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A Review of Localization Techniques for Macula using Fundus Images

Adeel M. Syed, Aleem Ahmed, Joddat Fatima

Bahria University, Software Engineering Department, Islamabad, Pakistan.

Corresponding Author's email: Adeel M. Syed(adeel@bahria.edu.pk)

***Abstract*-- Macula is also known as fovea and is present by both names in the literature. Localization of macula plays a vital role in computerized diagnosis of ocular diseases. If the macula is not localized properly, it leads to miscalculation and wrong verdict about the disease. Localization of macula has been an old task and a lot of research has been done in this field. Majority of the researchers have used public datasets and have published their results. Newer literature tries to update the existing work by bringing novelty in the work and increasing the performance parameters. It is therefore helpful for a lot of people in the field that a review of these techniques may be presented.**

***Index Terms*- Macula, Macula Detection, Fundus Image, Machine Learning.**

I. INTRODUCTION

Macula is a dark, roundish object when seen on a fundus image. It is responsible for the central vision of the eye that is needed for our daily routine tasks. Macula is present in every fundus image and hence its detection is termed as a one class problem. In order to detect macula different researchers have used different techniques. A summary of these techniques is presented in the following subsection.

II. LITERATURE REVIEW

Proposed in [1] the detection of Macula by using morphological image processing and Fuzzy C-Means clustering. Blood vessels segmentation was performed by using the Morphological operations and FCM clustering, and classification was performed using SVM Classifier. For classification using SVM total 75 images were taken. The dataset created for testing was based on total 30 normal images during result evaluation 29 test images were correct and 1 image was incorrectly classified. Classifier achieved an accuracy of 96.67%. Sensitivity 100% and specificity 95.83% [2]. Detected the macula using some image processing techniques on some colored fundus images. They converted the fundus images into grey scale image to help the morphological operations. Furthermore, grey image converted into green color image which was then passed through black top hat module. From the MESSIDOR database their technique gave the high performance when it was evaluated. Experiment was performed on 10 images and aggregate values of result was 94.08% accuracy, 97.7% sensitivity and 81.72% specificity [3]. Proposed robust and flexible approach for detection of Macula from fundus images. Their detection approach was based on three stages in the first stage they improve the visibility of retinal features, in the second stage patio-temporal retinal change location was detected. In the last stage various local intensity and shape descriptors were extracted from changes identified. They have tested the three classifiers but SVM produced the best results among them. The evaluation shows the best average result achieved is 80% sensitivity. (Hijazi, Coenen, & Zheng, 2014) proposed the best approach among three possible techniques these are Time series representation, tabular representation, and tree representation. Time series approach was coupled with CBR to classify the fundus images, tabular representation contained purely statistical data on which standard classification techniques could be applied. While in tree representation hierarchical mechanism was coupled with weighted sub-graph mining technique to generate feature so that standard classification could be applied. Experiment produced excellent results accuracy 99%, sensitivity 99.5% and specificity 96.8% and these results were produced by tree representation [4]. Devised a new method to detect the fovea center. The green channel was used to detect fovea center and it detected those areas, based on their anatomy, which were likely to have fovea center. This way, the appearance of abnormality became clearer and stronger in the eye fundus image. The results of fovea rate detection by using this method were 100% after using DRIVE image database and 92.13% after using DIARETDB1 database. They claimed that this approach was considerably better than the other methods. The shortcoming of this method was that green channel might fail in the presence of large hemorrhages [5]. Used computer algorithms. These algorithms detected those regions where fundus was found. The reliability of detection of fundus for blood vessels, fovea and optic disc was high. This method will help in examining the fundal disorders by detecting these regions. By carefully photographing the fundus, the chances to miss the fovea was diminished. NN analysis was used to detect major blood vessel. This method improved the proficiency of computer analysis by preprocessing along with the post processing. This way reliance on the NN was also reduced.

