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Full Length Article

Retrieval of pathological retina images using Bag of Visual Words and pLSA model

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ABSTRACT

Automated identification of pathological retina images is very important in retinopathy. Conventional methods of retrieval in the domain of retinopathy are based on the manual observation of different components of retina. However, manual observation becomes difficult due to the large diversity of images and the varying symptoms of diseases present in pathological images. For example, varying features such as color, shape and structure of lesions complicate the manual observations and subsequent assessment of the state of the disease. As a solution to these issues, this paper proposes an unsupervised technique known as probabilistic Latent Semantic Analysis (pLSA) along with Bag of Visual Words to discriminate diseased images from normal ones. The method was tested with images from publicly available standard retina fundus image databases and achieved better performance measures compared to the existing methods.

1. Introduction

Diabetic retinopathy (DR), an eye disease of diabetic patients caused due to high blood sugar, and consequent damages to blood vessels in the retina, whose progression though asymptotic in nature has the adverse effect of vision loss if the prevalence of disease is not taken care. The number of DR patients increased rapidly all over the world. According to WHO, prevalence of diabetic patients will be estimated to rise 79.4 million by 2030 where as it was 31.7 million in 2000 [1]. Timely diagnosis and treatment of disease will help to prevent the progress of disease, though complete cure of DR is remote.

The introduction of Computer Aided Medical Diagnosis (CAMD) of retina images helps to reduce the number of patients suffering from eye related diseases. However, their performance results depend on various processing blocks such as input image acquisition techniques and nature of algorithms used for retinal image processing and storage reduction, the algorithms used for compression and storage. The main problem here is the large diversity of images. Literature on these topics reveals that processing techniques suitable for such wide variety images of retinas is quite involved and difficult [2]. Pathological retinal images have different symptoms, characteristics and color artefacts which are difficult to recognize. However, pre-processing steps may overcome most of these drawbacks. The classification phase will classify the images as normal or pathological. CAMD systems allow to reduce the cost, workload of manual graders within shortest time and to make the patients aware about the consequence of the disease. Manual grading result depends upon the observer. This can also be overcome by the introduction of CAMD systems. Other retinal pathologies such as hypertension and glaucoma also affect the vision of DR patients.

Fig. 1 shows the example of retina fundus images from Methods for Evaluating Segmentation and Indexing techniques dedicated to Retinal Ophthalmology (MESSIDOR) database [3]. Various structures are marked in Fig. 1(a) and exudates are shown in Fig. 1(b). Some retina images complicate the diagnosis process due to heterogeneity in color and shape of various anatomical structures. Examples of such images, from MESSIDOR [3], Digital Retinal Images for Vessel Extraction (DRIVE) [4] and STructured Analysis of the REtina (STARE) [5] retina image databases are shown in Figs. 2–4.

People in Indian subcontinent have different lifestyles, diet habits, and ethnicity [1]. In [1], authors conducted a study of diabetic patients (a total of 62148 known diabetes) on behalf of AIOS (All India Ophthalmological Society) in November 2014. As per the study, out of 22.18 percent were found to have DR, suffered vision impairment of 6/18p.

Lesions are classified as exudates, drusen, microaneurysms and haemorrhages. Exudates (EX) are of two types: hard and soft. Usually exudates and drusen are categorized as white lesions and

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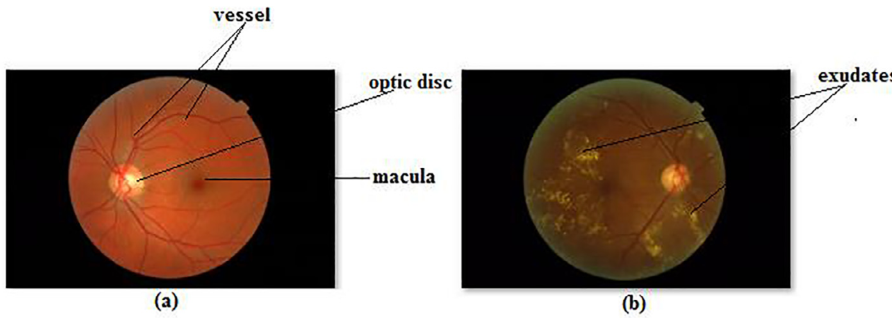

Fig. 1. Components of the retina, (b) Retina image containing exudate lesion.

Fig. 2. Samples of retina images taken from MESSIDOR database [3].

