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An Eye Disease Prediction System Using Bag of Visual Words and Support Vector Machine

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Abstract: *This paper proposes a prediction system to identify the type of eye diseases like glaucoma and diabetic retinopathy. The proposed system processes the images captured using the fundus camera that is connected to the computer. The acquired fundus images are fed into the proposed prediction system which can be deployed in the cloud, and it identifies the type of disease. This forms a cyber-physical system. Underdeveloped countries which do not have the necessary infrastructure can utilize this service when this system is deployed in the cloud. For identifying these diseases, ophthalmologists extract parameters manually from the fundus image, which is a difficult task. Hence, this research work attempts to develop a system to automate the feature extraction from fundus images and with the extracted features, eye diseases are predicted.*

From the literature, it is found that many research works were focused on the binary classification of any one disease. In this paper, a novel classification methodology is proposed that helps the experts and clinicians to classify Diabetic Retinopathy, Glaucoma and healthy eye images with more accuracy. The proposed system with high accuracy is designed with the following phases: i) image acquisition, ii) image enhancement, iii) local features extraction using Speeded Up Robust Feature (SURF), iv) Bag of Features/Visual Words (BoF/BoVW) obtained through k-means clustering of local features, and v) classification using Error-Correcting Output Code (ECOC) linear SVM. It is inferred from the results that the proposed method of classification using BoVW provided a maximum accuracy of 92% when compared to other state-of-the-art recent literature.

Keywords: Fundus image, image enhancement, bag of features, support vector machine, classification

I. INTRODUCTION

Change in lifestyle and work stress has made the younger generation vulnerable to health conditions like high blood pressure and high blood sugar. Diabetes Mellitus is a health condition in which the sugar level in blood is above the prescribed limit. The number of patients with Diabetes Mellitus is poised to grow drastically in the near future. It leads to a health condition in the eye called Diabetic Retinopathy (DR). If untreated, diabetic retinopathy causes permanent blindness.

The anterior and posterior chambers of the eye are filled with aqueous humor. It is a transparent watery fluid, which maintains the intraocular pressure and the ciliary processes continuously produce it. The fluid is drained from the anterior chamber into the blood vessels through the Canal of Schlemm. If there is a blockage in the draining of the fluid, pressure builds in the eye leading to a medical condition called Glaucoma. Both Glaucoma and Diabetic Retinopathy are the major causes of permanent vision loss.

Fundus photography helps in capturing the image of the back of the eye, i.e., fundus. Fundus images are ocular documentation that exhibits the appearance of the patient's retina. Clinically, these images are used to examine and diagnose diabetic retinopathy and glaucoma. Blood vessels and neurons of the retina are analyzed for diagnosing diabetic retinopathy, and the optic disc and cup of the eye are analyzed for diagnosing glaucoma. Manual examination of these images may lead to human errors, and these errors can be reduced by analyzing the images using advanced

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image processing algorithms. Diagnosis of Glaucoma is done by segmenting the optic cup and optic disc from the fundus image. Extraction of blood vessels, exudates, and microaneurysms will help in diagnosing diabetic retinopathy.

This research focuses on developing a classification methodology that can be deployed in the cloud so that clinicians can predict the type of eye disease remotely. In the proposed system, fundus images are acquired using fundus photography and given to the prediction system. The images are enhanced, and local features are extracted using SURF. After the extraction of local features, clustering is performed. Bag of Visual words or Bag of Features is formed using the cluster centers. This Bag of Features is given as input for classification of diseases.

II. MATERIALS AND METHODS

2.1. Image Acquisition

The retina details are captured using Fundus photography. The retina is acquired using a fundus camera by illuminating the retina with imaging light rays passed through the pupil. An ophthalmic photographer focuses and aligns the camera to capture the patient's retina. As the shutter release is pressed, a flash is fired. The captured images are stored for further analysis and classification of diseases.

2.2. Image Enhancement

Image enhancement is the process of boosting the image quality through noise removal and improving the contrast such that the enhanced image suits for further analysis. In this research work, contrast stretching is employed to improve the quality of the images and it helps in extracting fine features from the image. Pixel intensities are normalized such that these intensities span the required range of values. The enhancement is performed using the following formula:

$$Enhanced_{pixel} = (inputPixel - min_{lo}$$

2.3. Bag of Features (Visual Words)

BoF comprises of the following steps: i) extraction of local features from the image, and ii) building the vocabulary. Local features of the image are extracted using the SURF descriptor. From the extracted local features, the key points or predominant features are elected using k-means clustering and the vocabulary is built.

