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Automated Retinal Health Diagnosis Using Pyramid Histogram of Visual Words and Fisher Vector Techniques

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ABSTRACT

Untreated age-related macular degeneration (AMD), diabetic retinopathy (DR), and glaucoma may lead to irreversible vision loss. Hence, it is essential to have regular eye screening to detect these eye diseases at an early stage and to offer treatment where appropriate. One of the simplest, non-invasive and cost-effective techniques to screen the eyes is by using fundus photo imaging. But, the manual evaluation of fundus images is tedious and challenging. Further, the diagnosis made by ophthalmologists may be subjective. Therefore, an objective and novel algorithm using the pyramid histogram of visual words (PHOW) and Fisher vectors is proposed for the classification of fundus images into their respective eye conditions (normal, AMD, DR, and glaucoma). The proposed algorithm extracts features which are represented as words. These features are built and encoded into a Fisher vector for classification using random forest classifier. This proposed algorithm is validated with both blindfold and ten-fold cross-validation techniques. An accuracy of 90.06% is achieved with the blindfold method, and highest accuracy of 96.79% is obtained with ten-fold cross-validation. The highest classification performance of our system shows the potential of deploying it in polyclinics to assist healthcare professionals in their initial diagnosis of the eye. Our developed system can reduce the workload of ophthalmologists significantly.

Keywords – age-related macular degeneration; bag-of-visual-words; computer-aided diagnosis system; diabetic retinopathy; eye diseases; fisher vector encoder; fundus images; glaucoma; machine learning.

1. Introduction

The world is facing an ageing population with a total number of 901 million people over the age of 60 [1], [2]. The numbers are also expected to increase to 1.4 billion in the year 2030 [2]. Due to the massive increase of elderly in the society, there is a rising concern of the challenges in an ageing society. These challenges include the economic and social burden and also a decline in the efficiency of performing their daily activities. Furthermore, according to the United Nations, the life expectancy of an individual is continually increasing because of the improved quality of life [1]. So, to cope with the longevity, it is essential for the elderly to maintain a healthy eyesight so that they can continue to contribute to the society and at the same time, enjoy a good quality of life [3].

Eye diseases namely glaucoma, age-related macular degeneration (AMD) and diabetic retinopathy (DR) are the most prevalent conditions in the elderly [4] and they may cause vision loss. Glaucoma is one of the chief causes of vision loss in the elderly (age > 40 years old) [5]. It is a disease which impairs the optic nerve of the eye because of the raised intraocular pressure in the eye [6]–[8]. Hence, causing damage to the optic nerve [5]. AMD is another eye condition which is a common cause of blindness in the elderly [9]. It is caused by the degeneration of the macula in the retina. The macula is responsible for maintaining sharp vision, therefore when degeneration occurs at the macula, our central vision is affected [9]. In AMD, small yellowish deposits (drusens) grow under the retina. These deposits cause leakage of blood in the retina and thus damaging it [9]. Conventionally, there are two categories of AMD – the dry and wet AMD [10]. DR, on the other hand, affects diabetic patients when high blood sugars cause changes in the blood vessel (microangiopathy) leading to decreased oxygen supply to the retinal tissue [11]. Hence, in DR, the eye tries to grow new blood vessels, but they are often thin, fragile, and susceptible to blood leakage [12]. The DR can be classified into *four* stages depending on the severity [13], [14]. This grading is done based on the presence of exudates, haemorrhages, cotton wool spots, microaneurysms, and neovascularisation. The first three stages are categorized as

mild, moderate, and severe non-proliferative DR respectively, and the advanced stage of DR is categorized as proliferative DR.

These eye conditions are irreversible but detecting these disorders at an earlier stage will impede the progression of the diseases with proper treatment [15]. Therefore, it is of utmost importance to detect the various eye diseases early to prevent blindness. Fundus imaging is a non-invasive, safe, and economical diagnostic tool commonly adopted by ophthalmologists for diagnosis purpose. But the visual interpretation of the fundus images is subjective and laborious. In addition, it is difficult to detect the subtle microaneurysms, or exudates present in the fundus images and thus, resulting in misdiagnoses at times.

