Automated Detection of Retinal Hemorrhage based on Supervised Classifiers

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ABSTRACT

Supervised machine learning algorithm based retinal hemorrhage detection and classification is presented. For developing an automated diabetic retinopathy screening system, efficient detection of retinal hemorrhage is important. Splat, which is a high level entity in image segmentation is used to mark out hemorrhage in the pre-processed fundus image. Here, color images of retina are portioned into different segments (splats) covering the whole image. With the help of splat level and GLCM features extracted from the splats, three classifiers are trained and tested using the relevant features. The ground-truth is established with the help of a retinal expert and using clinical images the validation was done. The output obtained using the three classifiers had more than 96 % sensitivity and accuracy.

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1. INTRODUCTION

The World Health Organisation estimated that by 2030, there will be nearly 366 million people with Diabetic mellitus (DM) [1]. A microvascular complication of DM that is responsible for a major share of cases of blindness in the world is the Diabetic Retinopathy (DR). The severe complications like Microaneurysms, Exudates, Occlusion, hemorrhages, etc., together known as DR. The DR becomes more severe when it goes undetected for a long period of time. Retinal hemorrhages and other symptoms are usually diagnosed by an ophthalmoscope or a fundus camera that are capable to examine inside of eye. In order to reduce the diagnosing time, human error and increase the accuracy, several algorithms have been developed for the early detection of DR and all of them use machine learning techniques. An expert, usually an ophthalmologist or a retinal specialist provides the ground truth to train the system. The pre-processed fundus image features are extracted and applied to a supervised classifier which is trained with the relevant features by feature subset selection. In this paper, classification of hemorrhage and non-hemorrhage fundus images carried out using three different classifiers is presented. The techniques used to develop the algorithm is based on recent researches.

When compared to large hemorrhages, it is seen that small hemorrhages are irregular in shape. Many systems have been developed to find these abnormalities. DR detection based on Convolutional Neural Network (CNN) using binocular fundus images and its correlation is suggested by Zeng et.al [2]. The model has a Siamese-like architecture that predicts the possibility of DR for both the eyes by correlating the pathological as well as the physiological condition of eyes. In our work one of the classifier decision is based on Neural network (NN). D Kumar et.al. [3] presented a radiomics-driven Computer Aided Diagnosis (CAD) based method. In order to overcome the limitations with current CAD approaches such as decision making a CLass-Enhanced Attentive Response Discovery Radiomics CLEAR-DR is proposed to aid clinical diagnosis of DR. Another important symptom of diabetic retinopathy is exudates, which are similar to hemorrhage pixels.
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Since the topographic surface in watershed algorithm is important [11] to obtain genuine splats, the maximum of the gradient magnitude is taken for certain scale of Interest (SOI). Splats created using different scales exploiting the same watershed algorithm is shown in the Fig. 1.

![Fig. 1](image1.png)  
(a) (b) (c)  
Figure 1. Splats created using different scales.

Scale band taken for Fig. 1(a) is most accurate when compared to scales used in Fig. 1(b) and Fig. 1(c) as it comes under the desired SOI for hemorrhage detection. The retinal background is represented by larger splats and blood regions are represented as smaller splats Fig. 1(a). The scale in Fig. 1(c) is suitable in removal of larger areas such as optic disc. The scale used in Fig. 1(b) is a fine scale and also not in the desired SOI. Again this scale range can be used in the detection of Microaneurysms. The number of splats is kept under a certain limit or threshold to achieve speed without much compromising the accuracy.

### 2.1 Splat Based Labelling by ophthalmologist

The samples taken from watershed algorithm are labelled by experts as the supervised algorithms are to be labelled using the MATLAB software. Small hemorrhages shown as purple dots, are indicated by a single point in Fig. 2.

![Fig. 2](image2.png)  
Figure 2. Small hemorrhages noted as purple dots.