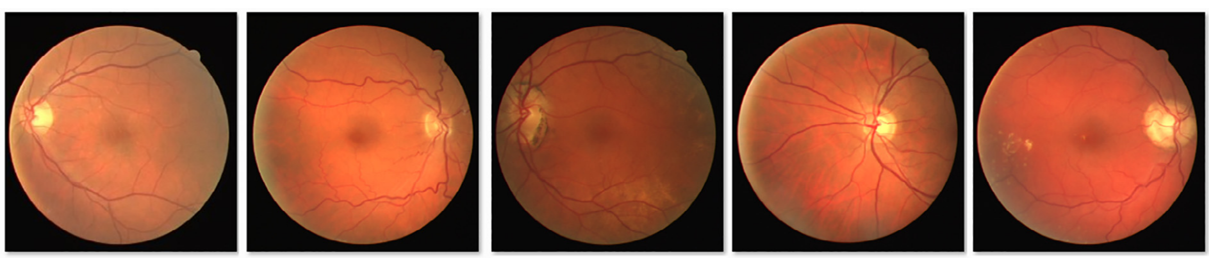

Fig. 3. Samples of retina images taken from DRIVE database [4].

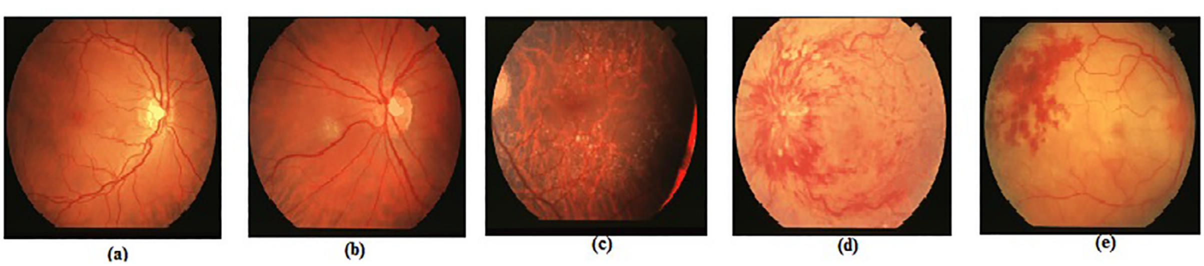

Fig. 4. Samples of retina images taken from STARE database [5].

microaneurysms and haemorrhages are categorized as dark lesions because of their color. Exudates are a type of unwanted protein deposit formed due to leakage from vascular network with yellowish color, well defined egde [6]. Microaneurysms (MA) and haemorrhages (HA) are usually seen in red color, so they are named as red lesions too. These are present in the retinal capillary vessel walls as small saccular bulges. The lesions location, size, shape and brightness vary within an image and among patients. This makes it difficult to detect the lesions.

The automatic analysis of diabetic retinopathy can substantially save time required for grading the diseases than manual grading. Thus many researchers in the area of ophthalmology have devoted their time in the process of automating the diagnosis of DR.

The approach proposed in this work discriminates the normal and pathological images using pLSA model. The approach first determines the interest points using hybrid descriptor, that is, Scale Invariant Feature Transform (SIFT) [7], Local Directional Pattern (LDP), Local Binary Pattern (LBP) and color descriptors. Then, the popular K-means clustering algorithm is employed to produce set of Bag of Visual Words (BoVW) to represent the images. Probabilistic latent semantic analysis (pLSA) model is used to reduce the feature dimensions making use of the concept of topics instead of words. Next, Support Vector Machine (SVM) classifier is employed to classify each image as normal or pathological using visual words.

The following sections of this paper are put forth as in the following way: Related works about retinal fundus image classification is described in Section 2. The proposed method of retrieval of pathological images are discussed along with the basics of topic modeling by pLSA, various features used in our proposed method required for better understanding of the paper is also presented in Section 3. Section 4 describes the dataset used, results obtained and further discussions of the proposed work. Conclusion about the paper is given in Section 5.

2. Related works

Two types of diagnosis of retinal diseases are available. In the first method, the lesions present in images are detected and, based on the result these images are discriminated as normal or pathological. In the second category, a key signature is detected using descriptors and classification is done based on these descriptors.

Many of the literatures on CAMD of diabetic retinopathy mainly focuses on detecting various lesions; it is a prominent task in CAMD. In order to detect these lesions, preprocessing step is done prior to actual method to achieve higher accuracy. Usually only the RGB image green channel is selected for processing.

In [8], Speeded Up Robust Feastures (SURF) descriptor is used as descriptors and then images are classified using multiple classifier systems (Naive Bayes, Random Forest, and SVM). They tested the method on DirectDB1, STARE and MESSIDOR retina databases. 97 percent accuracy is reported for images of MESSIDOR Database [3].

Sparse coded techniques along with SVM are used to discriminate the images containing bright and normal lesions in [9]. First, they extracted the features. Features used in this approach are color, SIFT, Histogram of Oriented Gradients (HOG), and LBP. Then, SVM classifier is used to discriminate the images.

