Survey on Detection of various Retinal Manifestations of Eye

Rashwinder Singh[1], Dr. Ranjit Kaur[2], Navneet Kaur[3]
[1]*Department of Electronics and Communication Engineering, Punjabi University, Patiala, India*
[2]*Department of Electronics and Communication Engineering, Punjabi University, Patiala, India*
[3]*Department of Computer Engineering, Punjabi University, Patiala, India*
[1]rashwinder1@gmail.com
[2]ranjit24_ucoe@pbi.ac.in
[3]mavi_navneet@yahoo.co.in

Abstract— **Identification of retinal diseases using various techniques is a very important area of ophthalmology. Traditional methods are highly subjective which are based on manual observation and highly prone to error. So, it is very essential to establish an automatic system for screening vision threatening diseases like diabetic retinopathy and others for huge number of people. Now days, image processing has become a very effective tool for the automated detection of abnormalities in retinal images. In this paper, the basic terminology related to automatic detection of various retinal manifestations is discussed. It also describes the steps required for automatic detection as well as the techniques used to implement these steps in recent years.**

Keywords— **Diabetes, Diabetic retinopathy, Fundus images, Exudates, haemorrhage.**

I. INTRODUCTION

For the automatic detection of retinal manifestations, the image of eye is taken as the input. This eye image is captured by fundus camera which gives the interior surface of the eye i.e. called a fundus image [2]. The interior surface of the eye includes the retina, optic disc, macula fovea and posterior pole as shown in Fig 1. Analysis of a fundus image is a complex task due to variableness of these images in terms of the morphology of the anatomical structures of the retina, colour/gray levels and the presence of a few features in different patients that may lead to a wrong interpretation [1]. Two performance parameters are used for analysis of the automated system: Accuracy and Quick Convergence Rate. The accuracy of the automated disease identification techniques should be high. Besides being accurate, the techniques also should possess a quick convergence rate which enables them to be suitable for real-time applications.

II. STRUCTURE OF AN EYE

The structure of eye includes the cornea, sclera, the colored iris and black pupil. When we look at something, light passes through the cornea, which focuses the image partially, then passes through the anterior chamber, the pupil, the lens which further focuses the image, the vitreous and is then focused on a small portion of your central retina called the macula [3]. This small specialized portion of retina is about a pinhead size. It is important as it allows us to see fine detail for activities such as reading and writing, and recognizing colors. The remaining portion of retina, called the peripheral retina, gives the side vision. The Retina is a layered tissue in eye which is responsible for conversion of incident light into neural signal for further processing [2]. The retina is operated by blood, which is supplied by a network of blood vessels. Diseases like diabetes damage these blood vessels which further disturbs the operation of the retina.

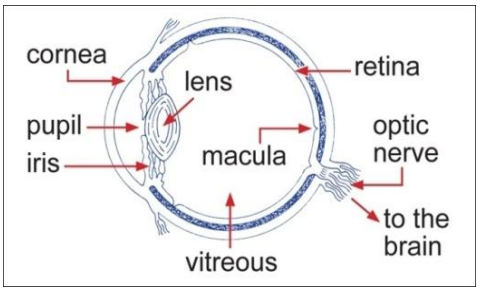

Fig.1. Structure of an eye

III. RETINAL MANIFESTATIONS OF EYE

Many diseases manifest themselves in the retina. The most prevalent diseases that can be studied via eye image analysis are discussed below:

1. *Diabetic retinopathy (DR):* It is a complication of diabetes. If a person has fasting plasma glucose over 7.0 mol/l, then this is a sign of Diabetes [7]. The high blood glucose (*known as hyperglycemia*) is known to damage small and large blood vessels, as well as nerve cells, and thereby damages the kidneys, heart, brain and eyes, and results in a retinal complication of diabetes called *diabetic retinopathy*. In the eye, hyperglycemia damages the retinal vessel walls, which can lead to:

(a) Ischemia: With progress in diabetic retinopathy, the blood vessels in the retina get blocked. Ischemia is caused when these blockages result in areas of the retina becoming starved of oxygen.
If this happens, the repair for the damage is done in a natural way by growing new blood vessels to supply oxygen to starved area of retina. This process of growing new vessels is termed as neo-vascularisation. Unfortunately, these new blood vessels are weak, so they can bleed very easily and also sometimes they grow in the wrong place on the surface of the retina or into vitreous gel, which may result in large hemorrhages. These hemorrhages can obscure the vision in the affected eye. Whenever these hemorrhages may keep happening, this can lead to permanent loss of sight [2].
(b) Diabetic Macular Edema (DME): As blood barrier potential breaks down, it causes leakage in capillaries and retinal tissues due to accumulation of fluid in macula, which affects central vision.