2.4. SURF (Speeded Up Robust Features)

SURF is a scale- and rotation-invariant detector and descriptor proposed by Bay et al. It detects interest points using a Hessian matrix approximation.

Hessian Matrix based interest points:

Consider a point $x = (x, y)$ in an image I, the Hessian matrix $H(x, \sigma)$ at scale σ is defined as:

$$H(x, \sigma) = \begin{bmatrix} L_{xx}(\\ L_{xy}(\end{bmatrix}$$

where $L_{xx}(x, \sigma)$ is the convolution of the second-order Gaussian derivative with the image I at point x. Integral images are used to support fast computation of box convolution filters.

2.5. k-means Clustering

Local features extracted using SURF are given as input for k-means clustering. This is an unsupervised learning algorithm that classifies the data with k clusters. In this research, $k = 10,000$ cluster centers were selected. Iteration stops when cluster centers cannot move or change further. These resulting clusters form the "Visual Words" vocabulary.

2.6. Support Vector Machine (SVM)

SVM algorithm is extended to solve multi-class problems by employing Error Correcting Output Codes (ECOC) for distributed output representation. ECOC model reduces the multi-class problem into a set of binary classifiers. If there are 3 classes (DR, Glaucoma, Healthy), then three SVM classifiers are employed for classification using a One-Versus-One (OVO) coding scheme.

III. PROPOSED CLASSIFICATION APPROACH

The workflow comprises:

Contrast Stretching: Normalizing contrast levels pixel by pixel.

Image Flipping: All images are flipped towards a uniform direction (left or right) to prevent orientation-based misclassification.

SURF Descriptor: Applied on the flipped images to extract features. From 45 images, 2,30,21,280 features were initially extracted, retaining 1,14,17,024 strong features.

k-means Clustering: Clustering the 1.14 crore data points into 10,000 cluster centers (vocabulary).

SVM-ECOC: Using the OVO coding matrix where Learner-1 compares DR vs Glaucoma, Learner-2 compares DR vs Healthy, and Learner-3 compares Glaucoma vs Healthy.

IV. RESULTS AND DISCUSSION

Experiments were conducted with the HRF dataset (15 glaucoma, 15 DR, 15 healthy). 33 images were used for training and 12 for testing.

Performance Summary Table:

Case #	Description	Accuracy
Case 1	Raw fundus images + 500 clusters	75%
Case 2	Enhanced fundus images + 500 clusters	58%
Case 3	Enhanced & flipped images + 500 clusters	83%
Case 4	Raw fundus images + 10,000 clusters	67%
Case 5	Enhanced fundus images + 10,000 clusters	75%
Case 6	**Enhanced & flipped images + 10,000 clusters**	**92%**

The results show that ECOC-SVM performed better than standard Decision Tree-based SVM (DT-SVM). Case 6 provided consistent results across all three classes with a precision for Healthy eyes reaching nearly 100%.

V. CONCLUSION

This research work successfully developed a system to classify fundus images using Bag of Visual Words. The maximum accuracy of 92% was achieved when using 10,000 cluster centers on contrast-enhanced and flipped images.

The limitation of this study is the exponential increase in processing time as cluster centers increase. Future work will focus on optimizing the clustering algorithm and exploring deep learning ensembles for multi-class eye disease detection.