A technique to classify image as normal or abnormal based on analysing Optic Disk (OD) and blood vascular network is presented in [10]. The classification process consists of the following three major stages: pre-processing of retina images, segmentation and extraction of segments, extraction of features from these segments and finally the classification. LAB color space based image preprocessing methods are employed in the first stage. Then, background subtraction is performed so that we can separate OD and vascular area. In the next stage, OD and vascular area are analysed for extracting features. Finally, the SVM classification technique is employed to classify images as abnormal or normal. The limitation of their proposed approach is that, here, classification is based only by checking the conditions of the OD and blood vessels' continuity network. The basic assumption used is that the OD shape is circular and blood vessels are continuous networks in the image. Performance was tested on images of DRIVE database, and reported average values of sensitivity and accuracy as 83% and 98%, respectively.

The work proposed by Jadhav et al. [11] in 2014, presented a classification of fundus images as normal or pathological based on the area of the blood vessel. They obtain the traces and areas of blood vessels by morphological operations on the gray scale image which is preprocessed for noise and enhanced for contrast. [12] reviews the works published related to the area of segmentation of exudates, red lesions and automated DR screening between the years 2005–2015. They concluded that the results of many works are promising but automation is still challenging. Most of the works published in the above areas used a small number of images as dataset. Moreover, the methods used for validation were not uniform and the test databases used in studies were not standardized.

In 2016, Nagendra Pratap Singh et al. [13] introduces Gumbel probability distribution function as kernel for the matched filter in order to detect the blood vessels. PCA based contrast enhancement on the gray scale image is used for further processing. For achieving better accuracy, optimal thresholding technique based on entropy and length filtering techniques are made use of. For performance analysis, average figures of accuracy, TPR, and FPR are computed. Those values obtained for DRIVE dataset are 0.9522, 0.7594, 0.0292 and for STARE dataset are 0.9270, 0.7939, 0.0624 respectively. Average Area Under Curve (AUC) of 0.9287 and 0.9140 for DRIVE and STARE datasets, respectively, are reported.

A combined approach based on skeletonization, adaptive filtering, and fuzzy entropy is used in [14] as an unsupervised method to segment blood vessels. The proposed method achieved an accuracy of 94.63% and 95.21%, for DRIVE and STARE databases respectively.

Many works related to: differentiating between normal and pathological images, locating various anatomical structures and grading stages of DR exists. An automated approach to discriminate normal and unhealthy retinal images is suggested by Raj et al. [15]. Images of various quality and resolution are used for performance testing; however, severity grading of DR was not reported. Performance study was conducted on different images of varying resolution and quality. No performance study on severity grading of DR was reported. Yet another approach is that by Pires et al. [16]; they developed a system that uses fusion of results by a meta classifier that assesses the need for referral.

3. Methodology

Fig. 5 shows the basic workflow of normal/ pathological classification of retina fundus images used in the proposed approach presented in this work. The first step is to extract different features. In our method, SIFT, LBP, LDP and color features are extracted. Then the Bags of Visual Words are generated from those extracted features. Next, pLSA method is applied, which discovers topical similarities and object categories for image classification. Then SVM classifier is employed to categorise images as normal or pathological.

3.1. Feature extraction

Feature extraction involves the separation or extracting discriminating features from the input image which can suitably represent the image. Various interest points are selected as an output of this process. In our work, local non-binary descriptors- SIFT, LBP, LDP and color features are selected and original RGB fundus image is used.

3.1.1. LBP (Local Binary Pattern)

The texture of the images can be represented by LBP descriptor. LBP converts local image primitives like curved edges, flat areas, and spots into a feature histogram independent of rotation and luminosity. Binary codes are created depending upon the relation between grey levels in a local neighbourhood. LBP is introduced by Ojala et al. [17]. In the work [18], LBP technique is used for the first time for visual categorization task by the researcher Zhang et al. [19] However, the original LBP is sensitive to rotation and noise, and hence it is not suitable for the cases of local texture changes. Recently, in [20], LBP is used with SVM classifier to detect haemorrhages, and reports 87.4% of sensitivity, 85.99% of specificity and 86.15% of accuracy on DirectDB1 database [21].

3.1.2. SIFT (Scale Invariant Feature Transform)

SIFT feature [7] is robust to pathological lesions because they are also treated as salient features. Here, denseSIFT features are extracted over a regular image grid. A descriptor of dimension 128 is extracted from each grid point. These features are, as implied by their category name, invariant to scale and orientation.

