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Case based Reasoning using SVM in the Detection of Retina Abnormalities

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***Abstract*—This paper aims to facilitate the diagnosis procedure of the ophthalmology specialists for the treatment of retina abnormalities due to Diabetic Retinopathy and Age related Macular Degeneration. Detection of the initial signatures of these two diseases in retina are challenging to the doctors due to the negligible size of the lesions. A Computer Aided Diagnosis system for the automatic detection of lesions from retina fundus image and classification of the lesion types using Machine Learning eases the job of the doctors. In this paper, an approach depending on the concept of Case Based Reasoning is implemented using Support Vector Machine classifier for the classification of the lesions. Detection of lesions uses Otsu multilevel thresholding for segmentation and morphological operations for the elimination of optic disc and blood vessel tree. Evaluation of a set of selected features for each lesion forms the feature vector set for machine learning. The Support Vector Machine classifier achieves an accuracy of 94.03% for bright lesion classification and an accuracy of 97.9% for dark lesion classification, which is promising.**

***Index Terms*— Age related Macular Degeneration, Case Based Reasoning, Diabetic Retinopathy; Support Vector Machine classifier.**

I. INTRODUCTION

The popularity of Computer Aided Diagnosis (CAD) systems are increasing in medical field as it can ease the diagnosis by providing useful information with high computational speed. CAD system in the detection of retina abnormalities is desirable as the initial clinical signs of Diabetic Retinopathy (DR) and Age related Macular Degeneration (AMD) is difficult to detect. The development of a CAD system can assist the eye specialist in the primary diagnosis of the retina. In this paper, automatic identification and classification of retina abnormalities is developed to help the ophthalmology specialists for their preliminary detection of abnormalities. A Case Based Reasoning (CBR) [1] inspired approach is used for classification through Machine Learning. The usefulness of CBR inspired approach lies in the way of a physician treats a patient. The physician's past experience and knowledge base becomes the driving force in treating a new patient. The solution to similar past cases is used with modifications, if required for the new case. Each successful treatment refines the experience of the physician. These steps are present in the CBR motivated approach for solving any real world problem. The similarity of CBR inspired approach with the way of handling patients was the positive force to adopt CBR in designing CAD system. Support Vector Machine (SVM) classifier, which uses supervised learning model is used in this research work for implementing CBR inspired approach for classification. The basic idea of supervised learning model is to map an input to an output depending on

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previously experienced input-output vector. The approach of SVM is suitable for implementing in CBR motivated approach. The patients suffering from type 2 diabetes may become the victims of DR. The effect of this abnormal situation includes blurred vision due to Diabetic Retinopathy. Microaneurysms (MA) [2] which are actually the bulges filled with blood in the retina artery wall are the first signs of DR. Identification of MA is very tough as no problem arises in the patient's eye sight at this stage. This stage is called mild Non-proliferative Diabetic Retinopathy (NPDR). If not identified, this stage leads to moderate NPDR containing lipid and protein precipitation in retina from thinned blood vessel. These yellow artefacts are called hard exudates (HE). As the disease progresses, accumulation of axoplasmic material causes cotton wool spots (CWS) from the leakage of nerve fibre. The sudden rupture of microaneurysms in deeper retinal layer produces haemorrhages (HAM) which threatens the patient's eye sight and advances the DR to Proliferative (PDR) stage. Age related Macular Degeneration is the other retina disease which deforms the macula resulting in reduced vision and blindness. This disease is becoming the research area of the ophthalmologists as the exact reason for the disease is still unknown. AMD is categorized into dry and wet depending on the change of retina. Drusens are the debris like material formed during dry AMD phase and these are deposited between the retinal pigment epithelium and Bruch's membrane [3]. Drusens are the first clinical hallmark of AMD and are similar to HE of DR. A total of six classes are considered in this research work: microaneurysms, hemorrhages are the classes under dark lesion group and hard exudates, cotton wool spots of DR along with drusens of AMD are the classes under bright lesion group. Normal retina is considered as the sixth class. The paper is presented as follows: literature survey is presented in Section 2, Section 3 describes the proposed methodology including lesion detection and classification, results and discussions are presented in Section 4 and Section 5 concludes the paper.

