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Novel risk index for the identification of age-related macular degeneration using radon transform and DWT features

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ABSTRACT

Age-related Macular Degeneration (AMD) affects the central vision of aged people. It can be diagnosed due to the presence of drusen, Geographic Atrophy (GA) and Choroidal Neovascularization (CNV) in the fundus images. It is labor intensive and time-consuming for the ophthalmologists to screen these images. An automated digital fundus photography based screening system can overcome these drawbacks. Such a safe, non-contact and cost-effective platform can be used as a screening system for dry AMD. In this paper, we are proposing a novel algorithm using Radon Transform (RT), Discrete Wavelet Transform (DWT) coupled with Locality Sensitive Discriminant Analysis (LSDA) for automated diagnosis of AMD. First the image is subjected to RT followed by DWT. The extracted features are subjected to dimension reduction using LSDA and ranked using t-test. The performance of various supervised classifiers namely Decision Tree (DT), Support Vector Machine (SVM), Probabilistic Neural Network (PNN) and k-Nearest Neighbor (k-NN) are compared to automatically discriminate to normal and AMD classes using ranked LSDA components. The proposed approach is evaluated using private and public datasets such as ARIA and STARE. The highest classification accuracy of 99.49%, 96.89% and 100% are reported for private, ARIA and STARE datasets. Also, AMD index is devised using two LSDA components to distinguish two classes accurately. Hence, this proposed system can be extended for mass AMD screening.

1. Introduction

Age-related Macular Degeneration (AMD) is an eye disease that affects people aged 50 years and above [1]. It slowly affects the central vision and worsens over time. Macula is responsible for sharp and central vision in the retina [2]. It is concentration of colored light sensitive nerve units called cones where light normally focusses in the inner layer of the eye (retina) [2,3]. Death of these receptors in the macula causes AMD. World Health Organization (WHO) and United Nations (UN) report reveal that AMD affects 20–25 million people globally and among them 8 million are experiencing loss of vision [4]. People aged 60 years and above is estimated to be 606 million in 2000 will increase up to 2 billion in 2050. Hence, the number of subjects suffering from AMD are likely to triple in another 30 to 40 years [4]. In some patients AMD can progress slowly without affecting the vision and in the rest, it may progress rapidly causing vision loss. The earliest signs of AMD are the presence of drusens in the retina. AMD can be classified in to dry (non- neovascular) or wet (neovascular) [5].

i. *Dry AMD*: it is the most common type of AMD and is caused due to thinning of tissues in the macula. It usually begins with the formation of drusens which tiny yellow fatty protein deposits are causing gradual vision loss [6]. People with dry macular degeneration need to regularly monitor their central vision. Dry AMD is further classified as early, intermediate and advanced. In early AMD, the size of the drusen varies from 63 μm to 124 μm in diameter and retinal pigmentation is present. In intermediate AMD, at least one drusen measuring more than 124 μm and also

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0010-4825/

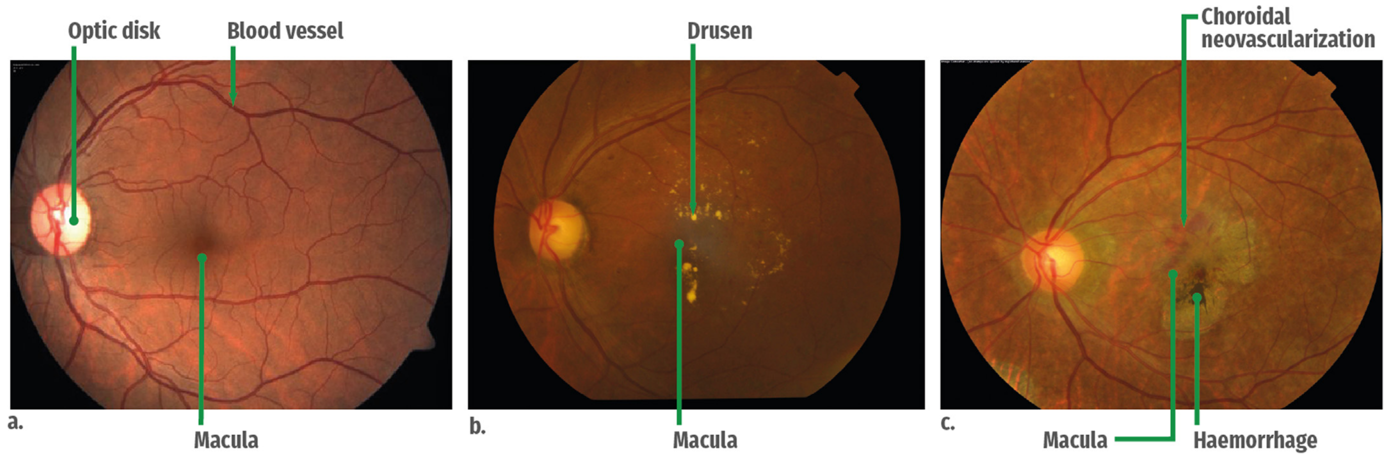

Fig. 1. Fundus images: (a) Normal, (b) Dry AMD, and (c) Wet AMD (Private dataset images). (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.).