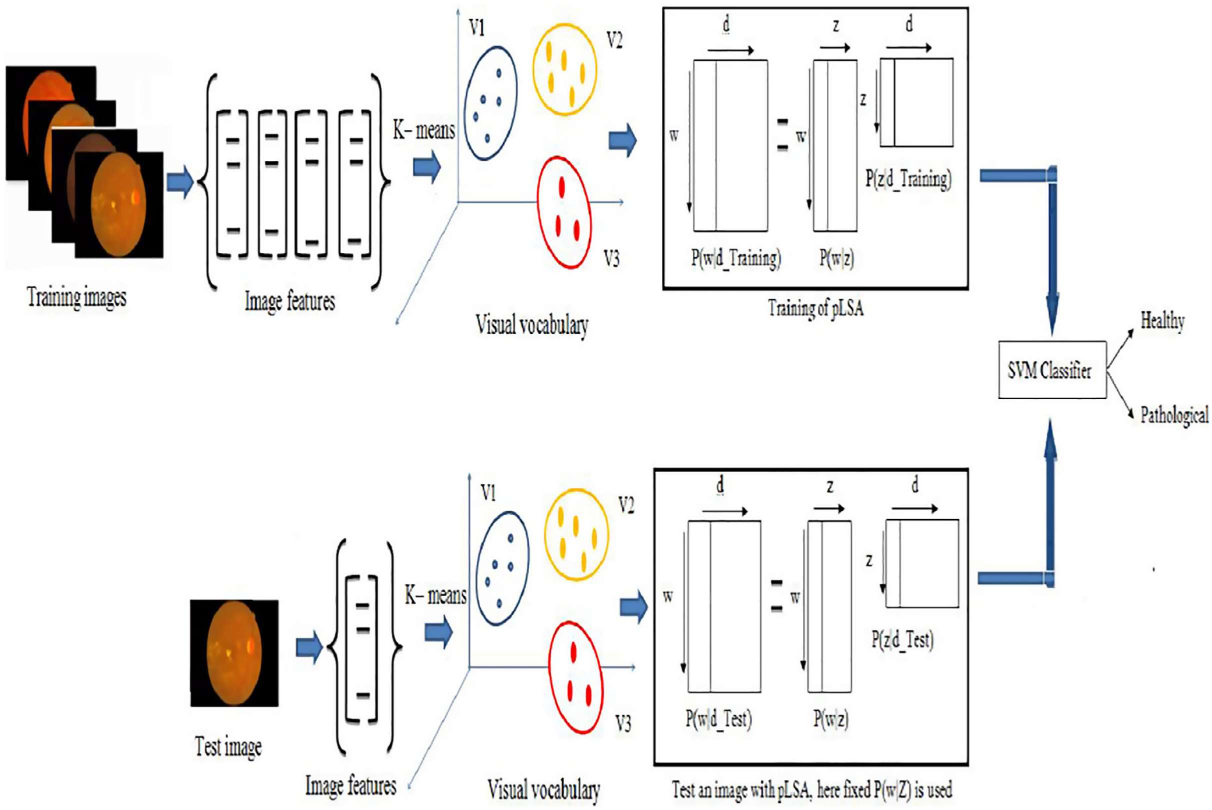

Fig. 5. Graphical representation of proposed method.

SIFT features are also partially insensitive affine distortions and illumination changes.

3.1.3. LDP (Local directional pattern)

LDP, known as local directional pattern, is a local feature descriptor used for describing local image features [22] LDP is inferior to LBP in terms of its robustness to monotonic illumination changes. However, performance of LBP is inferior when images contain random noise. The intensity edges in eight directions around each pixel point is computed for extracting the direction code of the strongest edge among them.

LBP is an operator that uses changes of intensity in local neighbourhood of a pixel whereas LDP operator makes use of the intensity edges to neighbourhood pixels [23]. LDP feature is commonly used in the areas of face recognition [24] and gender classification [25].

3.1.4. Color features

These features represent local color appearance of the image. All the features are computed on 12×12 grid. Thus, SIFT feature of 128×144, LDP feature of 1024×144, LBP feature of 256×144 and color feature of 3×144 are generated.

Each feature has merits and demerits. In order to overcome the limitations of individual use of these features, we use a hybrid descriptor, which is a combination of above features.

3.2. Visual dictionary creation

By using the training set of images, two sets of hybrid feature vectors are generated, one being normal and the other pathological. Then k-means clustering technique is employed to determine *k/2* clusters out of the vectors generated from the hybrid descriptor. Thus, we obtain a transformation of hybrid feature vectors to BoVW feature vectors. Next, quantization is performed. This involves assignment of points of interest of training data set images to the closest word of the dictionary. Thus, a set of visual words is obtained to represent each image in the dataset. Visual word dictionaries are represented as matrices in which rows are composed of words; they are the best representative interest points used in the hybrid descriptor to represent images. Fig. 6 shows the final histogram created using multiple dictionary from the above features.

3.3. Topic modelling by pLSA

Some of the most common reduction methods are Latent Semantic Analysis (LSA), non-negative matrix factorization, pLSA and Latent Discriminant Analysis (LDA). pLSA is a probabilistic generative model for words in documents introduced by T. Hofmann [26]. pLSA is influenced from the technique called LSA [27].

The basic assumption of pLSA model is that the latent topics exist among visual words and we can represent each image by topics rather than words [26]. Similarly pLSA can discover topical similarities among words and can avoid the polysemy of words. pLSA can also be made use of to determine the class of objects for the purpose of classification.

