International Journal of Engineering &Technology, 7 (1) (2018) 115-120

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet.v7i1.8969
Research paper

Analysis of gabor filter based features with PCA and GA for the detection of drusen in fundus images

Sheela. N.[1]*, L. Basavaraj [2]

[1]Research Scholar, ATME College of Engineering, Mysuru, India, (Sri Jayachamarajendra College of Engineering, Mysuru,India)
[2]Research Guide, ATME College of Engineering, Mysuru, India
**Corresponding author E-mail:sheelaraon@gmail.com*

Abstract

Human eye can be affected by different types of diseases. Age-Related Macular Degeneration (AMD) is one of the such diseases, and it mainly occurs after 50 years of age. This disease is characterized by the occurrence of yellow spots called as Drusen. In this work, an automated method for the detection of drusen in Fundus image has been developed, and it has been tested on 70 images consisting of 30 normal images and 40 images with drusen. Performance of the Support Vector Machine (SVM) and K Nearest Neighbor (KNN) classifier has been evaluated using Data's reduction using Principle Component Analysis (PCA) and Data's selection using Genetic Algorithm (GA).Performance evaluation has been done in terms of accuracy, sensitivity, specificity, misclassification rate, positive predictive rate, negative predictive rate and Youden's Index. The proposed method has achieved highest accuracy of 98.7% when data selection using Genetic Algorithm has been applied.

Keywords: Drusen; Gabor Filters; Genetic Algorithm; Principal Component Analysis; Support Vector Machine.

1. Introduction

Different types of changes may occur in the human eye with age. One such change is the accumulation of acellular polymorphous fine particles between retinal pigment epithelium (RPE) and Bruch's membrane. This appears as yellow spots during medical examination of the eye and is called as drusen. Drusen can appear either near the central region about the eye called macula or in the peripheral region of the retina. Size of the drusen may vary over a wide range of diameters. Appearance of drusen is an indication of the disease called as Age-Related Macular Degeneration (AMD/ARMD).According to World Health Organization (WHO), Age-Related Macular Degeneration (AMD/ARMD) is one of the major causes of irreversible vision loss in people aged above 50 years. AMD can be classified as Dry AMD and Wet AMD. Dry AMD is a symptom of early AMD, and it is characterized by accumulation of lipid and proteins under Bruch membrane. This leads to appearance of yellow spots called drusen. Wet AMD is characterized by the appearance of choroidal neovascularization (CNV). AMD is characterized into various stages based on number of and type of drusen present [1] [2]. A characteristic of early stage is the presence of a few medium-sized drusen. Middle stage is characterized by at least one large drusen with many medium-size drusen and advanced is characterized by large drusen.

A Survey [3] shows that global projected AMD cases will be 196 million in 2020 increasing to 288 million in 2040. At present, Europeans have the highest number of AMD cases but the number of cases is expected to increase faster in Asia as it has the highest population in the world. Hence, largest number of cases is expected to be in Asia reaching 113 million. Gender does not seem to be significant for this disease. Early detection of AMD is very important for the prevention of vision loss. Appearance of drusen is an indication of early AMD. Drusen detection using different methods has been proposed by many authors. Drusen detection based on contrast and intensity there by assessing the presence of AMD has been proposed by Mark J. J. P. van Grinsven et al. [4], Alauddin Bhuiyan et al.[5], in their work have used Gaussian derivative based technique for the detection of drusen. Drusen affected area detection using intensity gradient based segmentation. Gaussian function model has been suggested by Mora A et al. [6]. Wavelet transforms in combination with Fuzzy C Means clustering has been reported by Rama Prasath A et al[7]. Drusen detection using color features has been developed by Thanh Vân Phan et al., [8], Ziyang Liang et al. [9], P. Burlina et al. [10], Semantic Image Transformation (SIT) has been used by Xiangang Cheng et al. [11]. Wavelet transforms based features have been used by Muthu Rama Krishnan Mookiah et al. [12] for the developing a decision support system for AMD and in [13] they have proposed a method that uses entropy, Higher-OrderSpectra (HOS) and Gabor filter based features for the detection of Drusen. Saima Waseem et al. [14] have used Gabor filter features combined with color features.

In this work a Gabor filter based technique for the detection of drusen from fundus images using an optimized number of features has been proposed. The method consists of preprocessing, Gabor filtering using different orientation and scale, textural feature extraction using Gray Level Co-occurrence Matrix (GLCM), classification using Support Vector Machine (SVM) and K Nearest Neighbor (KNN). Performance of the classifier is evaluated by applying data reduction using Principal Component Analysis (PCA) as well as data selection using Genetic Algorithm (GA). A comparative study is finally presented.