2. *Age-Related Macular Degeneration:* AMD is deterioration of the macula due to age factor and generally found among the people of age 50 and above. Generally macular degeneration is categorized under two categories: Dry and Wet AMD [2]. Macular degeneration usually begins by the formation of drusen (tiny yellow or white pieces of fatty protein) under the retina. Vision loss is usually gradual in dry macular degeneration. Wet macular degeneration occurs due to abnormal blood vessel. Leaking of these blood vessels causes blurring or distorting central vision.
3. *Glaucoma:* It is often associated with a buildup of pressure called intraocular pressure inside the eye. Optic nerve gets damaged due to continuous rise in pressure. It happens when eye fluid does not circulate properly in the front end of the eye. This fluid is called aqueous humor. The visible manifestation of the optic nerve head causes cupping of disc that is the indication of glaucoma. The ratio of the optic disc cup and neuroretinal rim surface areas in the fundus images is called cup-to-disc ratio [2].
4. *Cardiovascular Disease:* Cardiovascular diseases are related to heart. The major cardiovascular diseases are: Hypertension and atherosclerosis. Hypertension is caused due to stress while Atherosclerosis is a disease in which plaque (made up of fat, cholesterol and other substances) builds up inside the arteries. Over time, plaque hardens and narrows the arteries. This limits the flow of oxygen-rich blood to the organs and other parts of the body. These can be identified by analyzing the change in the ratio between the diameter of retinal arteries and veins, known as the A/V ratio. Decrease in the A/V ratio is associated with an increased risk of stroke and heart attack.