In our method, pLSA is applied on to BoVW based representations of retinal images to automatically discover topics (lesions) from images (retina images) and each visual words corresponds to words. Probability distributions of images with respect to generated topics and the distribution of topics with respect to words are used to capture the relation between words and images. Thus, pLSA is appropriate for our problem because it provides a statistical model for classification of images containing lesions. A brief introduction to the theory of pLSA model is presented in the following:

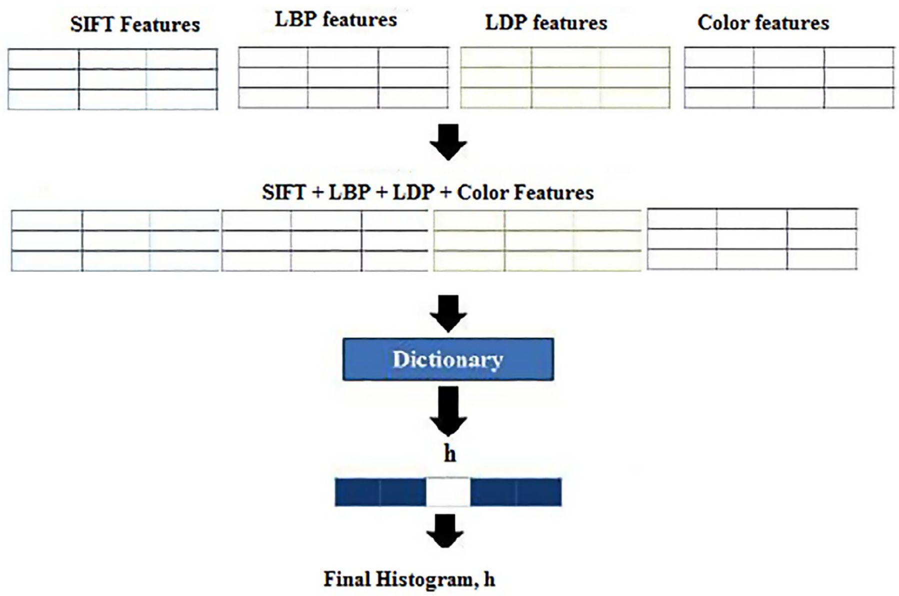

Fig. 6. Final histogram using multiple dictionary.

Let D be the collection of N images, $D = \{d_1, \ldots, d_N\}$ and W be the collection of visual words, $W = \{w_1, \ldots, w_M\}$, where M, the number of visual words, $\|W\|$.

A graphical representation of pLSA model is given in Fig. 7. The expression for joint probability of the model is as given in Eqn. 1.

$$P(d_i, w_j) = P(d_i)\sum_K P(z_k/d_i)P(w_j/z_k) \tag{1}$$

where,

$P(d_i)$ represents the probability of document d_i,

$P(z_k|d_i)$ represents the probability of a topic z_k in the document d_i,

$P(w_j|z_k)$ denotes the probability of a visual word w_j in the topic z_k.

Here, d and w are observed variables and z is the latent variable.

In matrix form, we can represent as in Fig. 8 The unobservable probability distributions from data are learnt using EM (Expectation–Maximization) algorithm, the steps of which are as given below:

E-Step: In this step, the posterior probabilities for latent variables are computed as:

$$P(z_k/d_i, w_j) = \frac{P(w_j/z_k)P(z_k/d_i)}{\sum_{l=1}^{K} P(w_j/z_l)P(z_l/d_i)} \tag{2}$$

M - Step: In this step, log likelihood, L of expected data value is maximized as follows:

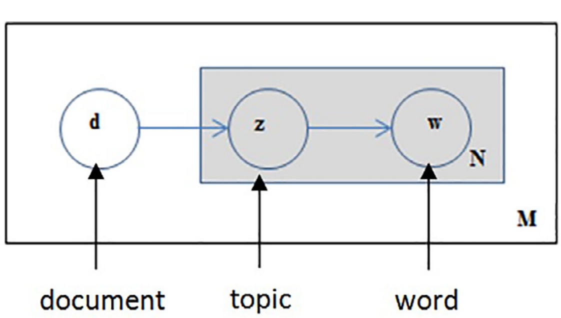

Fig. 7. Representation of pLSA as graph model [26].

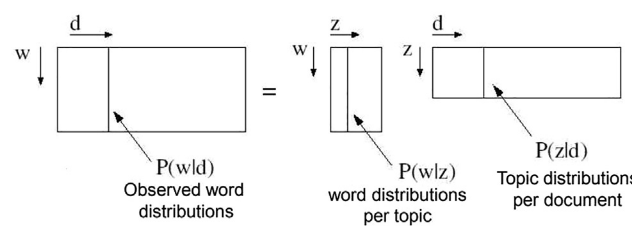

Fig. 8. pLSA model in matrix form.

$$P(w_j/z_k) = \frac{\sum_{i=1}^{M} n(d_i, w_j)P(z_k/d_i, w_j)}{\sum_{j=1}^{N}\sum_{i=1}^{M} n(d_i, w_j)P(z_k/d_i, w_j)} \tag{3}$$

$$P(z_k/d_i) = \frac{\sum_{j=1}^{N} n(d_i, w_j)P(z_k/d_i, w_j)}{n(d_i)} \tag{4}$$

and

$$n(d_i) = \sum_{j=1}^{N} n(d_i, w_j) \tag{5}$$

where,

$n(d_i, w_j)$ represents the occurrence frequency of word w_j in document d_i and $P(d_i), n(d_i), n(d_i, w_j)$ are estimated directly from the data.

