CHAPTER-6

DETECTION OF BRIGHT LESIONS IN DIGITAL FUNDUS IMAGES

Diabetic retinopathy is a serious complication of diabetes mellitus and primary cause of blindness in Indian adults. Bright lesions such as hard exudates and cottonwool spots are the visible signs of diabetic retinopathy. These bright lesions are also an indicator for the incidence of co-existent retinal edema. If present in the macular area, bright lesions are the major cause of visual loss. It would be helpful to have an automated method for detecting bright lesions in digital fundus images produced from screening programmes of diabetic retinopathy.

The shape, brightness and location of bright lesions vary a lot among different patients. Exudates are the serum lipoproteins which leak from the microaneurysms and capillaries that deposit on the retina. If these are untreated for long time, they will be transformed into clusters and finally become cottonwool spots. Cottonwool spots appear whitish with fuzzy boundaries. This chapter deals with these two kinds of bright lesions. A new method based on swfcm clustering is proposed to detect bright lesions in ocular fundus images. The SWFCM clustering is formulated by including the neighbourhood information into the standard FCM clustering. The SWFCM clustering can also be used to segment blood vessels.
This chapter is organized as follows. In Section 6.1, the design of the proposed method and its implementation details are presented. Section 6.2 describes candidate classification and the feature set used for classification of true bright lesions from bright non-lesions. Segmentation of blood vessels from fundus images based on SWFCM clustering is described in Section 6.3. In Section 6.4, experimental results are presented. Conclusions are provided in Section 6.5.

6.1. SWFCM CLUSTERING BASED BRIGHT LESION DETECTION

The proposed swfcm clustering based bright lesion detection method contains four steps as illustrated in fig.6.1. Firstly, the colour retinal image is preprocessed using local contrast enhancement technique in order to improve the contrast of the fundus image. Then the optic disk is eliminated because it appears in similar bright pattern, colour and contrast as the bright lesions. The bright lesions are segmented using swfcm clustering algorithm. The final stage aims to classify true bright lesions from bright non-lesions. For this purpose, knn and svm classifiers are used. The implementation details of swfcm clustering based bright lesion detection are as follows.

6.1.1 PREPROCESSING AND CONTRAST ENHANCEMENT

The contrast of the retinal images tends to reduce as the distance of a pixel from the centre of the image increases. The objective of
preprocessing is to reduce this effect by enhancing the contrast and normalizing the mean intensity. Firstly, the original image’s rgb space is transformed to hsi space. A local contrast enhancement method [14] is applied to the intensity image to improve both the contrast of bright lesions and the overall colour saturation of the retinal image. A transformation is applied to the pixel values inside small windows in the retinal image in such a way that all pixel values are distributed about the mean and show all possible gray level intensities. Hence, running a window $w$ of size $63 \times 63$ on the initial image, the image is filtered to produce a new image $g$:  

![Flow Chart of the Proposed Method](image)

Fig. 6.1. Flow Chart of the Proposed Method
\[ G[i, j] = 255 \left[ \frac{\phi_w(p) - \phi_w(Min)}{\phi_w(Max) - \phi_w(Min)} \right] \]  \hspace{1cm} (6.1)

And the sigmoid function is:

\[ \phi_w(p) = \left[ 1 + \exp \left( \frac{\mu_w - p}{\sigma_w} \right) \right]^{-1} \]  \hspace{1cm} (6.2)

The \textit{max} and \textit{min} indicate the maximum and minimum gray level intensities in the whole image, while \( \mu_w \) and \( \sigma_w \) refer to the mean and standard deviation of each window. A significant contrast enhancement is produced by this function when \( \sigma_w \) is small (low contrast) and low enhancement when \( \sigma_w \) is large (high contrast).

However, this local contrast enhancement not only corrects the contrast of the image but also enhances the noise. Therefore, a median filter is employed to decrease the noise prior to local contrast enhancement step. From figs. 6.2. (c) and (d), it can be viewed that the contrast of the lesions is enhanced and also the overall colour saturation is improved for the retinal images shown in figs. 6.2. (a) and (b).