The expert performs a single click on where hemorrhage is spotted and the pixel values are noted down. The images that contain hemorrhages are given a label of ‘1’ and the rest are given as ‘0’. The splats are designed to preserve hemorrhage boundaries, and the reference standard result obtained is less noisy.
2.2 Feature Extraction from Splits
After assigning reference labels for splats, a classifier can be trained to detect the target objects. An altogether of 352 potentially relevant features are taken to train the classifiers. They are:
1) **Color**: Colors of each splat is extracted in RGB color space and dark-bright (db), red-green (rg), and blue-yellow (by) opponency images [13], which comes to six colour components.
2) **Difference Of Gaussian (DoG Filter)**: Difference of Gaussian (DoG) kernels are applied at five different smoothing scales with one baseline scale in order to take advantage of Gaussian scale space [14][15].
3) **Responses from Gaussian Filter Bank** [13]: A Gaussian filter bank which include a first order derivative at two orientations and a second order derivative with three orientations are applied to the green channel.
4) **Responses from Schmid Filter Bank**: It has 13 kernels which are rotationally invariant and is applied to the dark bright opponent image.
5) **Responses from Local Texture Filter Banks**: This filter bank contains local entropy filter, local range filter and local standard deviation filter which compute the entropy, standard deviation and intensity range of one pixel in a given region [16].

The above features are aggregated to obtain a meaningful response image which has low inter splat similarity and high intra splat similarity [13]-[19]. The features mentioned are pixel-based responses. In addition to these features, we take splat wise features according to Gray-Level Co-occurrence Matrix (GLCM) [16]-[22] statistics. These are splat area, extent, texture, solidity and orientations. The complete feature set is shown in Table 1.

2.3 Preliminary Feature Selection and Classification
A two-step feature selection method is taken here so as to take only the relevant features and discard the irrelevant and redundant ones [23]. The preliminary feature selection is done using a filter approach in order to eliminate the features that are immaterial in discriminating hemorrhage and non-hemorrhage splats. A quadratic discriminant analysis (QDA) [24] is performed and by inspecting the features’ variation with misclassification error (MCE) [25]. The preliminary features are chosen when the smallest MCE is reached.

| Features                        | Number | Description                                      |
|---------------------------------|--------|--------------------------------------------------|
| **Shape Features**              |        |                                                  |
| Colour                          | 6 x 4  | RGB and dark-bright (db), red-green (rg), blue-yellow (by) opponency [13] |
| DoG filter bank                 | 30 x 4 | RGB and db, red-green rg, blue-yellow by [15]   |
| Gaussian Filter Bank            | 30 x 4 | First order and second order derivatives in horizontal and vertical plane. |
| Schmid filter bank              | 13 x 4 | 13 kernels [17]                                  |
| Local Texture filter            | 3 x 4  | Local range, standard deviation and entropy of a pixel in given neighborhood [16] |
| **GLCM Features**               |        |                                                  |
| Splat area                      | 1      | Number of pixels in splat                        |
| Splat extent                    | 1      | Proportion of pixels in bounding box that are also in splat. |
| Splat orientation               | 1      | Angle between horizontal and major axis of the ellipse having same second- moments as splats. |
| Splat Solidity                  | 1      | Proportion of pixels in convex hull that are also in splat. |
| Texture                         | 4      | Statistics of GLCM: Contrast, correlation, energy and homogeneity [16] |
| Tamura Signatures               | 3      | Coarseness, directionality and contrast of db opponency associated with each splat [20] |
| Edge Strength ratio             | 6      | Ratio of maximum and minimum edge strength between neighboring splats. |
| Vignetting artifacts            | 1      | Closest distance of splat centroids to boundaries of FOV. |
| Vessel probability              | 1      | Vessel probability map averaged within splats using vessel segmentation algorithm [21] |
| Impact of anatomical structures | 2      | Distance of automatically detected optic disc and fovea to splat centroids [22] |

After preliminary selection, a wrapper approach is performed in order to get an optimal combination of relevant features with minimum redundancy. It is the peculiarity of the wrapper approach that it assesses different combinations of feature subsets customized for a certain classification algorithm with higher computation time. The combinations are evaluated using a kNN Classifier. All the selected features are now applied to a sequential forward feature selection subset (SFS).

2.4 Classification using different classifiers
After feature selection, three-distinct trained classifiers are set up with the set of features and reference label instances.
A. kNN Classification

The kNN algorithm assigns soft class labels. The two classes defined or the outputs are hemorrhage splat or non-hemorrhage splat. The classifier decides the class of a particular splat based on the Euclidean distance of the features in an optimized feature space. As the value of k is increased the computation time increases and the splats are more accurately identified. But since all the k nearest neighbors are not near, an optimum value of k is chosen instead of an arbitrary value.