The two steps, E-step and M-step, are repeatedly applied till convergence condition is met.

Here, images are the documents, represented by vector D, and there can be N documents (N elements in D). The words in the documents are the features represented by visual words, there can be M visual words, denoted by the vector W. A topic consists of a few words of the document. There can be K topics in the documents/words domain under consideration, so the topic vector Z has K elements. We use variable d to denote any document (image), variable w to denote any word (visual word), and variable z to denote any topic (latent visual topic). The pLSA model computes the distributions *P(w/z)*, the distribution of visual words in topic (latent visual topic) z, and *P(z/d)*, the distribution of latent topics in image (document) d. In the model, from the training samples, the latent topics

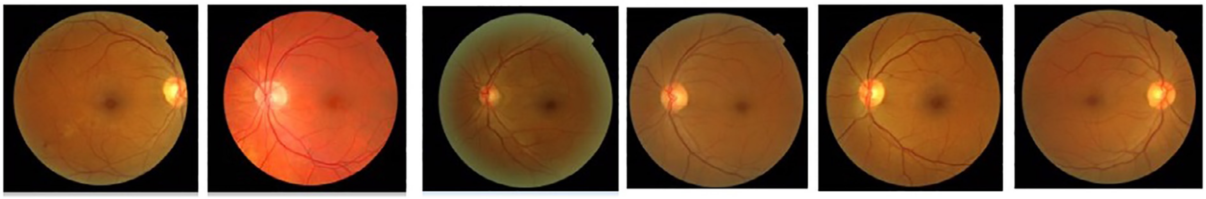

Fig. 9. Detected normal images from MESSIDOR database [3].

distributions for every document $P(z/d)$ vector can be learnt. This vector has L elements, the number of topics. When a query image q is obtained, its topic distribution is computed by applying M-step of EM algorithm maintaining word distribution of topic fixed to that learned while training. pLSA method is efficiently used for mammogram segmentation and retrieval of pathological breast cancer images [28,29] Use of multilayer pLSA for multimodal image retrieval (mm - pLSA) is described in [30]. In [31], a saliency map based algorithm along with BoVW and pLSA is presented.

3.4. Classification

After dictionary learning and topic reduction, we can represent each image as feature vector. This feature vector is used for training SVM classifier. Likewise, for a test image, first convert image to its feature vector and test with SVM classifier for discriminating test image as normal/pathological. Several variations of SVM classifier are available, here we use linear SVM classifier since the complexity of training and testing with linear SVM is linear.

4. Results and discussion

4.1. Dataset

DRIVE contains 40 normal/ pathological retina images with a size of 768 × 584 pixels. Among them 20 are train images and rest are test images, captured by Canon CR5 non-mydriatic 3CCD camera at 45 degree field of view (FOV). STARE images are captured by a TopCon TRV- 50 fundus camera at FOV of 35 degree and image size of 700 × 605 pixels. MESSIDOR database contains 1200 normal/ pathological retina images with a size of 2240 × 1488 pixels. In our study 800 images from MESSIDOR and 100 images from STARE and 20 images from DRIVE databases are used. These images contain normal and pathological images.

4.2. Retinal images classification

The results of proposed method on DRIVE, STARE and MESSIDOR databases for normal and pathological images are obtained as depicted in Figs. 9–12. Images in Fig. 10 shows the detection of pathological images of MESSIDOR database and that in Fig. 11 is the case of detection of normal images in STARE and DRIVE databases. Image in Fig. 12 are the results of detection of pathological images from STARE and DRIVE databases. Performance figures of the approaches are evaluated on the basis of sensitivity, specificity and accuracy as defined in Eqs. (6)–(8). Here, we implemented our method on Matlab 7.1.

$$Sensitivity = \frac{TP}{TP + FN} \tag{6}$$

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

where,

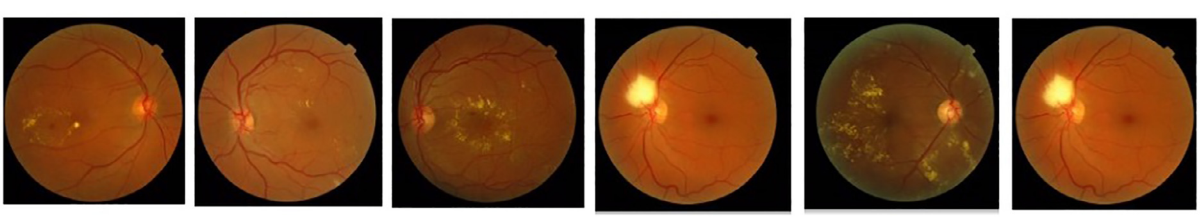

Fig. 10. Detected pathological images from MESSIDOR database [3].