\section*{6.1.2. OPTIC DISK ELIMINATION}

The optic disk is characterized by the biggest high-contrast area. The optic disk is roughly detected by using the entropy feature on the contrast enhanced image. The entropy is a measure of randomness
That is used to differentiate the texture of an input image. Entropy is defined as

\[ H(x) = - \sum_{i \in W(x)} p_i \log_2(p_i) \]  \hspace{1cm} (6.3) 

Where \( x \) refers to a set of pixels in a sub-window \( w(x) \), 

\( p_i \) indicates the histogram counts in the sub-window \( w(x) \) 

and \( i \in w(x) \).
A window of size 9 x 9 pixels is used. The resulting image is thresholded using otsu algorithm [107] in order to eliminate the regions with low local variation. To include the neighbouring pixels of the thresholded result, a dilation operator is used. A flat disk shaped structuring element having radius of eleven is employed for dilation. The eliminated optic disk regions for the images shown in figs. 6.2. (a) and (b) are as shown in fig. 6.3.

6.1.3. Segmentation of Candidate Bright Lesions

Bright lesion segmentation is a process of partitioning the image pixels depending on one or more selected image features. In this case gray level is selected as image feature. The aim is to separate the image pixels that have dissimilar gray levels into different regions and simultaneously, grouping the pixels which are spatially connected and having similar gray level into the same region. Here, swfcm clustering is proposed for bright lesion segmentation.

The standard fcm algorithm is a clustering technique that minimizes the objective function:

$$ J_q(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q d^2(x_k, v_i) $$  \hspace{1cm} (6.4) 

Where $x = \{x_1, x_2, \ldots x_k\} \subseteq r^n$,

$n$ - corresponds to the number of data items, 4 for the proposed case,
$C$ - refers to the number of clusters, also 4,

$\mathbf{v}_i$ - is the centroid of cluster $i$,

$u_{ik}$ - corresponds to the degree of membership of $x_k$ in the $i$th cluster,

$d^2(x_k, \mathbf{v}_i)$ - distance measure between cluster center $\mathbf{v}_i$ and object $x_k$ and

$q$ - is a constant. The fuzziness of the resulting partition is controlled by this parameter $q$ and $q = 2$ is selected for the proposed bright lesion detection method.

The flow chart of the swfcm clustering is shown in fig. 6.4. Since the fcm algorithm is an iterative process, it is time-consuming. To increase the speed of the clustering process, gray level histogram of the image is applied instead of the whole data of the image to compute the parameters for the FCM algorithm [108]. Let His(g) indicates the

Fig.6.3. Eliminated Optic Disk Regions of Fig. 6.2(a) and (b)
number of image pixels having a gray level \( g \), \( g \in \mathcal{G} \). The histogram function is as follows:

\[
\text{His}(g) = \sum_{s=0}^{S-1} \sum_{t=0}^{T-1} \delta(f(s,t) - g)
\] (6.5)

Where \( g = \{l_{\text{min}}, l_{\text{min}}+1, \ldots, l_{\text{max}}\} \), where \( l_{\text{min}} \) indicates the minimum gray level, \( l_{\text{max}} \) refers to the maximum gray level value, \( \delta(0)=1 \) and \( \delta(\neq 0)=0 \). For image of size \( s \times t \), \( f(s,t) \) corresponds to the gray level value at point \((s,t)\), with \( 0 \leq s \leq s-1, 0 \leq t \leq t-1 \).

The cluster center \( v_i \) is calculated using the following equation [108].

\[
v_i^{(b)} = \frac{\sum_{g=L_{\text{min}}}^{L_{\text{max}}}(u_{ig}^{(b)})^q \cdot \text{His}(g)g}{\sum_{g=L_{\text{min}}}^{L_{\text{max}}}(u_{ig}^{(b)})^q \cdot \text{His}(g)}
\] (6.6)

To consider the affect of neighbouring pixels on central pixel, the fuzzy membership function \( u_{ik} \) in eq. (6.4) is extended to \( u_{ik}^* = u_{ik} P_{ik} \), where \( k = 1,2,\ldots,n \), \( n \)-indicates the index of each image pixel and \( p_{ik} \) is the probability of a data point \( k \) belonging to cluster \( i \). It is referred as weight, which can be found based on the neighbourhood information inspired from KNN algorithm [109].
Set values for $c$, $q$ and $\varepsilon$