Therefore, a computer-aided diagnosis (CAD) system is proposed to aid the ophthalmologists in their diagnoses. A CAD system can also serve as a validation tool to take the second opinion for the ophthalmologists. Also, a CAD eye screening system enables hospitals to conduct a large-scale eye screening session for the elderly. Many works have been done on the automated identification of AMD [16], [17]. Also, a CAD screening tool has been proposed by Acharya et al. [18] to differentiate normal, dry AMD, and wet AMD fundus images. Automated differentiation of normal and DR [19], three-class classification (normal, non-proliferative DR, proliferative DR) [13] and five-class classification (normal, mild DR, moderate DR, severe DR, proliferative DR) [20] are proposed. Also, many automated diagnoses of normal and glaucomatous eye conditions [7], [8] have been proposed to diagnose glaucoma accurately.

Further, a few works have been conducted in this direction to develop the CAD algorithm for an automated diagnosis of AMD, DR, and glaucoma (refer to [Table 6](#)). The first study to categorize the various eye diseases (DR, AMD and glaucoma) as an abnormal class initiated by Acharya et al. [39]. In their work, they have decomposed the fundus images into 2-dimensional intrinsic mode functions using the bi-dimensional empirical mode decomposition technique. Later, several entropy features were extracted from the 2-dimensional intrinsic mode function and these extracted features were ranked according to their level of distinction. An accuracy of 88.63% was achieved with the support vector machine (SVM) classifier.

Both AdaSyn and particle swarm optimization(PSO) techniques were applied in the previous works by Koh et al. [40], [41]. Koh et al. [40] have applied a 2-dimensional continuous wavelet transform and extracted nonlinear features from the decomposed images. After which, AdaSyn operation was applied to equalize the number of features in the *two* classes. Then, an optimization

technique was employed to select highly distinctive features for classification and obtained an accuracy of 92.48%.

In another previous study, Koh et al. [41] extracted feature descriptors from pyramid histogram of oriented gradients (PHOG) and speeded up robust features (SURF). These extracted features for the normal and abnormal classes were balanced with AdaSyn. Subsequently, they used the canonical correlation analysis to fuse the features. They implemented an optimization technique to select distinct features and obtained an accuracy of 96.21% with k-nearest neighbour classifier.

The above discussed works classify two classes (normal vs abnormal). In this paper, we are proposing four class classification. Further, to the best of the authors' knowledge, this is the first work to classify *four* classes (normal, AMD, DR, and glaucoma) of eye diseases. The novelty of this study is to reliably diagnose the different eye conditions using one algorithm automatically. This four class (AMD, DR, glaucoma, and normal) identification can facilitate ophthalmologists in their diagnoses.

2. Data Used

The fundus images were acquired from the Ophthalmology Department of Kasturba Medical College in Manipal, India. In this work, we have used 2,220 images with a resolution of 360 x 480, and they were captured with a Zeiss FF450 plus mydriatic camera using a field of view of 50°.

Table 1 shows the number of fundus images used in each class. The fundus images were taken and labelled by experienced ophthalmologists from KMC, Manipal. Also, Figure 1 shows a typical illustration of a normal, AMD, DR, and glaucoma fundus image.

Table 1: Number of fundus images used.	
Classes	Number of fundus images
Normal	790
AMD	531
DR	346
Glaucoma	553
<i>Total</i>	<i>2,220</i>

Figure 1: Sample fundus images: (a) normal, (b) AMD, (c) DR, and (d) glaucomatous.

3. Methodology

Figure 2 shows the flowchart of the proposed work. Firstly, pyramid histogram of visual words (PHOW) are extracted from the fundus images, then Gaussian mixture model (GMM) is performed on the training set to obtain a vocabulary to encode the Fisher vectors for training and testing. PHOW, GMM and Fisher vector are implemented using VLFeat toolbox [21]. Then the performance of this algorithm is determined with both blindfold and ten-fold cross-validation approach (classification).

Figure 2: The proposed method for the development of a CAD eye screening system.