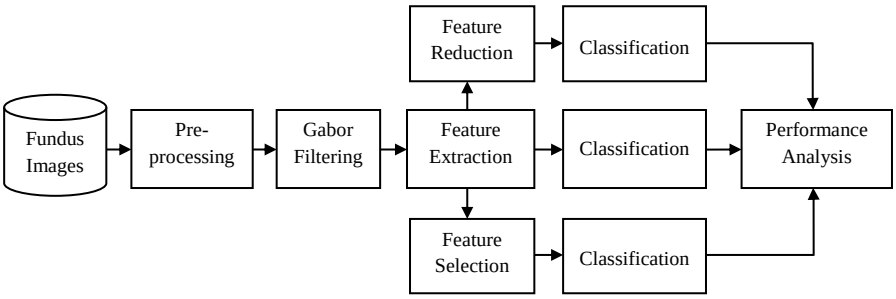

Fig. 1: Block Diagram of the Proposed Method.

2. Methodology

Methodology adapted in this work is as shown in Fig 1.

2.1. Database

Fundus images used throughout this work have been collected from Sushrutha Eye Hospital, Mysuru, Karnataka, India. The database used consists of 70 images out of which 40 are normal and 30 have drusen.

2.2. Preprocessing

Input images are RGB images. Green channel has the best contrast in fundus images hence only the green channel images are extracted and used for further processing. The images in the database are of different sizes. Therefore, they are all resized to 160x160 pixels. Adaptive histogram equalization is then applied for contrast enhancement.

2.3. Gabor filter

The Gabor filter is named after the Hungarian physicist Dennis Gabor (Gabor, 1946) who introduced it. Later the Gabor filter was extended to two dimensions by Daugman [15]. Gabor functions can be used to model the Simple cells present in the visual cortex of mammalian brains. Therefore, analysis of the images using Gabor filters is found to be similar to human visual system.
A two-dimensionalGabor Filter in the spatial domain is a Gaussian kernel function modulated by a complex sinusoidal plane wave, defined as:

$$G(x, y;\ \lambda, \theta, \Phi, \sigma, \gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\exp\left(j\left(\frac{2\pi x'}{\lambda}+\ \Phi\right)\right) \quad (1)$$

$$x' = x\cos\theta + y\sin\theta \quad (2)$$

$$y' = -x\sin\theta + y\cos\theta \quad (3)$$

f –Sinusoidal frequency, (f = 1/λ; λ – Wavelength)
θ –Orientation of the normal to the parallel stripes of Gabor function
Φ – Phase offset
σ – Standard Deviation of the Gaussian envelope
γ – Spatial Aspect Ratio specifying the ellipticity of the support of the Gabor function
In Equation (1), λ is the wavelength of the cosine term in the filter. The value of this parameter is in terms of pixels and its value can be ≥ 2. Gabor function consists of parallel stripes and θ specifies the orientation of the normal to these stripes. Its value can be fron 0° to 360 °. Gabor filter is usually implemented for different orientations.Φ is the phase offset of the cosine factor. Its value can be -180° to 180°. 0 and 180 are center symmetric, -90 and 90 are anti-symmetric and the remaining are asymmetric functions. γ is the aspect ratio which indicates ellipticity of the Gabor function where γ = 1 gives a circle. Its value is usually taken to be 0.5. σ is the Standard Deviation of the Gaussian envelope. The value of σ is related to half – response spatial frequency bandwidth (b) of the Gabor filter and wavelength (λ). If bandwidth is taken as 1 then σ = 0.56 λ.
Gabor filter with different orientation and scale are used for the extraction of information from the images. Simple cells in the Human Visual System are found to be sensitive to orientation and hence Gabor coefficients with eight different orientations are used in this work.Totally 16 Gabor images corresponding to 8 orientations and 2 scales are generated for each fundus image.

2.4. Feature extraction

Texture is an important component perceived by human visual system. A set of Gray Level Co-occurrence Matrix (GLCM) based texture features has been introduced [16] in the year 1973. These features are also called Haralick features and they are widely used in medical image analysis applications. The equations of the Haralick features are as given in Table 1.