IV. STEPS OF AUTOMATED SYSTEM FOR DETECTION OF LESIONS

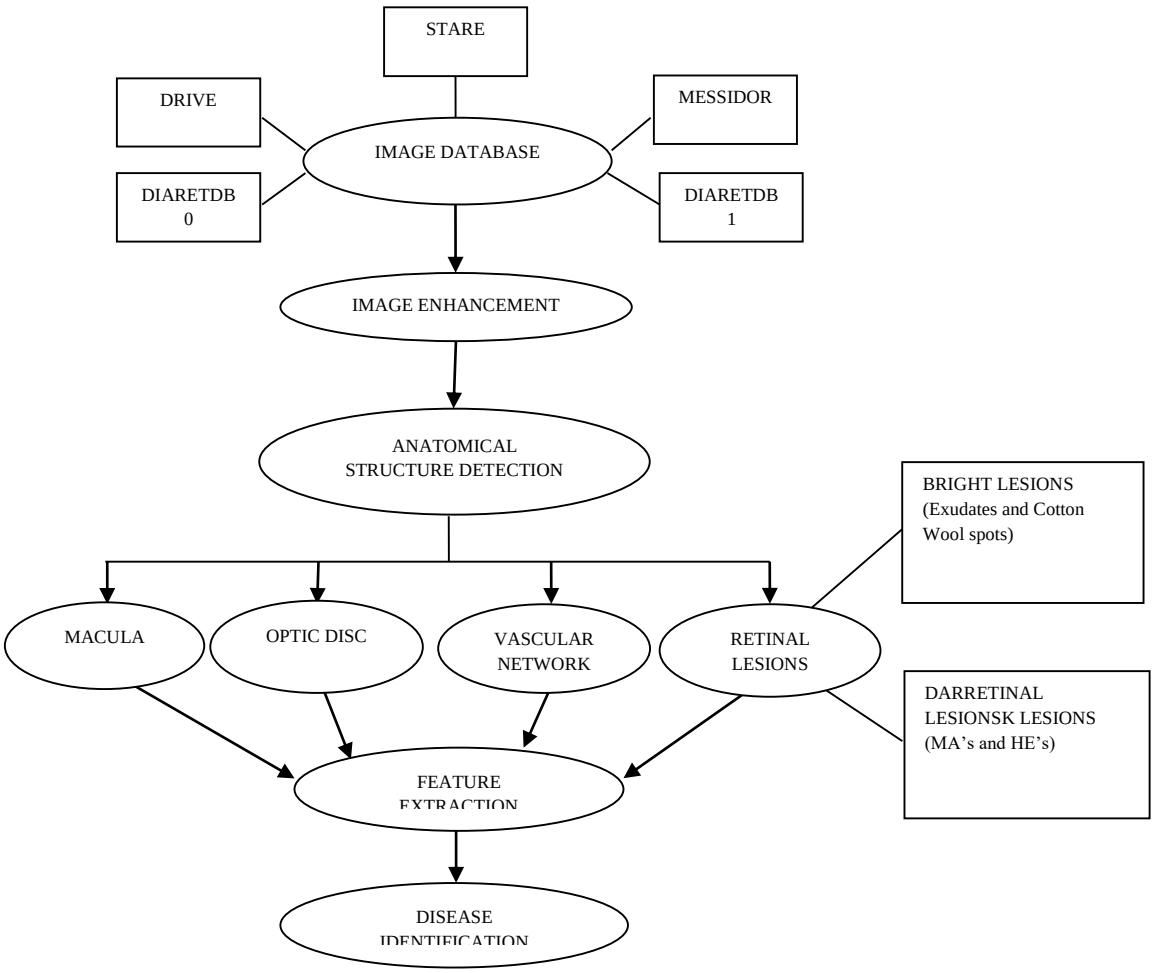

Fig.2. Flowchart for steps of automated system for detection of lesions in retinal images

A. *Image Database*

There are many databases available for the retinal images. Few of them are listed below in the Table 1.

TABLE 1
DATABASES AVAILABLE FOR RETINAL IMAGES

#	**Database**	**Images and pixel size**	**Ground truth**
1	STARE : Structured analysis of retina	Total 81: 31 normal, 50 disease , Pixel Size:605*500	Vessel
2	DRIVE : Digital retinal analysis for vessel extraction	Total: 40 , Pixel Size: 565*590,768*584	Vessel
3	DIARETDB1	Total: 89	Microaneurysms, Hemorrhages, hard exudates,soft exudates
4	DIARETDB0	Total 130: 20 normal ,110 pathological Pixel Size:1550*1152 pixels	Microaneurysms, Hemorrhages, hard exudates ,soft exudates
5	MESSIDOR: Method to evaluate segmentation and indexing techniques in field of retinal ophthalmology	Total :1200 Pixel Size: 1490*960, 1440*960, 2240*1488 or 2304*1536 pixels.	Retinopathy grading
6	E-OPHTHA: A Color Fundus Image Database	Exudates Database: 47 images with exudates and 35 images with no lesion. Microaneurysms Database: 148 images with microaneurysms or small hemorrhages and 233 images with no lesion.	Exudates , Microaneurysms
7	ROC: Retinopathy Online Challenge	50 images for Training, 50 images for Testing	Microaneurysms

B. *Image Enhancement*

It is very essential to have good quality of retinal images for accurate detection and diagnosis either manually or automatically. However, studies show that due to inadequate quality approximately 12% of retinal images can't be analyzed clinically [4]. This could be due to many reasons, some of them are:

1. Non uniform illumination and poor contrast due to the anatomy of eye fundus (the eye fundus with a three-dimensional concave shape)
2. Wide-angle optics of the fundus cameras
3. Insufficient pupil size
4. Sensor array geometry
5. Eye Movement

C. *Anatomical Structure Detection*

1) *Normal Features of Retina:* Every healthy retina has some normal features. These normal features are optic disc, blood vessels and fovea. Apart from these, an unhealthy retina might have some abnormal features like hemorrhages; micro-aneurysms and exudates. Some of the normal features are discussed below:

i. *Optic Disc:* Optic disc is the entry point for the major blood vessels and optic nerve into the retina. The optic disc is the bright hole in the back of the eye as shown in Fig.3. The location of the optic disc is an important aspect in retinal image analysis and detection as it is a significant feature in the retina. Optic disc in color fundus images is a bright yellowish or white region. Its shape is usually circular. Optic disk detection is not performed in the green component as the blood vessels usually interfere so it is performed only on the red component [5].

ii. *Blood Vessels:* The retina at the back of our eye requires a constant blood supply as shown in Fig.4. The blood supply should be efficient so that the cells of the retina get all the nutrients they need to continue working. There are two main types of blood vessels – arteries and veins. Arteries carry fresh blood from the heart and lungs to your eye and veins take away the blood that has been used by the eye and return it to the lungs and heart.

iii. *Fovea:* The fovea depicts the center of the retina and it is located in the center of macula which is the region of highest visual activity as shown in Fig.5. The position of an abnormality relative to the location of fovea is useful for effective diagnosis of diabetic retinopathy and other retinal diseases. It is present at approximately 2.5 times the optic disk diameter from the optic disk. The macula is a hazy darker area than the surrounding retinal tissue. Template matching approach is the most effective technique to identify fovea and macula.