Initialize the fuzzy partition matrix $U$

Set the loop counter $b \leftarrow 0$

Calculate $c$ cluster centers $\{V^{(b)}_i\}$ with $U^{(b)}$

$k \leftarrow 1$

If $k < n$

\[ I_k = \{1 \leq i \leq c, d_{ik} = \|v_i - v_k\| = 0\} \]

$\bar{I}_k = \{1, 2, \ldots, c\} - I_k$

If $I_k = \emptyset$

$\sum_{i \in \bar{I}_k} u^{(b+1)}_{ik} = 0$ for all $i \in \bar{I}_k$

$k \leftarrow k + 1$

$b \leftarrow b + 1$

If $\|U^{(b)} - U^{(b+1)}\| < \varepsilon$

Stop

Stop

$\sum_{i \in I_k} u^{(b+1)}_{ik} = 1$

Fig. 6.4. Flow Chart of SWFCM Clustering.
\[ u_{ik}^{(b+1)} = \frac{p_{ik}}{\sum_{j=1}^{c} \left( \frac{d_{ik}^j}{d_{jk}} \right)^{2/(q-1)}} \]  
\[ p_{ik} = \frac{\sum_{x_n \in N_k^i} 1/d^2(x_n, k)}{\sum_{x_n \in N_k} 1/d^2(x_n, k)} \]  

Where \( n_k \) refers to the data set of the nearest neighbours of central pixel \( k \) and \( n_k^i \) is the subset of \( n_k \). It composes the data belongs to class \( i \). Using these conditions, the flow chart for the swfcm algorithm can then be described as shown in fig. 6.4. Here, \( \varepsilon \) is the convergence threshold and \( \varepsilon = 0.01 \) is used for the proposed approach.

When the swfcm algorithm is converged, a defuzzification process takes place to change the fuzzy partition matrix into a crisp partition. The maximum membership procedure is used to defuzzify the partition matrix \( u \). This procedure allots object \( k \) to class \( c \) with the highest membership.

\[ C_k = \arg_i \{ \max(u_{ik}) \}, \ i = 1, 2, ..., c. \]

For the images shown in figs. 6.2(a) and (b), the yielded bright lesion candidates by swfcm clustering are in figs. 6.5(a) and (b). Overlay of the detected bright lesions on colour retinal images are shown in figs. 6.5(c) and (d).
6.2. CLASSIFICATION OF BRIGHT LESIONS FROM BRIGHT NON-LESIONS

The segmentation of bright lesions results in a set of candidate bright lesion objects. The aim of the candidate bright lesion classification system is to classify the detected objects as either bright lesion or bright non-lesions. The bright non-lesions (false positives) are due to the influence of cluster overlapping and non-uniformity of gray level. These false positives are also due to the presence of regions

Fig. 6.5. (a) and (b) Detected Bright Lesions for the Images shown in Figures 6.2(a) and (b); (c) and (d) Overlay of Detected Bright Lesions on Colour Retinal Images.
having high background brightness. Generally these regions are present above and below the optic disk and these are very noisy. Hence to discard such candidates, classifiers are used which are trained with the features derived from the candidates. The best classification requires good features as well as good classifier.

6.2.1. Extracted Features

In the proposed method, 12 features are extracted for each candidate and two kinds of classifiers are tested. Each feature can discriminate bright lesion from non-bright lesion candidate. The features are listed below.

1) The area \( a = \sum_{j \in \Omega} 1 \) where \( \Omega \) is the pixel set in the candidate bright lesion.

2) The perimeter is the length of boundary pixels of the candidate which is approximated using the chain codes \([110]\) of the object. In calculating perimeter, the length of vertical and horizontal neighbours are counted as one and diagonal neighbours are counted \( \sqrt{2} \) times.

3) The circularity \( = \frac{p^2}{4\pi a} \) where \( p \) indicates the perimeter of the candidate bright lesion and \( a \) denotes the area of the bright lesion region. Circularity helps in finding the circular and elongated objects.
4) The aspect ratio is measured as ratio of length of the largest Eigen vector to the length of second largest Eigen vector of covariance matrix of the object.

5) Solidity is measured as the ratio of area and area of the convex region that contains the candidate.

6) Total intensity is measured inside the candidate region in the original gray level image.

7) Mean intensity is calculated inside the candidate region in the original gray level image.