II. Related Work

A literature survey is carried out for the visualisation of the status for the automatic detection of Diabetic Retinopathy and Age related Macular degeneration. The Case Based Reasoning inspired approach with its four 'R' phases is described in the pioneering work of Aamodt and Plaza, 1994 [1]. This paper [1] relates the idea of Case Based Reasoning with the real life problem solving approaches. It is stated that to solve a problem using the approach standing on CBR, one has to use the past similar problems and its solutions. At the same time, the solution to the new case enriches the experience which advances the learning method. The use of CBR by physicians is also mentioned in the paper of Aamodt and Plaza [1]. Learning in CBR is considered as a very important step in Ref. [1]. It is also stated in Ref. [1] that the learning procedure advances the CBR system by adding new experiences collected from new case solving. Different types of abnormalities related to DR are discussed in the research work of Stratton et. al., 2001 [2]. It is stated in Ref. [2] that DR, the complication arising due to Type 2 diabetes, carries the threat of blindness. The aetiology of different abnormal artefacts are described in this paper [2]. Age-related Macular Degeneration and its stages are focused in the paper of Jager et. al, 2008 [3]. Types of drusens and phases of AMD are thoroughly described in this research work [3]. According to the report of Jager et. al. [3], the pale, yellowish circular material called drusens are deposited between the retinal pigment epithelium and Bruch's membrane as the eye ages. As many people fail to identify the delicate changes [3] of their vision, the disease progresses fast. A longitudinal vision check-up for elderly people is recommended in [3]. A survey is carried out in the work of Dasgupta and Banerjee, 2014 [4] and different approaches of detection of abnormalities in medical images are elaborated. The medical images include DR images and AMD images in this work [4]. In this paper [4], the discussed methodologies used to implement CBR include nearest neighbour approach, method of induction, database technology approach and fuzzy logic based approach. Different retinal abnormalities like AMD (including dry and wet AMD) and DR (including microaneurysms, haemorrhages and exudates) are briefly discussed in Ref. [4]. An overview of detection of microaneurysms and haemorrhages are also presented in the work of Dasgupta and Banerjee [4]. A notable work of Agurto et. al, 2010 [5] includes lesions due to AMD with DR and the detection of abnormalities is carried out in frequency domain. Small artefacts like microaneurysms are detected using high and medium pass filters whereas low pass filters are used for large lesion detection. The Amplitude Modulation-Frequency Modulation components of the retina images are extracted and the texture features corresponding to the AM-FM component are used to distinguish different types of abnormal retina [5]. The work of Osareh et. al., 2003 [6] for the detection of hard exudates used Fuzzy C means clustering for segmentation and artificial neural network for classifying the lesions through machine learning. The preprocessing steps include histogram specification with respect to a reference image [6]. Fuzzy C means clustering technique is used based on color feature of the image for

segmentation [6]. The features, namely, color, edge strength, size are used to distinguish the segmented regions [6]. Retina images are represented in LUV color space [6]. The features like mean and standard deviation of the LUV values inside and outside the region of interest, region size, edge strength and compactness are selected. [6]. A three layer perceptron neural network is used for machine learning. The research work of Akram et. al., 2014 [7] suggests a hybrid classifier combining m-Mediods based modeling and Gaussian Mixture Model. According to Ref. [7], Hough transform is used for optic disc elimination and a binary mask combining adaptive and multilevel thresholding is used for blood vessel tree elimination. The institutional work in the field of retina abnormality detection is done by Niemeijer et. al., (2005 and 2007) [8 & 9]. These two papers [8 & 9] aim to detect dark and bright lesions, respectively, with respect to the ground truths given by renowned ophthalmology specialists and develop the algorithm for classification of lesions through machine learning. Our earlier works include machine learning through different classifiers like Naïve Bayes and Support Vector Machine. The work of Saha et. al., 2016 [10] suggested the advantages of SVM classifier for dark lesion classification with the accuracy of 88.8889%. In our current research work, the accuracy of dark lesion classification is improved to the accuracy of 97.9% by changing the set of features. Another earlier work done by Banerjee & Roychowdhury, 2015 [11] used CBR inspired approach combining decision tree but no machine learning classifier was used. Machine learning using SVM classifier is used in one of our earlier works (Roychowdhury & Banerjee, 2016) [12] with lesser number of images and features. The performance analysis of the current research work is much better than that of [12] due to the addition of significant features with larger retina fundus image dataset. In the work of Dhiravidachelvi et. al., 2019 [13], microaneurysms, the first signs of DR, are detected. The microaneurysms are identified in [13] by candidate extraction using extended minima method. The features based on statistical measures are extracted in [13] using grey level co-occurrence matrix method. In table I, we represent the literature survey with the techniques used and the significance of the previous works.