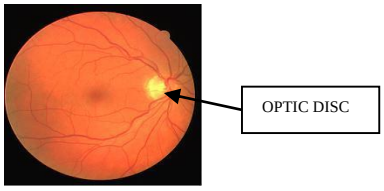

Fig.3. Optic Disc

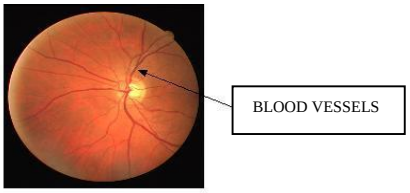

Fig.4. Blood vessels

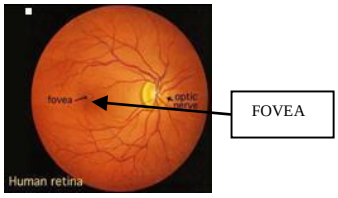

Fig.5. Fovea at the center of macula

2) *Abnormal Features of Retina:* Abnormal features of retina are classified under two categories: bright lesions and dark lesions. These are explained below:

i. *Bright Lesions*

a) *Hard Exudates:* Exudates are yellowish dark spots located in the posterior pole of the fundus image shown in Fig.6. Exudates are made up from serum lipoproteins and usually occur when fat leaks from abnormal blood vessel. Exudates are one of the main features of diabetic macular edema. As the severity of the disease changes, the size and shape of the exudates changes. Exudates appear most contrasted in green channel.

b) *Soft Exudates/Cotton Wool Spots:* Cotton wool spots may appear as small, yellow-white (or grayish-white), slightly elevated lesions, which look like clouds with a fimbriate border in the superficial retina shown in Fig.7. Usually they are less than 1/3 disc areas in diameter, and are commonly found in the posterior pole of the fundus images [2].

ii. *Dark Lesions*

a) *Micro aneurysms:* Microaneurysms are the focal dilations of retinal capillaries, and appear as small, round and dark red spots shown in Fig.8. Micro aneurysms occur when there is arterial blockage or retinal breakdown.

b) *Haemorrhage:* Haemorrhage occurs when blood leaks from the retinal vessels shown in Fig.9. Haemorrhage can be caused by hypertension, blockage of arterial vein or diabetes mellitus. Some retinal haemorrhage can cause severe impairment of vision.

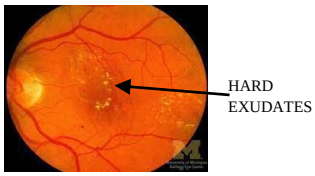

Fig.6. Exudates

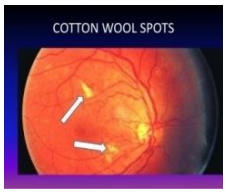

Fig.7. Cotton wool spots

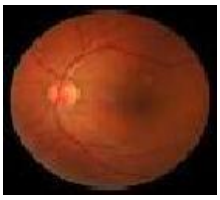

Fig.8. Micro aneurysms

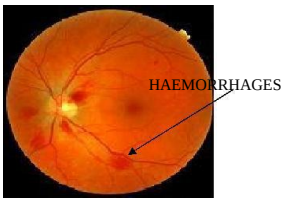

Fig.9. Haemorrhages

V. LITERATURE SURVEY

The literature survey related to techniques used by different authors for detecting abnormalities in the retinal fundus images are listed below in the table:

TABLE 2
LITERATURE SURVEY OF VARIOUS TECHNIQUES FOR ABNORMALITY DETECTION IN RETINAL IMAGES

Author	**Issues**	**Methodology**	**Database**	**Merits**	**Demerits**
[6] Walter 2002	Exudate detection	Morphological filtering and watershed transformation methods are used for enhancement and optic disc detection	Diaret db	The robustness and accuracy in comparison to human graders has been evaluated. It shows good results in terms of high sensitivity.	Proposed techniques in this paper are not suitable for detection of soft exudates i.e. cotton wool spots.
[7] Akara Sopharak 2008	Diabetic retinopathy exudates	Morphological operators	60 images from Thammasat University Hospital are captured by KOVA-7 non mydriatic retinal camera with 45 degree field of view	Proposed algorithm showed good results in non diluted pupil and low contrast images	This paper algorithm is not able to detect difference between hard and soft exudates.