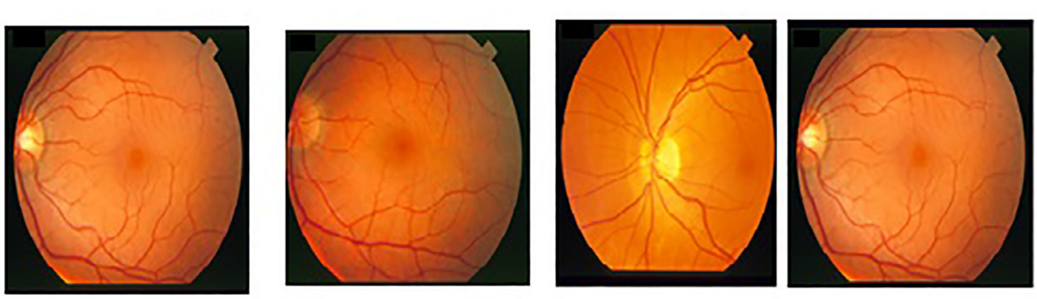

Fig. 11. Detected normal images from DRIVE [4] and STARE [5] database.

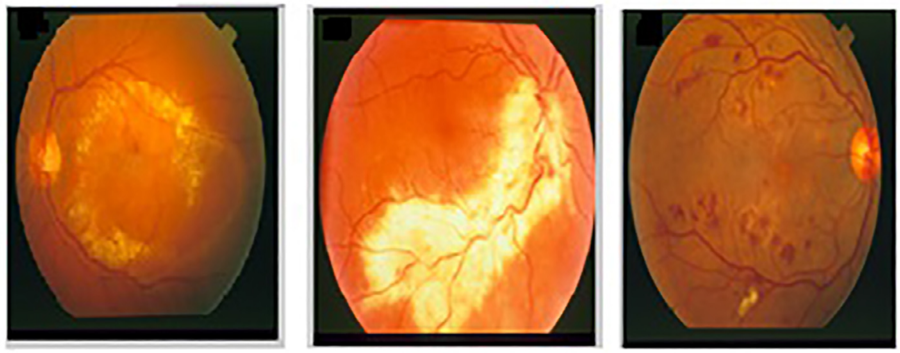

Fig. 12. Detected pathological images from DRIVE [4] and STARE [5] database.

TP represents the count of normal images that are correctly classified and TN represents the count of pathological images that are correctly classified and FP represents the count of normal images that are wrongly classified as pathological and FN represents the count of pathological images that are wrongly classified as correct images.

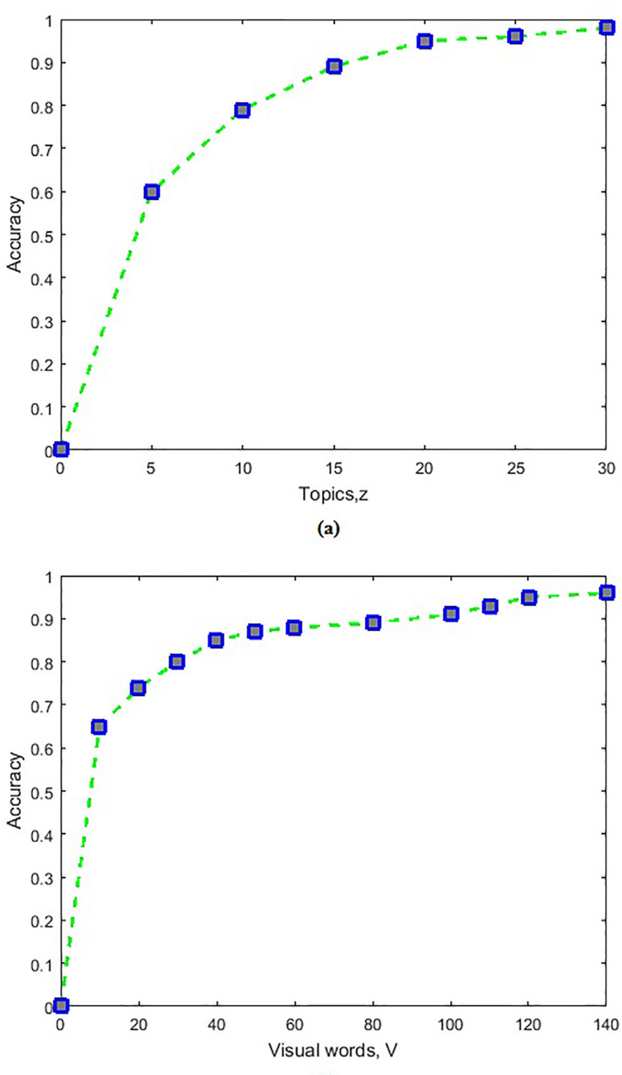

Fig. 13. Selection of parameter of pLSA: (a) Topic, Z versus Accuracy; (b) Visual words versus Accuracy.