This study allowed the researchers to detect those areas which were affected by abnormality in the fundus image. This method used computer algorithms to detect those regions of fundus which were affected. The results were quite accurate in recognizing the specificity and sensitivity of retinal components. For optic disc results were 99.1% and for blood vessels the results were 91% and 83.3%. The accuracy was 99.1% and 80.4% for fovea [6]. Used the method that located the fundus and optic nerve in fundus imagery which was red-free. Their method extracted statistical features like vascular density, thickness and orientation by using the features of vascular structure present in retina. To classify pixels of original images into binary category of optic nerve or not optic nerve by applying Bayesian classifier and trained using those features. They were using dataset of total 395 images but in first part they tested the performance of 100 subset images and got 96% to evaluate the feature performance without testing macula localization. When they applied algorithm on larger datasets their performance dropped to 90.4% correct ON detection and 92.5% macula localization [7]. Used a reliable and automated method of digital coloring of retinal images to detect fovea center. In this method Shaohua Z. and his colleagues also detected those MF regions where fovea center was most likely to be found by using the anatomic features. HEIMED, DRIVE and DIARETDB1 were the three databases which showed that this method gave better and accurate results in detection of fovea center. The detection rate of macular fundus was 100% in 35 of images by using DRIVE database. It was detected correctly 98.8% of 169 images by using HEI-MED dataset and it was detected in 89 of the cases images correctly 93.3% of the times by using DIARETDB1 database [8]. Devised an automatic method of detection of important structures like Blood Vessels, Optic Disc and Macula by the help of images of fundus retina. This technique used a novel method to localize blood vessels and macula. Principle Component Analysis (PCA) was used to localize optic disc. Afterwards, reliable segmentation of its boundary was done by an approach which used active contouring. Another approach based on morphology, called Blood Vessel Detection (BVD), was proposed. Since macula is the darkest region in the surrounding area of optic disc, it was easily identified by combining BVD with this property. This method was tested by using 100 images and the results were very reliable [9]. Proposed a method using computer-based automatic algorithms to detect fovea center. It was detected in the retinal fundus images. Fovea center was indicated by the minimum density of the vessel based on the prior knowledge of the anatomy of the retina. They applied algorithm on two different datasets one was Tayside diabetic screening programmed (TENOVUS) and the second one was MESSIDOR which was publicly available. TENOVUS was divided into three sets and MESSIDOR was divided into two, images with no hazard of macular edema and images with a danger of macular edema. Their algorithm showed good results TENOVUS images for all sets which are 92% estimated with 0.5%-disc diameter. Using MESSIDOR dataset their algorithm showed 80% without risk of macular edema and 59% with a risk of macular edema [10]. Used a very simple and useful method which didn't require prior knowledge for fovea localization methods. To use this method there was no segmentation/localization required for retinal structures. They changed the image quality by enhancing the contrast between fovea and its surroundings so that they can be viewed separated in retinal images. This method was tested on 520 images includes normal and pathological colour retinal images with an accuracy of 90.75% [11]. Applied various data mining techniques to enhance the image quality, segmentation and localization were done on images to get more accurate results. In the first part of their project, they proposed the framework by using cropping and green channel extraction. The removed the unwanted components from binary image, with the minimum intensity it was declared as macula and its center was called fovea. Their proposed framework produced some very efficient results as STARE reported as 90%, MESSIDOR 99.33%, DIARETDB0 96.92%, DIARETDB1 97.75%, DRIVE 100%, HRF 100% and HEI-MED 98.81% [12]. Used the combination of algorithms which were majority voting and weighted linear. Their combination produced better results as compare to individual algorithm performance. Retinal specialist chose the manually optic disc method which was producing closed results as their performance results [13]. Used the OD segmentation to detect the macula and boundary of OD in retinal fundus images. They carried out some good results on ONHSD and MESSIDOR, around 1200 fundus images were used and they achieved 94% accuracy by this method. Their approach detected the boundary and macula even if the color of the image changes [8]. Used the OD localization and Macula detection approach where principal component authority (PCA) is used to carry out the localization of OD and by combining the Blood Vessels Detection (BVD) with the vicinity of OD.