TABLE I: LITERATURE SURVEY WITH THEIR SIGNIFICANCE

Reference	Topic	Remarks
[1]	Case Based Reasoning	introduced the concept and steps of Case Based Reasoning
[2]	Diabetic Retinopathy	discussed about DR
[3]	Age Related Macular Degeneration	discussed about AMD
[4]	survey on the approaches of implementing CBR	detection of the abnormalities due to DR and AMD are theoretically discussed, not implemented
[5]	detection of lesions due to DR and AMD	-lesion detection is done in frequency domain -the texture feature corresponding to amplitude modulation-frequency modulation are used to detect the lesions
[6]	detection of hard exudates	-for segmentation, Fuzzy c means was used -for classification using machine learning, artificial neural network is used
[7]	detection of DR	-machine learning is done using a hybrid classifier which is a combination of m-Mediods based modeling and Gaussian Mixture Model
[8 & 9]	detection of bright and dark lesions of DR and AMD	-pioneering work on lesion detection where the lesions are detected with the help of ophthalmology specialists' guidance.
[10]	detection of lesions due to DR	-for classification, naïve Bayes classifier and SVM are used -SVM showed better performance for the detection of dark lesions
[11]	CBR motivated approach for lesion detection	-decision tree was used but machine learning was not implemented for classification
[12]	lesion detection using SVM	-number of images and number of features are less and hence the performance is poor than the current work
[13]	microaneurysms detection	-only microaneurysms are detected, not all types of DR abnormalities

III. PROPOSED METHODOLOGY

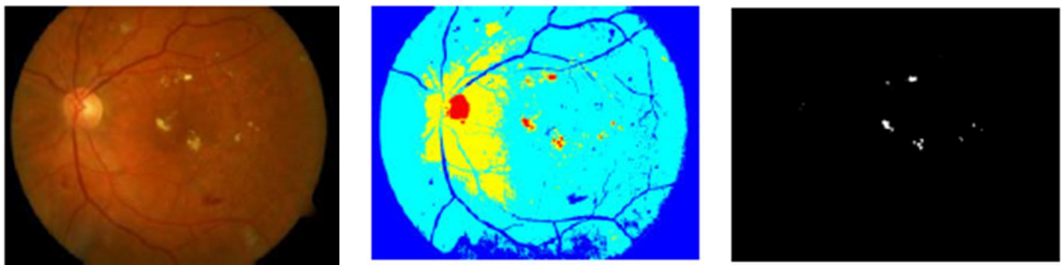
This section describes the steps of the proposed method for the implementation of a Computer Aided Diagnosis system to assist the ophthalmologists in the early stage detection of DR and AMD. The steps include formation of case base by collecting retina fundus images, detection of abnormalities of retina and then machine learning phase for the classification of abnormalities.

A. Case Base

Case base is formed by collecting the standard database images containing normal and DR affected retina images. The standard databases contain retina images with different abnormalities with their corresponding ground truth. Dry AMD affected images are collected from a local ophthalmology hospital. Seventy six images from DiaretDB0 [15], ninety images from DiaretDB1 [16], ten images from HRF database [17] and fourteen images from open access data source and local hospitals are collected. Some of the images collected from local hospitals were not macula–centric and some were poor in illumination and hence those were discarded. A total of one hundred and ninety images are considered in this research work. This data repository works as the case base for our research work.