3.1 Building Vocabulary and Features Extraction

The PHOW is employed in this work. It is a form of feature representation technique based on bag-of-words approach [22]. The PHOW treats the image features as words. The colour fundus images are divided into a dense grids in steps of 2 with scales of 4, 6, 8, and 10. Then SIFT descriptors are extracted from the different scales. The SIFT extracts the gradient and orientation around the neighborhood using equation (1) and (2) respectively. An orientation histogram is built from the neighborhood gradient orientations with 36 bins covering 360° and each point added to the histogram is weighted by its gradient magnitude. The orientation of the points is given by the peak of this histogram.

$$m(x, y) = \sqrt{(L(x + 1, y) - L(x - 1, y))^2 + (L(x, y + 1) - L(x, y - 1))^2} \quad (1)$$

$$\theta(x, y) = \tan^{-1} \frac{L(x, y + 1) - L(x, y - 1)}{L(x + 1, y) - L(x - 1, y)} \quad (2)$$

where $L(x \& y)$ is the gaussian blurred image, m is magnitude and θ is the orientation.

The descriptor vector is obtained using 4x4 grid centered over each point orientated to the point orientation and orientation histogram in 8 directions is calculated for all 16 grids. The descriptor is normalized to unit length and a threshold of 0.2 is applied to reduced influences from large gradient magnitudes and renormalized. Finally, a random selection of 100,000 sub-set of columns was selected to build the vocabulary. The Gaussian mixture model (GMM) is then applied to find the mean, diagonal covariance, and prior probabilities of the GMM. Subsequently, the extracted vocabulary is used to encode improved Fisher vector. The power normalization or signed square-rooting is used to “un-sparsify” the vector to keep the dot-product similarity by making the distribution of features less peaky around zero [23], [24]. Also, the L2 normalization, which is the square root of the sum of the squares of the absolute values, is used to cancel the effect of dependency on image specific information [25].

In this work, both experiments build up the vocabulary from PHOW feature extraction. After that, the Fisher vector [26] is used to generate the term vector (representation of the fundus image).

3.2 Fisher Vector

The Fisher vector [26] encoding is based on the Fisher kernel which groups a dense set of local features into a high-dimensional descriptor representing the image-level features. The descriptors use the gradient, based on probability density function to calculate the log-likelihood of the local features. The gradient is assumed to follow a GMM model to approximate the Fisher information. Fisher vector not only considers the gradient with respect to the weights but also the derivatives with respect to the mean and standard deviation [22]. Thus, it encodes the number of occurrences of each visual word with additional information about the distribution of the descriptors for the same vocabulary size. Using the 500 GMM cluster centers, the Fisher vector are encoded based on the differences between the image descriptors and centers. Thus, distinct features extracted from the four classes (AMD, DR, glaucoma, and normal) are encoded into the Fisher vector for classification.

3.3 Adaptive Synthetic Data Sampling (AdaSyn)

It can be seen from **Table 1** that the distribution of data for the four classes (normal, AMD, DR, and glaucoma) is unequal. Therefore, AdaSyn is applied to the fundus images to make the number of training data (features) to be equal in four different classes. AdaSyn [27] is an algorithm which generates synthetic data to balance the number of data in each class. Firstly, the algorithm decides the extent of imbalance in the four classes then it computes the number of data to be generated. The algorithm randomly selects a sample from the minority class and uses its k-nearest neighbours to generate several synthetic samples.

3.4 Classification

The random forest (RF) classifier [28] was employed as the classifier in this work. It is an ensemble learning algorithm for classification. This algorithm is based on the classification outputs made from a set of decision trees. Each decision tree will determine the output and the final decision is based on the majority votes. 500 decision trees were used to determine the class. Also, ten-fold

cross-validation [29] and blindfold [30] strategies were employed to validate the proposed algorithm.

Table 2 records the total number of fundus images used for the training and testing of the proposed algorithm. The data is randomly split into training and testing set. 70% of the minimum class is used and the same number of images are randomly sampled from the other classes. The same is done with the 80% and 90% dataset splits. Likewise, the data is split into 70%, 80%, and 90% for the ten-fold cross-validation technique.

Table 2: The number of fundus images used in different percentage split for the blindfold approach.