Parameter selection of pLSA is done by experimenting the proposed method several times. Fig. 13 depicts the selection of parameters topic and visual words. In our method, we choose value of topic, z as 20 and number of visual words as 120.

4.3. Performance evaluation

Table 1 shows the performance comparison with different features and with combination of features on MESSIDOR database. It can be observed that there are marked improvements in the case of SIFT feature, and adding any of the features like color, LBP and LDP enhances the performance. Adding LDP to SIFT is found to improve the performance better, and the combination of LBP, LDP and SIFT provides still better performance. The best performance is noted for the case when all the four features are used. Table 2 shows the comparative performance with existing methods. Uniform patch sampling strategy based on retinal anatomical landmarks used in Grinsven et al. [32], which require prior knowledge about optic disc and macula distance. Pires et al. [16] requires manual annotation of unhealthy images. Accurate segmentation of lesions is required in the method proposed in [33]. Bag of visual words and a meta classification step that decides whether a patient needs referral is proposed by Pires et al. [16]. Input of the metaclassifier is the output of several lesion detectors. Deepak et al. [33] proposed visual saliency based method but their output depends upon the visual saliency detector. Sadek et al. [20] proposed a method based on histogram concatenation of features. This method requires removal of blood vessels. Silva et al. [8] used SURF feature for creating visual dictionary and then multiclassifier is used to discriminate the images.

The proposed approach provides performance figures of 98.35% for sensitivity, 97.43% for specificity and 98.13% for accuracy on MESSIDOR database, 94.44% for sensitivity, 96.88% for specificity and 96% for accuracy on STARE database and 94.74% for sensitivity, 100% for specificity and 95% for accuracy on DRIVE database.

Table 1
Comparison of different features on MESSIDOR database

Feature	Sensitivity (%)	Specificity (%)	Accuracy (%)
SIFT	95	94	94
LBP	88	76	87
LDP	85	72	84
Color	92	80	91
SIFT + Color	96	95	95
LBP + SIFT	95	95	95
LDP + SIFT	96	97	97
LBP + LDP + SIFT	97	97	97
LBP + LDP + SIFT + Color(Proposed method)	**98**	**97**	**98**

Table 2
Comparison with existing methods.

Researcher	Methodology	Features	Performance measures (%)			
Grinsven et al. [32]	Bag of words	Color, texture, edge orientation, size distribution, and patch location	415 images of two dataset constructed from public and local dataset.			
Deepak et al. [33]	Visual saliency computation	Radon and LBP features	Correct discrimination rate of 96.41% between respectively 171 drusen and 217 hard-exudates images.			
Pires et al. [16]	Bag of Visual Words	SURF	AUC = 93.4 using a dataset of 1077 images.			
Sadek et al. [20]	Histogram concatenation of different features	LBP,HOG and SURF with SVM	430 images show a mean classification accuracy of about 97.2%.			
Sadek et al. [9]	Sparse coding	SIFT,HOG,LBP and color features	Sen. = 97.4		Spec. = 98.20	Acc. = 97.60
			828 images selected images from different datadases			
Silva et al. [8]	Visual dictionary	SURF and multiclassifier	MESSIDOR	Sen. = 97.22	Spec. = 97.27	Acc. = 97.25
			STARE	Sen. = 91.66	Spec. = 98.51	Acc. = 96.12
Proposed Method	**Bag of Visual Words, pLSA**	**SIFT, LBP, LDP, color features with SVM classifier**	**MESSIDOR**	**Sen. = 98.35**	**Spec. = 97.43**	**Acc. = 98.13**
			STARE	**Sen. = 94.44**	**Spec. = 96.88**	**Acc. = 96**
			DRIVE	**Sen. = 94.74**	**Spec. = 100**	**Acc. = 95**
			800 images from MESSIDOR, 100 images from STARE and 20 images from DRIVE databases.			

In future, we can apply fuzzy based control techniques as specified in [34] to the proposed method to improve the results.

5. Conclusion

This work proposes an automatic approach to identify the pathological images using topic modelling making use of pLSA model. The method uses the low level features - color, SIFT, LBP, and LDP on RGB color images. A visual dictionary is created after quantization. Then topic modelling is performed employing pLSA which provides a generative model for topics in documents. After topic modelling, normal/ pathological classification is performed by SVM classifier. The method does not require any pre-processing techniques on images. The approach was tested with DRIVE, MESSIDOR and STARE databases, and demonstrated better performances when compared with the other existing methods. In future, we can expand the proposed method to include fuzzy based techniques to improve the results.

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