B. Detection of abnormalities through image processing

Image processing steps include grayscale conversion, contrast enhancement by gamma correction, multilevel segmentation by Otsu method, extraction of region of interest and detection of abnormalities after optic disc and blood vessel tree elimination. Colored retina fundus images are considered as input. After grayscale conversion of the color input image, contrast enhancement using gamma correction is done. The gamma value is set bigger than one for bright lesion detection and for dark lesion detection, gamma value is set in the range of 0 to 1. The gamma value bigger than one makes an image darker which makes the bright lesions prominent. On the other hand, the gamma value less than one brightens the image which distinguishes dark lesions from the background. After the pre-processing step, segmentation of the input image is performed on the pre-processed image. The fundus retina image contains mainly four colors: bright yellow color for optic disc and bright lesions, dark red color for blood vessel tree and dark lesions, yellowish red color for the retinal fluid and membrane and black corner portions. Otsu method is preferred as it is efficient for multilevel thresholding. After Otsu multilevel segmentation is applied on pre-processed image, four clusters are generated. The next step includes extraction of region of interest. For bright lesion classes, the cluster containing bright yellow pixels is extracted. This cluster contains optic disc and bright lesions. To eliminate the optic disc, morphological operations are applied. As bright lesions are small in size compared to optic disc, these are eliminated by morphological erosion operation. This leaves optic disc as the foreground object. Then by analogical operations, like XOR and subtraction between the image containing optic disc with bright lesions and the image containing only optic disc, bright lesions are detected. For detecting dark lesions, the cluster corresponding to dark red pixels is extracted after segmentation. This cluster contains blood vessel tree and dark lesions. To eliminate the blood vessel tree, morphological erosion is applied. After the detection of bright and dark lesions, feature selection and evaluation is performed. The retina fundus image with hard exudates is presented in Figure 1(a), segmented image with four clusters is represented in Figure 1(b) and Figure 1(c) is the output image with detected hard exudates.



(a) (b) (c)

Figure 1. (a) Retina fundus image with hard exudates (b) Multilevel segmentation (c) detection of hard exudates

C. Selection of features for machine learning

Selection of features is done depending on their significance in the identification of different lesions. In this research work, selection of features is done after analyzing the significance of some statistical and geometrical features using a decision tree based approach that might be helpful for the identification of different classes considered here. The features, namely, convex area and mean are discarded by decision tree based approach as the information gain of these two features is low. Table II shows the selected features with their description.

TABLE II: DESCRIPTION OF SELECTED FEATURES

Feature name	Description
Area	Number of Pixels in the affected region
Perimeter	Distance between each adjoining pair of pixels around the border of the region.
Circularity	(perimeter)2/ (4 × π × area)
Compactness	(area)/(perimeter)2
Standard deviation	The measurement of the deviation of the class members from the mean value of the class
Smoothness	1-1/(1+ σ2) where σ denotes the Standard deviation
Eccentricity	Ratio of the distance between the foci of the ellipse and its major axis length for the ellipse that has the same second-moments as the region.
Euler number	(Number of objects in the region) – (number of holes in those objects)
Color	Color of the abnormal objects
Shape	Shape of the abnormal objects
Size	Size of the abnormal objects
Sharpness of edge	Sharpness of edge of the abnormal objects

Also after interaction with ophthalmology specialists, the color, shape, size of abnormal artefacts arising from DR and AMD are found to be helpful features for the identification of different types of lesions. Color feature distinguishes bright lesions like hard exudates, cotton wool spots and drusens from dark lesion classes consisting of microaneurysms and hemorrhages. Among bright lesion classes, hard exudates are bright yellow whereas cotton wool spots are whitish yellow. Microaneurysms are red Colored artefacts and hemorrhages are of dark red color. Hard exudates and drusens have sharp edges but cotton wool spots have blurred edges. Drusens have uniformity in shape unlike hard exudates and cotton wool spots. Microaneurysms are very small in size whereas hemorrhages are medium to large in size. The features area and perimeter in terms of pixels are useful for the evaluation of the size of abnormal objects mathematically. In addition to that, the features like circularity and compactness give concrete information about the shape of the lesions. Eccentricity and Euler number are mathematical descriptors of the geometric structures of the lesions. Standard deviation and smoothness are statistical features which are useful for distinguishing normal retina with the affected retina. For each abnormal artefact, the entire selected feature values are evaluated which introduces a feature vector along with its class type using the ground truth information. Thus, a set of feature vectors generated by the evaluation of all abnormal artefact's features are used for machine learning. A total of two hundred and eighty feature vectors are generated from one hundred and ninety images. Two third of the feature vector set is treated as training data while the rest as test data. In this research work, CBR inspired machine learning approach is implemented using Support Vector Machine classifier.