TABLE I

Author	Year	Database	Techniques	Accuracy	Sensitivity	Specificity	Number of Images
(Mookiah, et al., 2015)	2015	ARIA KMC STARE	LCP SVM-MV classifier	90.68% 92.96% 97.59	90.10% 90.00% 97.87	91.67% 95.93% 97.22%	161 540 83
[14]	2016	ARIA KMC STARE	DWT,RT AMD index SVM-RBF classifier DT-Classifier	96.89% 99.49% 100.00%	100.00% 99.21% 100.00%	91.67% 99.75% 100.00%	161 785 83
[15]	2017	KMC	PHOG, Non-linear features SVM classifier	83.30%	82.60%	84.80%	945
(Mookiah, et al., 2015)	2015	ARIA KMC STARE DB	EMD, entropies, HOS,RT SVM Classifier	85.09% 91.67% 100.00%	86.14% 90.74% 100.00%	83.33% 92.59% 100.00%	161 540 83
(Hijazi, Coenen, & Zheng, 2014)	2015	AMD and STARE	Tree Based Approach	99.90%	100.00%	99.00%	263
(Mookiah, et al., 2014)	2014	KMC	Energy, entropies, DWT, first-order statistics	93.70%	91.11%	96.30%	540
(Mookiah, et al, 2014)	2014	ARIA DB KMC STARE	Entropies, HOS, fractal dimension, RT, Gabor wavelet SVM-linear classifier	95.07% 90.19% 95.00%	96.09% 88.89% 96.00%	93.33% 91.48% 93.33%	161 540 83
(Hijazi, Coenen, & Zheng, 2012)	2012	ARIA	Hierarchical decomposition (1,262 features)	100.00%	100.00%	100.00%	161
[16]	2012	ARIA and STARE DB	Weighted frequent sub-graph mining	99.60%	99.40%	100.00%	258
[1]	2016	Not mentioned	Fuzzy C-Means clustering (FCM) SVM classifier	96.67%	100.00%	95.83%	75
[17]	2017	KMC	14 Layer deep CNN	95.45%	96.43%	93.75%	1110
(Adal, Martinez et al, 2018)	2017	Local	KNN, RF, SVM	NA	80%	NA	81
[18]	2016	Not mentioned	Wavelet Feature Extraction, SVM Classifier	95%	93.3%	100%	85
(Taori, Chaudhari et al, 2016)	2016	MESSIDOR database	Automated Seeding Region Growing	94.08%	97.7%	81.72%	Not Mentioned
[13]	2016	ONHSD and MESSIDOR	OD Segmentation Method	94%	NA	NA	1200
[8]	2007	DRIVE (20 Images) STARE (Images)	BVD, OD localization using PCA	96%	70.14% 64.37%	96.44% 97.08%	20 100

[4]	2011	Drive DIARETDB1	mathematical morphology technique for OD localization	100% 92.13%	NA	NA	37 89
[12]	2012	Diaretdb0 Diaretdb1 DRIVE	OD localization and Macula detection using morphology operators	96.79% 98.74% 91.73% Avg: 96.87%	NA	NA	130 89 40
[6]	2007	Local STARE	Optic nerve localization and Macula localization	92.5% 87.7%	NA	NA	395 81
[9]	2013	MESSIDOR	OD detection and Fovea center localization	80%	NA	NA	303
[19]	2013	MESSIDOR	thresholding and feature extraction	93.93%	NA	NA	1200

They applied BVD on 100 fundus images where 20 images were taken from DRIVE and 20 images were taken from STARE database. They achieved an overall 96% accuracy on total images whereas sensitivity and specificity are 70.14% and 96.44% respectively on DRIVE dataset and sensitivity and specificity on STARE database are 64.34% and 97.08% respectively. [4] claimed that their approach achieved better performance than the approaches used in literature. Their approach was based on fovea center detection in color eye fundus images. They applied experiments on two different databases DRIVE and DIARETDB1 where success rate to detect the fovea on DRIVE 37 images were 100% and success rate on DIARETDB1 89 images were 92.13%. [12] used the various approaches to detect the fovea in fundus images. They have used majority of voting and weighted linear combination scheme to detect the fovea where they claimed that they get their best results as various approaches. They used various databases for experiments like DIARETDB0, DIARETDB1 and DRIVE using 130, 89 and 40 images respectively. Their accuracy for fovea detection were 96.79% from DIARETDB0, 98.74% from DIARETDB1 and 91.73% from DRIVE. [6] Digital red-free photography for localization of macula and detection of optic nerve. They used 2 different datasets for localization of macula, Local database and STARE database. 345 images were tested, and they reported 90.4% detection on optic nerve and 92.5% localization of macula. [9] Used the approach of OD detection and fovea center localization. They performed experiment on MESSIDOR database fundus images, total number of tested images were 303 and accuracy achieved from them is 80%. [19] used their own algorithm to locate the fovea from the fundus images. Their approach based on to find out the darkest area in the image by applying feature extraction techniques and thresholding. They applied their algorithm on 1200 MESSIDOR fundus image and their accuracy was 93.93%.

III. DISCUSSION

Different researchers have presented their work in localization of the disease. Majority of the work is done on publicly available datasets, as mentioned in column 3 of the table. The researchers have used different techniques and performance parameters have been calculated.

It is important to mention here that one of the most important performance parameters is accuracy. To mention accuracy, the researchers must have the ground truth. It is therefore, sometime unfair to compare two papers just on the basis of accuracy. This is due to the fact that the ground truth is not publicly available for all datasets. For example, DiaRetDB1 and MESSIDOR has annotation of exudates but annotation of macula is missing. The distance between the detected macula and the ground truth is used for calculation of the accuracy. A threshold is defined for this purpose. For instance, if macula detected is present at a distance of 101 pixels and the threshold defined by a researcher is 100 pixels, it will be marked as in correct and would therefore deteriorate the accuracy. However, another researcher might have set the threshold to be 115 pixels and with the same performance, their accuracy would be much higher.

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