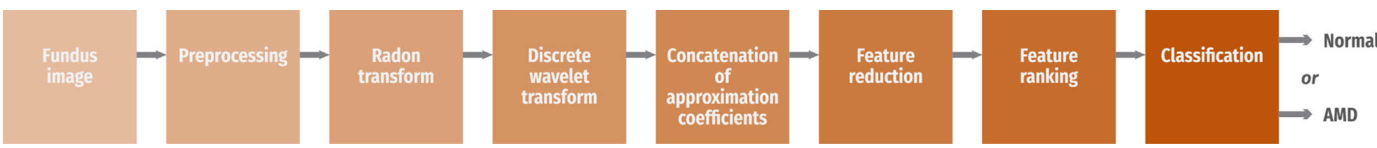

Fig. 2. Block diagram of AMD detection system.

medium sized drusens are present [7]. In both early and intermediate AMD, the drusen are mostly present away from macular center. Advanced AMD is characterized by the presence of drusens at the macular center or periphery. Also, there will geographic atrophy (area with 175 µm diameter) and neovascular lesions present [8]. Fig. 1(b) shows the sample Dry AMD fundus image.

ii. *Wet AMD*: caused due to Choroidal Neovascularization (CNV) which is an abnormal blood vessel formation from choroid region of the retina [8–10]. These vessels are very thin and leak blood, leading to vision loss. Wet AMD is more visible as compared to dry AMD and damages the retina more severely [8–10]. Among AMD subjects 10% of them are affected with wet AMD [8–10]. Fig. 1(c) shows the sample wet AMD fundus image.

Table 1
Summary of automated drusen detection methods.

Authors	Segmentation methods	Important features	Segmentation evaluation
Rapantzikos et al. (2003) [11]	Histogram-based adaptive local thresholding	Segments small and vague drusen	Sen-98.85% Spec-99.32%
Brandon and Hoover (2003) [12]	Multi-level image analysis	Pixel, region, area and image level classification	Acc-87%
Freund et al. (2009) [13]	Multiscale analysis and kernel based anomaly detection	–Support vector data description –Mexican hat wavelet transform	Acc-100%
Mora et al. (2011) [14]	Segmentation using image gradient	Gaussian modeling of drusen	Sen-68% Spec-96%
Liang et al. (2010) [15]	Region based segmentation	Blood vessel removal from choriod	Sen-75% Spec-75%
Niemeijer et al. (2007) [16]	Gaussian derivative filters and *k*-Nearest Neighbor	Fails to detect few bright spots	Sen-77% Spec-88%
Cheng et al. (2012) [17]	Biologically inspired features	Gabor filtering	Sen-86.3% Spec-91.9%
Burlina et al. (2011) [18]	Adaptive segmentation	Over/under segmentation detection	Sen-95% Spec-96%

[Acc: accuracy; Sen: sensitivity; Spec: specificity]

Many studies have been conducted to segment the drusens using advanced image processing techniques. Table 1 summarizes the various methods used for the drusen detection.

Above mentioned methods rely on segmentation of drusen which is a challenging task due to the presence of other lesions and noise with same contrast as drusen [19]. Hence, in this work we have proposed an automated classification of fundus images into normal and AMD without segmenting the drusen. Fig. 2 show the steps involved in the proposed system. Contrast enhancement is performed on green channel of fundus image using Contrast Limited Adaptive Histogram Equalization (CLAHE). Radon Transform (RT) is applied on preprocessed image at each one degree to get the sinogram. Further, *three* level 2D Discrete Wavelet Transform (DWT) decomposition is performed on sonogram. Only approximate coefficients of three levels are concatenated and subjected to Locality Sensitive Discriminant Analysis (LSDA) to reduce the number of features. Further, LSDA components are ranked using t-value and then fed to various classifiers and compared the performance of various classifiers to find the best classification performance using minimum number of features with 10-fold cross validation.

Image acquisition, preprocessing, Radon transform, discrete wavelet transform, feature reduction, ranking and classification steps are explained in Section 2. Results are presented in Section 3. The results of the proposed approach are discussed in Section 4 and the paper concludes in Section 5.

2. Materials and methods

2.1. Image acquisition

Private dataset: retinal fundus images were collected from Department of Ophthalmology, Kasturba Medical College, Manipal, India and images were acquired using mydriatic fundus camera