D. Case based Reasoning using Support Vector Machine classifier

Case Based Reasoning is the way of solving a problem using the experiences of past similar cases. The approach of a physician while treating a patient matches with Case Based Reasoning approach as the physician uses his experience for the diagnosis of the patient. Case Based Reasoning approach for solving a new case follows four steps, namely, Retrieve phase which fetches similar cases from the past experiences, Reuse phase which applies the past case solution to solve the current case, Revise phase which refines the solution as needed by the new case and Retain phase which adds the refined solution to the knowledge base for future use. As our research work is intended to assist the ophthalmology specialists, Case Based Reasoning approach is adopted. Support Vector Machine classifier is used for implementing CBR approach in machine learning using WEKA [14]. Support Vector Machine (SVM) classifier is a supervised learning algorithm which uses a hyperplane for discriminating different datasets. For linearly separable datasets, the hyperplane, which maximizes the distance between the datasets of different classes, is selected. The points which are closest to the hyperplane are called support vectors. For the datasets which are not linearly separable, kernel tricks are used to qualify the low dimensional input space to higher dimension.

Let $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ be the training set with n number of instances. Each x_i ia a multidimensional vector. The hyperplane, which separates the different classes, satisfies the equation (1) with the points x_i . Equation (1) is defined as follows:

$$\omega . x - b = 0 \quad (1)$$

In equation (1), ω is the normal vector and $\frac{b}{\|\omega\|}$ indicates the offset of the hyperplane with respect to the origin along ω.

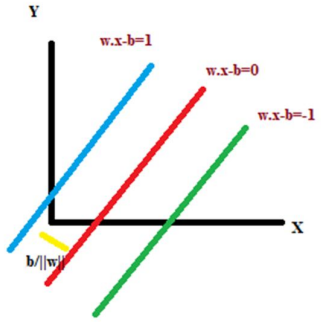


Figure 2. Separating hyperplane of SVM

In this figure, the points which falls on the upper side (line corresponding to w.x-b=1) of the hyperplane (line corresponding to w.x-b=0) are classified as class 1. The points which falls on the other side of the hyperplane are classified as class 2. The function that minimizes the training dataset error is selected. Then the training error is defined by equation (2):

$$E(\alpha) = \frac{1}{n} \times (\sum L(f(x_i, \alpha), y_i)) \quad (2)$$

Here, α is the functional parameter, the function L is defined by L(y,y')=1 if $y \neq y'$ and 0 otherwise. The range of i is from 1 to n, where n is number of training elements.
The Support Vector Machine (SVM) classifier follows supervised learning procedure. This implies that the knowledge of previously known cases is applied for the classification of new cases. This is similar to the Retrieve and Reuse phases of Case Based Learning.

IV. Results and Discussions

A set of one hundred and eighty five feature vectors are considered as the training set to the SVM classifier. For each instance of the test set, SVM classifier's predicted class and the actual class type of the instance is compared which results in generating the confusion matrix. The associated terms of confusion matrix are: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) which are described below:

TPi : number of correctly classified instances of i^{th} class
TNi: number of instances which are classified as not of i^{th} class and actually so
FPi : number of instances classified as of i^{th} class but actually not so
FNi : number of instances classified as not of i^{th} class but actually not so
The performance measures for the classifier depends on the above mentioned terms and are described using equation (3) to (5) with their short descriptions:
Sensitivity: measurement of detecting positive class and is defined by equation (3)
$Sensitivity_i$ = TPi / (TPi + FNi) (3)
Specificity: measurement of detecting negative class and is defined by equation (4)
$Specificity_i$ = TNi / (TNi + FPi) (4)
Accuracy: efficiency of correct classification and is defined by equation (5)
$Accuracy_i$ = (TPi + TNi) / (TPi + TNi + FPi + FNi) (5)