8) Standard deviation inside the candidate region in the original gray level image is measured.

9) Total intensity inside the candidate region in the intensity image is evaluated.

10) Mean intensity is measured inside the candidate region in the intensity image.

11) Standard deviation inside the candidate region in the intensity image is measured.

12) Region edge strength $\nabla f(x, y) = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$

6.2.2. CLASSIFIERS

To classify bright lesions from bright non-lesions knn and svm classifiers are tested.
6.2.2.1. KNN CLASSIFIER

The choice of appropriate classifier has two important aspects:

1. The classifier must be robust against outliers present in the training set.
2. The distribution of the features is unknown.

Here knn classifier [109] is chosen because it satisfies the above two aspects. The method will be robust against outliers if k is reasonably large, non-parametric and makes no assumption regarding the distribution. The drawback of knn classifier is that the method may not work properly if the training data is asymmetric.

6.2.2.2. Support Vector Machine Classifier

SVMs are statistical learning methods based on structural risk minimization. The purpose of training SVMs is to find the decision hyper plane with highest margin. If the margin is higher then the generalization of the classifier is better. Sometimes, it is necessary to do the classification in higher dimensional space where there could be some chances for the data to be separable. By choosing a non-linear mapping kernel, SVMs map the input vector to a high dimensional feature space. The best separating hyper plane in the feature space is [111]:

\[ f(x) = \text{sgn} \left( \sum_{i=1}^{l} y_i \alpha_i K(x, y) + b \right) \]  

(6.10)
where $b$ is the bias,

$$K$$ indicates the kernel function,

$y_i$ refers to the labels and

$\alpha_i$ are the Lagrange multipliers.

A Gaussian radial basis function is applied as the kernel.

$$K(x,y) = \exp\left(-\frac{||x-y||^2}{2\sigma^2}\right)$$

The optima values of $\sigma$ and $C$ are found using grid search on training data. $C$ is varied from $2^{-5}$ to $2^{15}$ in multiples of 2 and $\sigma$ is varied from $2^{-15}$ to $2^3$ in multiples of 2. The values corresponding to minimum 4-fold validation error are taken. The detected bright lesions after SVM classification for the images in Fig.6.2 (a) and (b) are shown in Fig.6.6 (a) and (b). Overlay of these true bright lesions on respective colour retinal images are shown in Fig.6.2 (c) and (d).

6.3. SEGMENTATION OF BLOOD VESSELS USING SWFCM CLUSTERING

The SWFCM can also be used to extract the blood vessels of retinal images. The method comprises four main steps as illustrated in chapter - 3. Firstly, the histogram of the green component is modified by employing the histogram of red component (of the same fundus image) to obtain a new processed image. In order to increase the contrast of vessels, matched filter is applied to the histogram matched image. Then instead of using thresholding based on local relative
Entropy, SWFCM clustering based thresholding can be used to differentiate vessel segments from the background in the matched filter response image. To remove the misclassified pixels, label filtering technique is used.

6.4. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental results of the proposed bright lesion detection and blood vessel segmentation methods based on SWFCM clustering are described in this section.

Fig. 6.6. (a) and (b) Detected Bright Lesions after SVM Classification for the Images in Fig. 6.2(a) and (b); (c) and (d) Overlay of True Bright Lesions on Colour Retinal Images.
6.4.1. Bright Lesion Detection

The proposed SWFCM clustering based bright lesion detection method is tested and evaluated on DIARETDB1, a publicly available database of coloured images and corresponding groundtruth images. Lesion based evaluation and image based evaluation are employed to measure the accuracy of the SWFCM clustering based bright lesion detection method at the pixel level. These evaluations consider four values: True Negative (TN), False Negative (FN), True Positive (TP), and False Positive (FP). From these quantities, the sensitivity is computed by TP/TP+FN and specificity is also calculated by TN/TN+FP. The proposed method is implemented in MATLAB 7.4 on a core 2 Duo 1.8 GHz PC with 1GB memory.

