standard deviation, skewness, kurtosis) Runlength features (short run emphasis, long run emphasis, grey-level non-uniformity, run percentage, Runlength non-uniformity, low grey-level emphasis, high grey-level emphasis) Co-occurrance matrix features (energy, entropy, correlation, contrast, homogeneity, variance, mean, inertia, cluster shade, cluster tendency, maximum probability, intensity variance).

A. ***Intensity features***

Features derived from this approach include moments such as mean, standard deviation, average energy, entropy, skewness and kurtosis. The histogram of intensity levels is a simple summary of the statistical information of the image and individual pixels are used to calculate the gray-level histogram. Therefore, the Table.1 contains the first-order statistical information about the image (or sub image).

B. ***Runlength features***

Another method characterizes texture images based on run-lengths of image gray levels. Galloway, Chu *et.al.* and

Dasarathy and Holder introduced different run-length matrices as feature representatives. For a given image, a run-length matrix is defined as the number of runs with pixels of gray level and run-length.

C. *Co-Occurrence Matrix*

Texture can be characterized by regular or random patterns that repeat over a region. As one of the most important features for image analysis; texture provides information regarding structural arrangement of surfaces or changes in intensity or color brightness. Despite the accuracy of the visual human system to recognize textures, it is a complex task to define a set of textural descriptors for image analysis on different domains of knowledge. The large number of definitions and descriptors found in the literature reflects such

Table 1. Intensity features.

Class	Mean	Variance	SD	Skewness	Kurtosis
Mild	0.06	231.8769	15.2	0.92470	0.85329
Medium	0.44	12470.36	111	0.98175	0.96384
Severe	1.67	177960.4	421	0.98883	0.97780
Mild	0.30	5661.882	75.2	0.97681	0.95412
Medium	0.36	8347.486	91.3	0.97919	0.95881
Severe	1.20	91072.95	301	0.98470	0.96963

SD – Standard Deviation

difficulty. Although there is no a unique categorization of the main relevant methods for texture description, they can be classified as statistical approaches, signal- processing based approaches, geometrical approaches, and parametric-model based approaches. Among the statistical approaches, gray level co-occurrence matrices (GLCM) have been proved to be a very powerful texture descriptor used in image analysis.

V. *Classification*

A. *Extreme Learning Machine:*

This is a non-iterative learning algorithm named extreme learning machine (ELM) to train the Single Layer Feedforward Network (SLFN). The input weights and hidden layer neuron biases were arbitrarily assigned. Though this makes fast learning speed, but the recognition rate varies with some standard deviation value. As the SEAD layers of retina has the problem is highly nonlinear and non-convex, ELM does not provide desirable performance, if the number of hidden layer neurons is small. To achieve less error rate, we require large hidden layer neurons for ELM.To overcome these problems, we propose a new learning algorithm for SLFN, in which the input weights and biases are assigned from approximate basis vectors of input training space. The output weights and biases are decided through inverse operation on output matrix of hidden layer. Our learning algorithm provides not only better generalization performance but also faster learning rate. Fig.4 shows the structure of Extreme Learning Machine

B. *Self-adaptive Resource Allocation Network*

SRAN classifier uses a sequential learning algorithm, employing self-adaptive thresholds to select the appropriate training samples and discard redundant samples to prevent over-training. These selected training samples are then used to evolve the network architecture efficiently. The basic building block of SRAN classifier is a radial basis function network. SRAN classifier starts with a zero hidden neuron and builds an appropriate number of hidden neurons to approximate the decision surface. SRAN classifier employs a sequential learning algorithm with self-adaptive thresholds to select the appropriate training samples required to approximate the decision function efficiently.

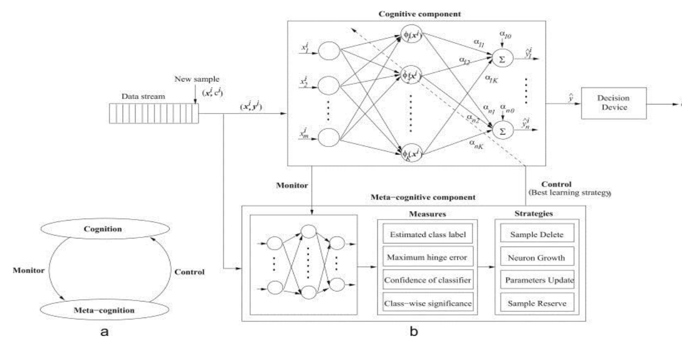


Fig.5a: Nelson and Narens model of Meta-Cognition. Fig.5b. Schematic diagram of McNN learning algorithm.
Source : www.sciencedirect.com/science/article/pii/s0925231211006862#