The values of TP, TN, FP and FN for each class are calculated from the confusion matrix generated by the SVM classifier in WEKA [13]. After the detection of abnormal objects from retina fundus images, each artefact is represented by its feature vector along with its class. When the set of feature vectors are provided to the classifier for machine learning, the classifier creates a knowledge base from the training set and depending on this knowledge base, the test set is classified. The performance of the classifier's predictability of class for an artefact is judged by comparing the assigned class value by the classifier to the original class value of the artefact. If the artefact is correctly classified, then it can be counted as a true positive (TP) value for the actual class and a true negative (TN) value for all the remaining classes. If it is incorrectly assigned to some other class, then it is counted as a false negative (FN) value for the actual class and a false positive (FP) value for the classifier's assigned class. The values of TP, TN, FP and FN for each class are represented using a confusion matrix. These values are used for evaluating the sensitivity, specificity and accuracy of the classifier for each class.

Prior to this research work, Naïve Bayes classifier is also used along with SVM classifier in one of our earlier work [10]. But with the increased size of retina input image dataset and feature set, it is examined that the performance of Naïve Bayes classifier dropped significantly compared to that of SVM classifier. Hence, Naïve Bayes classifier is not used in this work. Our another work [11] prior to this current research work, we have proposed the decision tree model. But as decision trees are unstable in nature and the small change in training data introduces a large change in the classification, decision tree is also discarded.

Table 3 describes the performance measures of SVM classifier for the case base. In Table 4, the classifier's performance for bright and dark lesion classes is analyzed. It is observed that the average accuracy and ROC area for the classification of bright lesion classes are less than those of dark lesion classes. Two main reasons are responsible for that. One reason is the similarity between hard exudates due to DR and drusens due to AMD. Hard exudates and drusens are yellowish in color with clearly visible edges. Both are medium in size. The only difference is that, drusens are normally circular but hard exudates are not uniform in shape. The difference in circularity is not sufficient for distinguishing these two abnormalities and hence misclassification occurs for the classification of drusens and hard exudates. The other reason arises due to the normal retina portion being misclassified as hard exudates. It is observed that, due to high illumination near optic disc, some bright portions close to optic disc may be retained after optic disc elimination. These portions are actually part of normal retina but are treated as abnormal artefacts. The class of cotton wool spots is distinct in nature according to color, shape and edges and hence achieves high accuracy of classification. In case of dark lesion classes, microaneurysms are distinguishable for their small size from hemorrhages class. In Table 5, the proposed method is compared with some relevant previous works in terms of performance measures. It is observed from Table 4 that, the performance measures of our proposed method is comparable to the other relevant works though the accuracy of bright lesion classification can be increased to 1 if hard exudates, cotton wool spots and drusens are clubbed together as done by Akram et. al., 2014 [7]. Consideration of drusens due to AMD as a bright lesion class adds advantage to our proposed method as in a practical field, the discrimination of drusens and hard exudates are a real challenge to the physicians. The column diagram represented using Fig. 3 shows the classifier's performance analysis for different lesion classes.

TABLE III: PERFORMANCE ANALYSIS OF SVM CLASSIFIER

Class	Sensitivity (%)	Specificity (%)	Accuracy (%)	ROC area
HE	96.3	77.9	83.2	0.883
CWS	100	100	100	1
MA	80	98.9	97.9	0.969
HAM	94.1	98.7	97.9	0.989
Drusens	100	98.8	98.9	0.994
Normal Retina	42.3	100	84.2	0.875
Average	85.45	95.7	93.68	0.928

TABLE IV: ACCURACY FOR THE DETECTION OF BRIGHT AND DARK LESION CLASSES

Classes	Sensitivity (%)	Specificity (%)	Accuracy (%)	ROC area
Bright lesion classes	98.76	92.23	94.03	0.959
Dark lesion classes	87.05	98.75	97.9	0.979