In the classification stage, a training set obtained from 30 images, consisting of 432 segmented bright non-lesion areas and 213 bright lesions is used. A testing set with 59 images selected randomly from DIARETDB1 database consisting of 1281 bright non-lesion areas and 755 bright lesions is employed. The optimal number of features and classifier parameters are derived using the classification accuracy on the training data. For KNN classifier, 12 features and 9 neighbours are used. For SVM classifier 12 features are used. All these values are corresponding to the highest accuracy. Sensitivity and specificity can be enhanced further at the cost of each other.
The lesion based results of the SWFCM clustering method are given in Table 6.1. These values correspond to the true and false candidates in the detected candidate set. There is no much difference between the performances of the classifiers but SVM is slightly better than KNN.

Fifty nine retinal images are tested by the proposed bright lesion detection algorithm. In these 59 images, seventeen images are identified to have no bright lesions, while bright lesions are present in the other 42 images. Table 6.2 reports the image based results of the proposed method. An image is judged to be true if it has a minimum of two bright lesion candidates detected in it, otherwise false.

In the SVM results, two images are detected as false positives. These two images have only drusen and in the groundtruth these drusen deposits are labeled as non-bright lesions. As no mechanism to differentiate drusen from exudates is incorporated so comes the false positive.

To compare the performance of the classifiers ROC curve is used. The ROC curves obtained for the classifiers are as shown in Fig. 6.7. The area under the ROC curve specifies with how much accuracy the given classifier is correctly classifying two randomly selected true and false samples. It can be noticed from Fig. 6.7 that SVM classifier has more area under the ROC compared to KNN classifier.

Two examples of bright lesion detection results are shown in Fig. 6.8. The detected bright lesions are represented by the white colour. From these two figures, it can be seen that most of the bright lesions can be identified successfully in these two retinal images. The bright
lesions present nearer to fovea region will influence the vision of patients more than the bright lesions in the other locations. Clinically, the ophthalmologists will treat these cases in Figs. 6.8 (a) and (b) by Laser. In order to study the severity of retinal diseases the distribution of bright lesions need to be analyzed.

<table>
<thead>
<tr>
<th>Table 6.1 Lesion Based Results</th>
<th>Classifier</th>
<th>KNN</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>True positives</td>
<td>707</td>
<td>732</td>
<td></td>
</tr>
<tr>
<td>False positives</td>
<td>92</td>
<td>51</td>
<td></td>
</tr>
<tr>
<td>False negatives</td>
<td>48</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>True negatives</td>
<td>1189</td>
<td>1243</td>
<td></td>
</tr>
<tr>
<td>Accuracy</td>
<td>93.12%</td>
<td>96.36%</td>
<td></td>
</tr>
<tr>
<td>Sensitivity</td>
<td>93.64%</td>
<td>96.95%</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>92.81%</td>
<td>97.03%</td>
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<table>
<thead>
<tr>
<th>Table 6.2 Image Based Results</th>
<th>Classifier</th>
<th>KNN</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>True positives</td>
<td>39</td>
<td>42</td>
<td></td>
</tr>
<tr>
<td>False positives</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>False negatives</td>
<td>3</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>True negatives</td>
<td>16</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Accuracy</td>
<td>93.22%</td>
<td>96.61%</td>
<td></td>
</tr>
<tr>
<td>Sensitivity</td>
<td>92.85%</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>94.11%</td>
<td>88.23%</td>
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6.4.2. Segmentation of Blood Vessels

The proposed algorithm is tested and evaluated on two publicly available databases of coloured retinal images and corresponding manual segmentations: the DRIVE [94] and STARE [20] databases. The proposed method is coded in MATLAB 7.4 on a core 2 Duo 1.8 GHz PC with 1GB memory.

In order to evaluate the performance, simulation results of the proposed blood vessel segmentation method are compared with the state-of-the-art results obtained from piecewise threshold probing [20] and hand-labeled groundtruth segmentations. The images are as shown in Fig 6.9. Although results of algorithm in [20] demonstrate a better performance, a noteworthy improvement is attained by the
Fig. 6.8. Results of Bright Lesion Detection
(a) Left Eye and (b) Right Eye
Fig. 6.9 Results Produced by the Proposed SWFCM Clustering Method and Manual Segmentations for Two Images from STARE Database. Top Row Results Originate from a Normal Case, While the Bottom Row Results Originate from an Image having Pathology. (a) Retinal Images. (b) First Observer (c) Segmentation Results of Hoover et al.[20] (d) Segmentation Results of Proposed SWFCM Clustering Method.