B. SVM Classification

Support Vector Machines include the concept of hyperplanes to distinguish between classes. The features are transformed to the required form using a linear kernel. The features were optimized and only the relevant number of features were trained to the classifier. A least squares SVM classifier with Radial Basis Function (RBF) Kernel is used here[26]. The RBF Kernel function is defined as

\[ K(x, x') = \exp\left(\frac{||x - x'||^2}{2\sigma^2}\right) \]  

Where \( x \) and \( x' \) are two feature vectors and \( \sigma \) is a free parameter and \( ||x - x'||^2 \) is taken as squared Euclidean distance parameter.

C. ANN Classification

ANNs rely up on the concept of artificial neurons which is biologically inspired based on the function of brain. Here each neurons or nodes are held within a layer. The Neural Network consists of input layers, hidden layers and a transfer function or a threshold function. All the nodes are interconnected and they form a network. The nodes are trained using backpropagation algorithm. The nodes are trained by reducing their error through several iterations. The input to the ANN classifier is the relevant feature set and they are transformed using the desired weights from the hidden layer. Finally using a Sigmoid transfer function the output class is determined.

3. RESULTS AND DISCUSSION

3.1 Data Collection and Pre-processing

Images were acquired from two sources. One from the publically available database DIARETDB1(http://www.it.lut.fi/project/imageret/diaretdb1/index.html) and the second set of clinical images from Dr. Bhejan Singh’s eye hospital solely for educational and research purpose. The clinical image was captured using a “Remedio Non-Mydriatic Fundus On Phone (FOP-NM10)” Camera with an FOV of 40°, working distance of 33mm and an ISO range from ISO 100 to 400. A total of 1500 images were taken 1050 for training, 225 images for testing and 225 for validation. The reference standard observations were accomplished by an ophthalmologist expert using the splat-based interpretation. Overall 1200(950 from training set 150 from testing) images were marked by the expert from a total of 1500. Preprocessing is done in order to adapt the colour variation throughout the dataset and also to equalize the intensity of the image. Histogram equalization is done using Contrast limited Adaptive Histogram Equalization(c)\[27].Also Each image is normalized according to its prevailing pixel value at the three colour channels. The pixel values that occur frequently are shifted to the beginning of RGB colour space.

3.2 Feature Subset selection

From the 1050 training images, 10500 splats were created among which 300 are hemorrhage splats. This counts to a very low number of hemorrhage splat density. So images with at least 6 splats are taken for training, where 6 is arbitrarily chosen. After sequential forward feature selection subset(SFS) only the relevant features were considered whereas the insignificant and redundant ones were removed from the feature set. The final feature set consists of 50 features from the 352 features obtained by filter approach and from this set 19 features were finally obtained by wrapper approach. The details of the final selected features are given in Table 2.

| Features                      | Number       | Description                                      |
|-------------------------------|--------------|--------------------------------------------------|
| DoG filter bank               | s2=s0.5      | from Green channel                               |
| DoG filter bank               | s4=s0.5      | from db and rg opponency                         |
| DoG filter bank               | s8 - s0.5    | from db opponency                                |
| Gaussian Filter Bank          | s=8 orientation:2,3 | Mean of second order Gaussian derivative from green channel |
| Gaussian Filter Bank          | s=1,2,4 orientation:1,2,3 | Mean of second order Gaussian derivative from green channel |
| Schmid filter bank            | response=11  | from db opponency                                |
| Mean of Gaussian              | s=8,16       | from Green channel                               |

Table 2. The details of final selected features.
3.3 Classification of splats using different classifiers

The splats are represented as a 19 dimensional feature vector and each classifier is trained based on these features.

a. kNN Classifier

Different values of k were tested whose values are chosen between 15 to 160 that involves both feature selection as well classification. After repeated iterations, the value of k was fixed at 105 without compromising the computation time and prediction accuracy. The algorithm was validated using the image from the dataset DIARETDB1 and the ROC curve was plotted with an AUC of 0.94.