C. **Meta-Cognitive Neural Network**

Fig.5a and Fig.5b shows McNN network structure.McNN architecture is developed based on the Nelson and Narens meta-cognition has two components, a cognitive component and a meta-cognitive component.The cognitive component of McNN is a three layered feed forward radial basis function network with Gaussian activation function in the hidden layer and the other contains copy of the cognitive component. When a new training sample arrives, the meta-cognitive component of McNN predicts the class label and estimates the knowledge present in the new training sample with respect to the cognitive component. Based on this information, the meta-cognitive component selects a suitable learning strategy, for the current sample. Thereby, addressing the three fundamental issues in learning process: (a) what-to-learn, (b) when-to-learn and (c) how-to-learn.

VI. *Results and discussion*

A. *Performance of filters*

In preprocessing, the noise in the image is reduced. There are four type filters are used for this purpose and they are weiner filter, median filter, anisotropic diffusion filter and shock filter. While removing noise, shape information must be

Class	Clinician result	SRAN		ELM		MCNN	
Mild	5	TP	5	TP	4	TP	5
		FN	0	FN	1	FN	0
Medium	5	TP	4	TP	4	TP	4
		FN	1	FN	1	FN	1
Severe	5	TP	4	TP	4	TP	3
		FN	1	FN	1	FN	2

preserved. The best filter is estimated based on the four parameters listed in the Table 2. From the table it is clear that the shock filter with lest mean square error and high peak signal to noise ratio gives best outcome.

Table.2 Validation of filter

Filter coefficient	Median filter	Weiner filter	Anisotropic diffusion filter	Shock filter
MSE	306.1032	282.576	796.77929	235.795
PSNR	+23.30 dB	+29.26 dB	+19.151 dB	+24.43 dB
RMSE	17.495	16.81	28.22	15.35
UIQI	0.46492	0.56829	0.46044	0.65599

MSE: Mean square Error,
PSNR: Peak Signal to Noise Ratio,
RMSE: Root Mean Square Error,
UIQI: Universal Image Quality Index

B. Performance of Classifier

The severity level of the disease condition was classified from the segmented region of interest by using three types of classifiers like Extreme Learning Machine, Self-adaptive Resource Allocation Network and Meta-cognitive Neural Network.

Table.3, Table.4 and Table.5 shows the performance of different classifiers like SRAN, ELM AND McNN respectively. The overall classifier efficiency of 87 percentage was achieved for SRAN and for ELM and McNN 80 % is achieved.SRAN found to be useful compared to ELM and McNN. Sensitivity and specificity of mild and severe type is high in SRAN and ELM whereas sensitivity and specificity of medium type is better in McNN.

Table.3 Self-adaptive Resource Allocation Network(SRAN)

Classes	Accuracy	Error rate	Sensitivity	Specificity
Mild	0.93	0.07	1	0.90
Medium	0.87	0.13	0.80	0.90
Severe	0.93	0.07	0.80	1
Overall efficiency		0.87	**Error rate**	0.13

Table.4 Extreme Learning Machine(ELM)

Classes	Accuracy	Error rate	Sensitivity	Specificity
Mild	0.87	0.13	0.80	0.90
Medium	0.80	0.20	0.80	0.80
Severe	0.93	0.07	0.80	1
Overall efficiency		0.80	**Error rate**	0.20

Table.5 Meta Cognitive Neural Network(McNN)

Classes	Accuracy	Error rate	Sensitivity	Specificity
Mild	0.80	0.20	1	0.70
Medium	0.93	0.07	0.80	1
Severe	0.87	0.13	0.60	1
Overall efficiency		0.80	**Error rate**	0.20

Table.6 Validation of classifier

TP: True Positives, FN: False Negatives

The performance classifiers are validated against the clinician's result and better correlation between the results was obtained. Table.6 shows the validation of classifier.

VII. *Conclusion*

The proposed work thus classifies the severity of the Age Related Macular Degeneration (ARMD). The classifications of the severity also help the doctors in finding the impact of the drug, dosage and the frequency on the treatment of the disease. Hence the doctors can opt for other drug or change the dosage if the severity remains the same. In addition to Age-Related Macular Degeneration (ARMD) other associated disorders like Macular Edema, Macular Hole diagnosis were also a challenging task. Algorithm can be developed to diagnose and classify the severity of these retinal disorders along with ARMD.

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