Classification of Diabetic Retinopathy Images Using Multi-Class Multiple-Instance Learning Based on Color Correlogram Features

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¹Ragav Venkatesan, ¹Parag S. Chandakkar, ¹Baoxin Li and ²Helen K. Li. {ragav.venkatesan, pchandak, baoxin.li} @asu.edu; hli@communityretina.com ¹Computer Science and Engineering, Arizona State University

²Weill Cornel Medical College/The Methodist Hospital, The University of Texas Health Science Center Houston, and Thomas Jefferson University

OBJECTIVE

To automatically classify diabetic retinopathy (DR) images into three classes based on their severity, using multi-class multiple-instance classification framework and modified color correlogram features.

MOTIVATION

- DR is a common cause of blindness among diabetic people. Despite the advancement in diabetic care, vision loss is still a devastating complication.
- Timely diagnosis and treatment of DR can significantly reduce the risk of vision loss.
- DR diagnosis is a laborious process and is prone to human error. It is very costly in monetary and personnel terms.
- Lack of a unified DR grading system.

BACKGROUND



Normal



Proliferative DR



Non-prolifearative DR

Fig. 1. Red and blue arrow indicate hemorrhages and cotton wool spots respectively. White and yellow arrow indicate microaneurysms and yellow, waxy exudates.

RELATED WORK

- Boundary detection is performed using morphological operations to detect exudates. Distribution of exudates was used to determine the severity of DR in [1].
- Naïve Bayes classifier was used to classify DR images using the size foveal avascular zone [2].
- STARE project was aimed at automatic diagnosis and comparisons of retinal fundus images. The approach segments the image into 11 predefined regions and then uses primitives like color features to perform automated diagnosis [3].









PROPOSED APPROACH

- Color correlogram (CC) is a well-studied feature for image retrieval. A quantization scheme for CC, modeled after HVS was proposed in [4].
- CC features are unsuitable for DR images due to the unique color spectrum of DR images.

- Fig. 2. Color spectrum of a natural and a DR image. Design of a quantization scheme for DR images: Equalize red channels of all images. \succ Extract all the unique shades in the training set.
- \succ Group the color space into 64 clusters.
- Build codebook out of centroids.

Fig. 3. Visualization of quantization schemes.

• Algorithm for computing CC features:

 \succ The 64-bin histogram for the instance is recorded

 \succ For any pixel, a neighborhood of 3X3 is considered. The pixel value of the center pixel is compared with the pixel value of all the 8 pixels in the neighborhood. A count is made of the number pixels that hold the same value as the pixel under consideration. This count gives us the local spatial distribution of the pixels.

- for all the pixels in the instance.



approach is used [5].

Approach

SIFT+BoW+SV Gabor features-HNM + SVM**Original AutoCC Proposed Algor**

Experiments were performed and the said results were obtained from a database containing 425 images with 160 Normal, 181 MA and 84 NV images.

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[4] M. Li, "Texture moment content-based image retrieval," in IEEE ICME, 2007.

[5] J. Wang and J.-D. Zucker, "Solving the multiple-instance problem: A lazy learning approach," in 17th International conference of Machine Learning, 2000.



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 \succ This count is added to that bin of a spatial distribution histogram to which the pixel under consideration belongs. This process is repeated

> The vector thus formed is divided by the count of global distribution of pixels to get the color autocorrelogram of the instance. This results in a 64 dimensional feature vector for every instance.



Fig. 4. Necessity for MIL Framework. For classification using MCMIL, a Citation-KNN

EXPERIMENTAL RESULTS

l	Mean Accuracy
VM	51.14 %
+SVM	64.71 %
Ŋ	75.76 %
C+MIL	78.01 %
rithm	87.61 %

KEY REFERENCES