b. SVM Classifier

The features were optimized and only the 19 relevant features were trained to the classifier. A least squares SVM classifier with Radial Basis Function (RBF) Kernel is used here. The confusion matrix for the hemorrhage splat detection is shown in Table 3.

| Actual NO | Predicted NO | Predicted YES |
|-----------|--------------|---------------|
| TN= 5250  | FP=139       | 5389          |
| FN= 621   | TP=4490      | 5111          |

| 5871      | 4629         |

Table 3. The confusion matrix for SVM classifier

(c) ANN Classifier

The input to the ANN [28] classifier is the 19 feature set and they are transformed using the desired weights from the hidden layer. Finally using a sigmoid transfer function, the output class is determined. The network protocols used for detection of hemorrhage class from the splats is given in Table 4.

| Features                  | Hemorrhage splats |
|---------------------------|-------------------|
| Learning rule base        | Delta rule        |
| Transfer function         | Sigmoid           |
| Hidden Layer Elements     | 30                |
| Preprocessing filter      | Feature set       |
| Number of training iterations | 1000            |
| Training algorithm        | Bayesian           |
| Neural network            | Fitting network   |
| Training time- Core i5, 4.10 GHz | 10 min         |
| Number of training splats | 7350              |
| Number of testing splats  | 3150              |

Table 4. The protocols used for detection of hemorrhage class.

The hemorrhage splats were successfully detected using the three classifiers and the result of a fundus image along with its receiver operator characteristics are shown in Figs.3. Splat based ROC curves corresponding to fundus image using the three classifiers is shown in Fig. 4. The AUC for ANN Classifier was 0.96 for SVM it was 0.94 and using the kNN classifier was 0.93. The best operating point on the curve for different classifiers are shown in Table 5.

In this manuscript, a set of features are extracted from each splat for defining its characteristic properties. In a selected feature space, these splats are taken as supervised classification samples. Splat based image annotations makes it easier for ophthalmologists for modeling unevenly shaped abnormalities in images. Further, it is resistant to intensity bias and noise. Analyzing how the performance of a DR detection system is related to the detection of rare large hemorrhages is quite interesting and challenging. It is found that the un-weighted performance metrics like AUC or sensitivity and specificity will not be affected if we integrate the present hemorrhage detection system at a suitable threshold level. The reason is that, only the presence or absence of DR is usually indicated by the binary reference labels. In this approach, color images of retina are partitioned into different non-overlapping segments (splats). A set of features are extracted from each splat this inturn help us to detect retinal hemorrhage.
Hemorrhage splats detection: (a) Input image; (b) Image enhanced and splats generated; (c)–(e) Hemorrhage classification using ANN, SVM and kNN respectively.

The corresponding ROC curve for the input image is given in Fig. 4.

Figure 4. ROC curves for ANN, SVM and kNN classification for hemorrhage detection.

| Classifier | Sensitivity | Specificity |
|------------|-------------|-------------|
| ANN        | 0.96        | 0.67        |
| SVM        | 0.94        | 0.44        |
| kNN        | 0.93        | 0.42        |

Superior results were obtained using ANN classifier when compared with other classifiers such as SVM and kNN classifiers. All the classifiers are proven to detect retinal hemorrhages with very high accuracy and since different splats in the image represents a large feature space, the neural network classifiers can outperform other classifiers. This was one of the reason to take ANN classifier into consideration. While other classifiers such as SVM and kNN are proven to provide superior results. When compared with the work of [29] the method has proved a sensitivity of 0.96 using ANN classifier against the sensitivity of 0.82 with kNN classification used in [29]. Compared with the work presented in [30], where fuzzy logic is used for classification, this method has proven superior results with a sensitivity of 0.96 against 0.86.
4. CONCLUSION

A splat based feature classification is presented for the detection of retinal hemorrhage. The proposed classification strategy can model different lesions with different texture size and appearance. The algorithm is validated on the publically available database DIARETDB1 and clinical image which was captured using a “Remidio Non-Mydriatic Fundus on Phone (FOP-NM10). The proposed method when compared with other methods in the literature suggest that it provides superior results when neural network classifier is being used. So the detection strategy can be incorporated into comprehensive DR assisting system for ophthalmologists.

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