Data Split (%)	Training	Testing
70	NOR: 242	NOR: 548
	AMD: 242	AMD: 289
	DR: 242	DR: 104
	GLA: 242	GLA: 311
80	NOR: 277	NOR: 513
	AMD: 277	AMD: 254
	DR: 277	DR: 69
	GLA: 277	GLA: 276
90	NOR: 311	NOR: 479
	AMD: 311	AMD: 220
	DR: 311	DR: 35
	GLA: 311	GLA: 242

NOR: Normal, AMD: Age-related macular degeneration, DR: Diabetic retinopathy, GLA: Glaucoma

4. Results

Table 3 and **Table 4** show the results using the ten-fold cross-validation (balanced dataset) and blindfold (unbalanced dataset) respectively. Three different performance results are obtained using 70%, 80%, and 90% data split respectively. It can be noted that the overall diagnostic accuracy for both validation techniques regardless of percentage split is relatively high.

It can be seen from **Table 3** that the highest accuracy of 96.79% is obtained from 90% data split for the unbalanced dataset. Similarly, the highest accuracy of 90.06% is obtained from the 90% data split for unbalanced dataset as listed in **Table 4**.

From the confusion matrices provided in Table 5, it can be observed that regardless of data splits (70%, 80%, or 90%) more DR images are misclassified as AMD. This might be due to the similarities between drusens (in AMD) and exudates (in DR). In addition, it can be observed that the proposed algorithm works well for glaucoma class.

Table 3: Results using ten-fold cross-validation (balanced dataset).

Data Split (%)	TP	TN	FP	FN	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
70	2287	753	37	88	96.05	98.41	96.29	95.32
80	2295	756	34	80	96.39	98.54	96.63	95.70
90	2306	766	24	78	96.79	98.97	96.73	96.96

TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative, PPV: Positive Predictive Value

Table 4: Results using blindfold validation (unbalanced dataset).

Data Split (%)	TP	TN	FP	FN	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
70	623	503	45	81	89.94	93.26	88.49	91.79
80	524	464	49	75	88.85	91.45	87.48	90.45
90	438	441	38	59	90.06	92.02	88.13	82.07

Table 5: Confusion Matrix using blindfold validation (unbalanced dataset).

70%		Ground Truth			
		Normal	AMD	DR	Glaucoma
Predicted	Normal	503	11	3	13
	AMD	28	242	10	6
	DR	14	30	91	2
	Glaucoma	3	6	0	290
80%		Ground Truth			
		Normal	AMD	DR	Glaucoma
Predicted	Normal	464	12	1	13
	AMD	43	208	6	3
	DR	2	27	59	3
	Glaucoma	4	7	3	257
90%		Ground Truth			
		Normal	AMD	DR	Glaucoma
Predicted	Normal	441	12	1	12
	AMD	28	187	2	9
	DR	7	16	32	2
	Glaucoma	3	5	0	219

5. Discussion

In this current work, a novel technique is proposed by implementing PHOW to describe the fundus images with Fisher vector to build up visual vocabularies for the classification of the various eye conditions. We have achieved the highest diagnostic accuracy of 96.79% using the ten-fold cross-validation technique and obtained 90.06% classification accuracy even with blindfold cross validation.

Further, the diagnostic performance has improved from our first work published in 2016 to the subsequent works until the presently proposed CAD system (see Table 6). Moreover, the number of fundus images used have increased. In Acharya et al. [31], there were only 800 (400 normal and 400 abnormal) fundus images whereas the current work consists a total of 1,804 fundus images.

Given the high performance in this work, it can be noted that the PHOW can represent the frequency of word occurrence in the fundus images accurately. It can pick up the subtle variations recurring in the pixels of the images and build the vocabulary which can categorize the fundus images accordingly into their respective classes. Moreover, this method is resistant towards the orientation and position of the features [32]. Hence, we have obtained 90.06% classification accuracy even with blindfold cross-validation.

In our previous works, we have grouped the different eye conditions as one abnormal class. In this study, the CAD eye screening system can identify the different eye abnormalities (AMD, DR, and glaucoma) individually. Thus, able to assist the ophthalmologists to provide a reliable diagnosis of each eye class.

Furthermore, the published works documented in Table 6 validated their algorithms with ten-fold cross-validation. In this work, we have performed both ten-fold and blindfold validation. It is observed that the proposed algorithm yielded the highest diagnostic performance with the ten-fold cross-validation. Besides, it can be noted that using the ten-fold strategy (balanced dataset) achieved the better performance due to the application of AdaSyn strategy before training of the features. AdaSyn balances the number of data in each class, and therefore, there is an increase in the overall number of data for training and testing of the proposed algorithm. With more number of synthetic data generated, there are more data to train the algorithm and hence, this increased in diagnostic performance using the ten-fold approach.