Author	Issues	Methodology	Database	Merits	Demerits
[8] Hussain F. Jaafar et. al. 2010	Automatic detection of exudates	Local variation operation for coarse segmentation, For fine segmentation adaptive thresholding and split-and merge algorithm	Total 64 images (47 from DIARETDB1 and 17 from Messidor databases)	Improvement in the specificity and accuracy measures	Fails to exclude some non-exudate objects particularly those that have similar features to real exudates
[9] Ivo Soares 2011	Exudates dynamic detection based on the noise map distribution	Morphological operations and adaptive thresholding	The DIARETDB1 data base with 89 images (29 for training and 61 for evaluation)	Gives good results for images where contrast changes and illumination is non-uniform	Images with no exudates tend to create spurious segmented regions, due to the dynamic thresholding and so decreases accuracy
[10] Mehdi Ghafourian Fakhar Eadgahi et. al. 2012	Localization of Hard Exudates by Mathematical Morphology Operations	Hard Exudates (HEs) are segmented by morphological operations such as Top-hat, Bottom-hat and reconstruction operations	DIARETDB1 database	Fast and efficient method. Can work with lower quality retinal images	Sensitivity achieved is low in this method
[11] Sharib Ali et. al. 2013	Statistical atlas based exudate segmentation	Test image is first made on the atlas co-ordinate and then a distance map is obtained with the mean atlas image. This leaves behind the candidate lesions	HEI-MED data-set	Gives high accuracy rate for detection of hard exudates	Noise effect is there
[12] Xiwei Zhang 2014	Exudate detection in color retinal images	New pre-processing methods that detect reflections and artifacts in the image based on mathematical morphology. Features are computed such as Intensity, Geometric, Textural and Hybrid features. Then A Random Forest method is used to perform the classification of the exudate candidates	Clinical database, e-ophtha EX with manually contoured exudates	The method deals with images showing large variability in terms of quality, definition and presence of artifacts	Not good for small-scale applications
[13] Ramon Pires 2014	Detection of hard exudates and red lesions	Feature extraction using SVM and classification is done by BossaNova	DR1 and DR2 publically available datasets.	One important point of this design is the use of the class-based scheme, that it creates not only a unique codebook, methodology even performs well for two-class problems (e.g., normal/abnormal).	A deeper analysis on key aspects of the parametric space of Bossa Nova e.g., number of bins B and range of distances in the visual recognition task is required.
[14]R.A.Welikala2015	Detection of proliferative diabetic retinopathy	Support vector machine classifier is duly combined with Genetic algorithm for better classification	60 images from 4 publically available databases	Main contribution of this paper is creation and selection of large feature set in combination with dual classification method.	Only a single set of SVM parameters was selected by GA, further exploration to the SVM parameters is required.
[15] Elaheh Imani 2015	Automated diabetic retinopathy screening	Morphological component analysis	Messidor	Firstly this method is robust to noise. Secondly component analysis technique is independent of any segmentation technique. Due to	The biggest drawback is that the only use of textual features reduces the algorithm precision.

				which it takes less time in processing.	
[16] Ivo Soares 2016	Optic Disc Localization based on Cumulative Sum Fields	New vessel enhancement method based on a modified corner detector. A weighted version of the vessel enhancement is combined with morphological operators, to detect the four main vessels orientations. The final optic disc localization is determined by a vessel convergence algorithm	All publically available datasets. Stare, Drive, DR1, DR2, Messidor, ROC and e-optha	High accuracy rate. Robust for all publically available databases	Used implementation is not optimized, the algorithm already provided an average computation time of 18.34 s per image.
[17] Bo Wu 2016	Detection of microneurysms	For preprocessing Histogram equalization, CLAHE for enhancement, smoothing , region growing for segmentation and KNN classifier for classification is used	Two publically available databases: ROC and e-optha	In feature extraction 27 features are used which contain both local as well as profile features, which helps in better performance of system.	Time consuming algorithm as large number of features need to be extracted.