Fig. 6.10 (a) Retinal Image from the DRIVE database (b) Manual Segmentations from Set A (c) Manual Segmentations from Set B (d) Segmentation Results of SWFCM Clustering Method.
The proposed method for normal fundus images where in there is a sharper segmentation of the vessels. The performance on abnormal fundus image is shown in second row. The result shows that the proposed SWFCM clustering based blood vessel segmentation method is an effective method and outperforms the vessel segmentation method in [20] when the fundus image contains abnormalities. In [20] the abnormalities are segmented as blood vessels. The proposed method successfully extracted both the thick and thin vessels with good accuracy.

The ROC curve for the proposed method, method of Jiang et al. and method of Chaudhuri et al. is shown in Fig. 6.11. Table 6.3 reveals the comparison of area under ROC curve and average accuracy for different supervised and unsupervised blood vessel segmentation methods. It can be seen from the table that, generally supervised methods outperform unsupervised methods. Though the proposed method is unsupervised, the area under ROC and the average accuracy for the fundus images in STARE database are very close to the supervised methods. The performance of this method is superior compared to unsupervised approaches.

6.5. CONCLUSIONS

In this chapter, an efficient approach for bright lesion detection in fundus images is presented. The proposed SWFCM clustering approach not only takes into account the advantage of the fuzzy
Fig. 6.11 (a) ROC Curve for Classification on the DRIVE Database. The point marked as ‘□’ corresponds to set B, the second set of manual segmentations. The Proposed Method has $A_z = 0.9410$. (b) ROC Curve for Classification on the STARE Database. The point marked as ‘□’ corresponds to set B, the second set of manual segmentations. The Proposed Method has $A_z = 0.9505$. 

(a) 

(b)
framework, but also considers the spatial relation among pixels. The weight in the SWFCM algorithm is inspired by KNN classifier. The weight is modified on the basis of the influence of neighbourhood on the central pixel to improve the performance of image thresholding. Due to the consideration of the neighbourhood information, the method becomes noise resistant. The gray level histogram of the image is employed in the proposed SWFCM clustering instead of the whole data of image. Hence, the proposed SWFCM clustering is very fast compared to other FCM based methods.

The proposed method for bright detection presents encouraging results in identification of important features of diabetic retinopathy.

Table 6.3. Results for Different Blood Vessel Extraction Methods and a Second Human Observer.

<table>
<thead>
<tr>
<th>Segmentation Method</th>
<th>Database</th>
<th>Comment</th>
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<tbody>
<tr>
<td></td>
<td>DRIVE</td>
<td>STARE</td>
</tr>
<tr>
<td></td>
<td>$A_z$</td>
<td>Accuracy</td>
</tr>
<tr>
<td>Staal et al.</td>
<td>0.9520</td>
<td>0.9441</td>
</tr>
<tr>
<td>Soares et al.</td>
<td>0.9614</td>
<td>0.9466</td>
</tr>
<tr>
<td><strong>SWFCM Clustering method</strong></td>
<td><strong>0.9410</strong></td>
<td><strong>0.9442</strong></td>
</tr>
<tr>
<td>Jiang et al.</td>
<td>0.9327</td>
<td>0.8911</td>
</tr>
<tr>
<td>Chaudhuri et al.</td>
<td>0.9103</td>
<td>-</td>
</tr>
<tr>
<td>Lam et al.</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>2nd. observer</td>
<td>*</td>
<td>0.9473</td>
</tr>
</tbody>
</table>

*- Not available
The results of the proposed SWFCM clustering method on a per image basis show that the proposed approach achieved an accuracy of 96.61%, sensitivity of 100% combined with 88.23% specificity. The performance of the proposed method is fine even for lesion based evaluation. It achieves an accuracy of 96.36%, sensitivity of 96.95% and a specificity of 97.03%. By increasing the training data for the candidate bright lesion object classification, the performance of the proposed method may be further improved. The SWFCM clustering algorithm can also be used for segmenting blood vessels. The proposed approach achieves an area under ROC of 0.9410 for DRIVE database and 0.9505 for STARE database. As the proposed bright lesion detection system achieved a high sensitivity with reasonable specificity, it can be used to assist an ophthalmologist in the detection of bright lesions and also in mass screening of diabetic retinopathy.