TABLE V: COMPARISON OF THE PROPOSED METHOD FOR LESION CLASSIFICATION

Method	Detected lesion type	Performance			
		Sensitivity(%)	Specificity (%)	Accuracy (%)	ROC area
Osareh et al, 2003[6]	Detection of hard exudates only from bright lesion classes due to DR and no dark lesions of DR and AMD is not considered	93	94.1	-	-
Niemeijer et al, 2005 and 2007[8-9]	Dark lesions (microaneurysms and hemorrhages) and bright lesions (drusens of AMD, exudates and cotton wool spots of DR) and the detection of lesions were not fully automated and was with carried out by doctor's advice	For dark lesion classification			
		100	87	-	-
		For bright lesion classification			
		95	88	-	0.95
Agurto et. al., 2010[5]	Detection of exudates, microaneurysms, haemorrhages and neovascularisation and cotton wool spots of DR and drusens of AMD were not considered	92	54	-	0.84
Akram et. al, 2014[7]	Dark lesions (microaneurysms and haemorrhages) and bright lesions (both of hard exudates class and cotton wool spots class are merged as exudates) and AMD is not considered	For dark lesion classification			
		97.83	98.36	98.12	0.974
		For bright lesion classification			
		97.39	98.02	97.56	0.97
Proposed method	Dark lesions (microaneurysms and haemorrhages) and bright lesions (drusens of AMD, exudates and cotton wool spots of DR)	For dark lesion classification			
		87.05	98.75	97.9	0.979
		For bright lesion classification			
		98.76	92.23	94.03	0.959

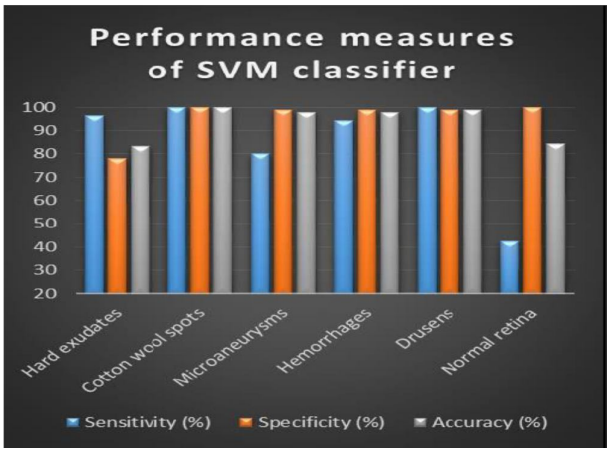


Figure 3. Column diagram representation of SVM classifier's sensitivity, specificity and accuracy for six different classes

V. CONCLUSION

In this research work, the approach relying on CBR is implemented for the classification of different retina abnormalities. The CBR inspired approach is the way of finding the solution to a new problem depending on the experience of the previously solved similar problems. This approach is used by the doctors while diagnosing a new patient. A case base is formed with one hundred and ninety images. The input retina images are pre-processed and segmented for the detection of abnormalities. Then the features of the abnormalities are evaluated. The classification of the abnormalities by SVM depending on the feature values are performed next. The comparison of actual class type and the predicted class type of an instance produces the metrics which are used in the performance analysis of the SVM classifier. It is observed that the classifier produces 94.03% of accuracy on an average for the classification of bright lesion classes with 0.959 as the value of area under Receiver Operating Characteristic (ROC) curve. The average accuracy of dark lesion classes achieved by SVM classifier is 97.9% with 0.979 as an area under ROC. Hard exudates, cotton wool spots and drusens are among bright lesion classes and hard exudates are quite similar to drusens. The accuracy of classification of bright lesion classes can be increases by introducing more significant features which can distinguish hard exudates with drusens. Classification accuracy of dark lesion classes, especially

microaneurysms, is promising. Among the four phases of Case Based Reasoning approach, Retrieve and Reuse phases are implemented through Support Vector Machine classifier. In future, the Revise and Retain phase are to be incorporated for the implementation of the approach of Case Based Reasoning.

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