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REFERENCES

[1]. J. Odstrcilik, et al., "Retinal vessel segmentation by improved matched filtering," *IET Image Processing* 7 (4), 2013.
[2]. J. Liu, et al., "ARGALI: An automatic cup-to-disc ratio measurement system," *Springer*, 2009.
[3]. J. Liu, et al., "Aglaia system architecture for glaucoma diagnosis," *APSIPA*, 2010.
[4]. R. Bock, et al., "Glaucoma risk index: automated glaucoma detection," *Medical Image Analysis* 14 (3), 2010.
[5]. C. Muramatsu, et al., "Detection of retinal nerve fiber layer defects," *Journal of Biomedical Optics* 15 (1), 2010.
[6]. M. Madhusudhan, et al., "Image processing techniques for glaucoma detection," *Springer*, 2011.
[7]. J. Cheng, et al., "Superpixel classification based optic disc and optic cup segmentation," *IEEE Transactions on Medical Imaging* 32 (6), 2013.
[8]. C.B. Anusorn, et al., "Image processing techniques for glaucoma detection using CDR," *Thammasat Int. Journal of Science*, 2013.
[9]. A.A. Salam, et al., "Autonomous Glaucoma detection using cup to disc ratio," *IEEE ISSPIT*, 2015.
[10]. A.A. Salam, et al., "Automated detection of glaucoma using structural features," *Springerplus* 5 (1), 2016.
[11]. H. Fu, et al., "Joint Optic Disc and Cup Segmentation Based on Multi-label Deep Network," *IEEE TMI* 37 (7), 2018.
[12]. G.G. Gardner, et al., "Automatic detection of diabetic retinopathy using ANN," *British Journal of Ophthalmology* 80 (11), 1996.
[13]. G. Csurka, et al., "Visual categorization with bags of keypoints," *ECCV Workshop*, 2004.
[14]. A.D. Fleming, et al., "Automated detection of exudates for diabetic retinopathy," *Physics in Medicine & Biology* 52 (24), 2007.
[15]. A Sopharak, et al., "Automatic detection of diabetic retinopathy exudates," *Computerized Medical Imaging* 32 (8), 2008.
[16]. R. Acharya, et al., "Application of higher order spectra for DR identification," *Journal of Medical Systems* 32 (6), 2008.
[17]. O. Faust, et al., "Algorithms for automated detection of DR: a review," *Journal of Medical Systems* 36 (1), 2012.
[18]. K.S. Sujatha, et al., "Fuzzy based multiple dictionary bag of words," *Procedia Engineering* 38, 2012.
[19]. R.A. Welikala, et al., "Automated detection of proliferative DR," *Computer Methods and Programs in Biomedicine* 114 (3), 2014.
[20]. Y. Shinomiya, et al., "Bag of Features Based on Feature Distribution Using Fuzzy C-Means," *Springer*, 2014.
[21]. G. Azzopardi, et al., "Trainable COSFIRE filters for vessel delineation," *Medical Image Analysis* 19 (1), 2015.
[22]. V. Gulshan, et al., "Deep learning algorithm for detection of DR," *JAMA* 316 (22), 2016.
[23]. M.D. Abramoff, et al., "Improved automated detection of DR through deep learning," *Investigative Ophthalmology* 57 (13), 2016.
[24]. P.J. Saine, et al., *Ophthalmic Photography*, Butterworth-Heinemann, 2002.

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[25]. P. Costa, et al., "Convolutional bag of words for DR detection," *IPSJ Transactions*, 2017.

[26]. H. Bay, et al., "SURF: Speeded Up Robust Features," *Computer Vision and Image Understanding* 110 (3), 2008.

[27]. P. Viola and M. Jones, "Rapid object detection using simple features," *CVPR*, 2001.

[28]. J.J. Koenderink, "The structure of images," *Biological Cybernetics* 50, 1984.

[29]. T. Lindeberg, "Scale-space for discrete signals," *PAMI* 12 (3), 1990.

[30]. D.G. Lowe, "Distinctive image features from scale-invariant keypoints," *IJCV* 60 (2), 2004.

[31]. A Neubeck and L. Van Gool, "Efficient non-maximum suppression," *IEEE ICPR*, 2006.

[32]. M. Brown and D.G. Lowe, "Invariant features from interest point groups," *BMVC*, 2002.

[33]. J. MacQueen, "Methods for classification and analysis of observations," *Berkeley Symposium*, 1967.

[34]. J.A. Hartigan and M.A. Wong, "A k-means clustering algorithm," *Applied Statistics* 28 (1), 1979.

[35]. J.R. Quinlan, *C4.5: Programs for Empirical Learning*, 1993.

[36]. L. Breiman, et al., *Classification and Regression Trees*, 1984.

[37]. T. Dietterich, et al., "Solving multiclass learning problems via ECOC," *JAIR* 2, 1995.

[38]. S. Escalera, et al., "Separability of ternary codes for ECOC," *Pattern Recognition Letters* 30 (3), 2009.

[39]. A.C. Lorena, et al., "Evolutionary design of multiclass SVM," *Journal of Intelligent & Fuzzy Systems* 18 (5), 2007.

[40]. J. Hong, "Multimodal brain-computer interface," *Journal of Intelligent & Fuzzy Systems*, 2017.

[41]. X. Wang, et al., "An improved algorithm for decision-tree-based SVM," *IEEE WCICA*, 2006