Having a mass screening program will also create awareness of various eye diseases and the importance of an early detection of any eye conditions. Besides, the CAD system can be installed in polyclinics to assist healthcare professionals in the initial diagnosis of the eye and issue referral only to patients with diseased eyes. This way, the workload of ophthalmologists in hospitals will reduce, and ophthalmologists can focus more on patients requiring immediate medical attention.

The benefits of the proposed algorithm:

- i. No pre-processing of the fundus images.
- ii. It is validated with both ten-fold and blindfold strategies.
- iii. It can be used to assist the clinicians to cross-check their decision on the eye screening.
- iv. Used maximum number of images in Table 6 and obtained the highest performance.

The drawbacks of the proposed algorithm:

- i. It is computationally intensive as we need to generate the vocabulary from the data.
- ii. More fundus images are needed to boost the performance of the proposed algorithm.

The developed system can be used by general practitioners and at polyclinics. The clinicians can refer only the abnormal class (DR, AMD or glaucoma) to the main hospital ophthalmology department for further confirmation and treatment. Therefore, our CAD eye screening system can help to alleviate the workload of the ophthalmologists in eye screening and assist in making accurate diagnosis.

We are unable to run our proposed algorithm on the public database, as we do not single public database for all *four* classes (normal, DR, glaucoma and AMD) of images. So, we need to use the images from *four* different databases with different resolutions and field of views which may not yield good classification results. Hence, we intend to employ deep learning techniques to diagnose the various eye conditions in our next work.

Table 6: Selected studies of CAD system to automatically detect the various eye conditions.

Authors	Year	Number of images used	Techniques employed	Accuracy (%)	Sensitivity (%)	Specificity (%)
2-class (normal and abnormal)						
Acharya et al. [31]	2016	Normal: 400 Abnormal: 400	▪ Bidimensional empirical mode decomposition	88.63	86.25	91.00

		(115 AMD, 170 DR, 115 glaucoma)	<ul style="list-style-type: none"> Entropies and energy features Chernoff bound and Bhattacharyya distance Support vector machine classifier (10-fold cross-validation) Retinal risk index 			
Koh et al. [33]	2017a	Normal: 404 Abnormal: 1,082 (381 AMD, 195 DR, 506 glaucoma)	<ul style="list-style-type: none"> Continuous wavelet transform Entropies features AdaSyn Particle swarm optimization RF classifier (10-fold cross-validation) 	92.48	89.37	95.58
Koh et al. [34]	2017b	Normal: 404 Abnormal: 1,400 (529 AMD, 365 DR, 506 glaucoma)	<ul style="list-style-type: none"> Pyramid histogram of oriented gradients Speeded up robust features AdaSyn Canonical correlation analysis Particle swarm optimization K-nearest neighbour classifier (10-fold cross-validation) 	96.21	95.00	97.42
4-class (normal, AMD, DR, and glaucoma)						
Present work	2017c	Normal: 404 AMD: 529 DR: 365 Glaucoma: 506	<ul style="list-style-type: none"> PHOW GMM Fisher vector AdaSyn RF classifier (10-fold cross-validation and blindfold) 	10-fold: 96.79	10-fold: 96.73	10-fold: 96.96
				Blindfold: 90.06	Blindfold: 88.13	Blindfold: 82.07

6. Conclusion

An original approach to develop a CAD eye screening system for the detection of various eye diseases (glaucoma, DR, AMD, and normal) is proposed in this work. Blindfold and ten-fold cross-validation techniques are implemented in this study. This proposed work is an extension of our previous studies (Table 6). Therefore, it is an innovative approach, and the first work to the best of our knowledge proposed to assist the ophthalmologists in making an accurate diagnosis of the various eye conditions by providing an adjunct tool. Our proposed CAD system can be placed in third world countries and remote villages where the healthcare services are

limited. Additionally, the proposed CAD eye system can be used to conduct a mass eye screening session for the elderly as an early detection of any eye abnormality. The performance of the system can be further improved by taking more diverse images in each class. Also, our proposed technique can be used to detect other eye diseases like diabetes maculopathy, floaters, retinal detachment and macular hole.

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