VI. EVALUATING PARAMETERS

A. *Accuracy:* The accuracy is measured by the ratio of the total number of correctly classified pixels (sum of true positive and true negative) to the number of pixels in the image field of view.

$$\text{Accuracy} = (TN+TP) / TN+TP+FN+FP$$

Where TP, TN, FN, FP stands for true positive, true negative, false negative, and false positive respectively.

B. *Positive Predictive Value* is the proportion of the true positives to positive test results.

$$PPV = TP / TP+FP$$

C. *Sensitivity* is the proportion of true positives classified by the system. In other words, the percentage of sick people who are correctly identified as having the condition.

$$\text{Sensitivity} = TP / (TP+FN)$$

D. *Specificity* is sometimes called the true negative rate. It measures the proportion of negatives which are correctly identified. In other words, the percentage of healthy people who are correctly identified as not having the condition.

$$\text{Specificity} = TN / (TN+FP)$$

E. *ROC* is receiver operator characteristic. The graph which gives the performance of a binary classifier system by varying its threshold. By plotting True positive rate (Sensitivity) against the false positive rate (Specificity) ROC curve is created. The area under the curve called AUC will give the probability that a classifier will rank a randomly chosen positive instance than a randomly chosen negative one.

Following Table 3 shows the comparison of performance of various methods discussed in Table 2.

TABLE 3
PERFORMANCE EVALUATION OF VARIOUS TECHNIQUES USED FOR RETINAL IMAGE ANAYSIS

Author and Year of Publication	**Performance Evaluation**
[6] Walter et. al. , 2002	Sensitivity: 0.76, Mean predictive value : 0.59, F-Score: 0.67
[7] Akara Sopharak et. al. , 2008	Sensitivity: 0.40, Mean predictive value : 0.91, F-Score: 0.56
[8] Hussain F. Jaafar et. al. , 2010	Sensitivity: 89.7%, Specificity: 99.3%, Accuracy: 99.4%
[9] Ivo Soares et. al. , 2011	Sensitivity: 97.49% , Specificity: 99.95%, Accuracy: 99.91%
[10] Mehdi Ghafourian Fakhar Eadgahi et. al., 2012	Sensitivity: 78.28%
[11] Sharib Ali et. al. ,2013	Accuracy: 82.60%
[12] Xiwei Zhang et. al., 2014	AUC: 0.95
[13] Ramon Pires et. al., 2014	AUC: 96.4% for hard exudates and 93.5% for red lesions
[14] R.A.Welikala et. al. , 2015	Sensitivity: 0.9138, Specificity: 0 .9600
[15] Elaheh Imani et. al. , 2015	Sensitivity: 0.9201, Specificity: 0 .9545, Accuracy : 0 .9282
[16] Ivo Soares et. al. 2016	Accuracy: 99.15%
[17] Bo Wu et. al., 2016	Overall F-Score : 0.202

VII. CONCLUSION

The enhancement of the important features such as optic disk, fovea, exudates and blood vessels in the fundus image of the retina is an important step for detection of any kind of abnormalities in the eye, especially diabetic retinopathy. Most of the experiments are carried out on publicly available databases. This paper has shown different techniques for detection of diabetic retinopathy in terms of exudates, microaneurysms and hemorrhages with their benefits and limitations. The survey suggested that to ensure the robustness of the automated systems we need to have a large dataset. Green channel plane of the input RGB retinal image is widely used for processing. Less emphasis is provided on feature extraction techniques based on textural features. Very few works are based on soft computing techniques for anatomical structure detection. Combination of textural based features and anatomical structure based features are very rarely used. The usage of optimization strategies for feature selection is very low. Most of the works are based on only anatomical structure identification and no emphasis is given on disease classification techniques. Artificial Intelligence techniques are rarely used for the retinal image processing applications. Most of the results are reported in the form of qualitative analysis only i.e. not in quantitative analysis. As we have studied that by combining the Genetic algorithm with SVM [14], a large number of features can be extracted. This combined algorithm showed very good results in terms of sensitivity and specificity. So, in future other optimization techniques like PSO, ACO can be combined with SVM or any other classifier to improve the results in precision as well as computation time.

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