Table 1: Haralick Features

Sl. No.	Haralick Features Equations
1	$Energy = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} p(i,j)^2$
2	$Contrast = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} \lvert i-j\rvert^2\, p(i,j)$
3	$Correlation = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} \frac{(ij)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$ Whereμ_x, μ_y and σ_x, σ_y are the means and standard deviations.
4	$Variance = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} (i-\mu)^2 p(i,j)$
5	$Homogeneity = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} \frac{p(i,j)}{1+(i-j)^2}$
6	$Sumaveage = \sum_{i=2}^{2(N-1)} ip_{x+y}(i)$
7	$Sumvariance = \sum_{i=2}^{2(N-1)} (i-f_8)^2 p_{x+y}(i)$
8	$Sumentropy = -\sum_{i=2}^{2(N-1)} p_{x+y}(i)log(p_{x+y}(i))$
9	$Entropy = -\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} p(i,j)\,log(p(i,j))$ where p(i,j) is the $(i, j)^{th}$ element of the normalized GLCM of size MxN
10	$DifVar = Variance\ of\ P_{x-y}$
11	$Difentropy = -\sum_{i=2}^{2(N-1)} p_{x-y}(i)log(p_{x-y}(i))$
12	$IMC1 = \frac{Entropy - HXY1}{max(HX, HY)}$
13	$IMC2 = \left[1-exp\left(-2(HXY2-Entropy)\right)\right]^{1/2}$
14	$MCC = (Second\ Largest\ Eigen\ Value\ of\ Q)^{1/2}$

Where

$$Q(i,j) = \sum_k \frac{P(i,k)P(j,k)}{P_x(i)P_y(k)}$$

where p(i,j) is the normalized co-occurrence matrix obtained from the Gabor coefficients, μ_x and μ_y are the mean of p_x and p_y respectively, σ_x and σ_y are the standard deviation of p_x and p_y respectively.

The parameter

$$p_{x+y}(k) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)$$

for k = 0,1, …2(N-1)

In this work all the 14 Haralick features have been extracted from each of the Gabor filtered images. Since we have used 8 orientations and 2 scales, a total of 224 features have been extracted from the images used.

2.5. Feature reduction

Balance between the number of training images and number of features used (dimension of the features) plays an important role in machine learning. For a fixed number of training images, over-fitting occurs if morefeatures are added.Over-fitting may lead to unnecessarily high accuracy. A number of methods are available for data reduction. Principal Component Analysis (PCA) is used for this work.

Principal Component Analysis (PCA) is a linear transformation method that maps large set of data into a small set of data without losing information [17]. These are called principal components. First principal component corresponds to largest variability in data. Successive components correspond to as many remaining variability as possible. PCA involves computation of covariance matrix, Eigen value and Eigen vector calculation, Arrange Eigen values in decreasing order, finally retain only the required number of largest eigen values.

2.6. Feature selection

Data selection is a method of finding features whose contribution is more relevant for classification of the data in hand. It helps in removing redundant features, and this may lead to improved accuracy. Data selection has been done in this work using Genetic Algorithm (GA).

A Genetic Algorithm (GA) which was proposed by J. H. Holland [18] is a method of solving an optimization problem that works similar to biological evolution. In genetic algorithm, an initial population of solutions (similar to chromosomes) is taken, and they are subjected to repeated modification. A fitness value is assigned to everyonein the current population. The fitness value is evaluated by training the predictive model with the training set of data and then selection error is calculated. Higher the value of selection error lower will be the fitness. Therefore, individuals with higher fitness value will be selected to generate next population. Genetic algorithm mainly uses three important steps to generate new population. They are, (1) Selection: to select parents to generate new population, (2) Crossover: to combine two parents to create offsprings for the new population and (3) Mutation: to modify parents randomly to create offerings. Evolution of population takes place over successive generations, which suit the environment better than the parents to achieve optimal solution.

2.7. Classification

In this work classification has been done using Support Vector Machine (SVM) and K Nearest Neighbor (KNN).

2.7.1. Support vector machine (SVM)

SVM is a supervised, two class, classifier. It transforms the features as points in n – dimensional space. The value of n will be equal to number of feature vectors and the value at a particular point in the coordinate is the feature value. Co-ordinate of individual feature is called as support vector. SVM finds a hyperplane that can separate out two different classes. Many hyperplanes can be generated to separate it but SVM finds a hyperplane that gives largest margin between the two classes.

In SVM, data will be separated into two sets, a training set and a testing set for classification purpose. Each instance in the training set will have one target value and a large number of associated features values. Training data based model will be formed by the SVM. SVM uses this model to predict target values when the test data features alone are given to it for classification.

If we take a training set with label pairs (x_i,y_i),i = 1. . .l where $x_i \in R^n$ and $y \in \{1, -1\}^l$, the support vector machines find the solution to optimize the problem given below [19].

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \quad (4)$$

Where

w – Weight Vector
b – Bias
ξ – Degree of misclassification
C – Penalty parameter of the error

Subject to $y_i (w^T(x_i) + b) \geq 1 - \xi_i$,

Where $\xi_i \geq 0$

In SVM, training vectors x_i are transformed into a higher dimensional space by the function φ. SVM finds a hyperplane that separates the vectors with maximal margin. C > 0 is the penalty parameter of the error and $K(x_i,x_j) \equiv \varphi(x_i)^T \varphi(x_j)$ is the kernel function. The kernels used in this work are

Linear:

$$K(x_i,x_j) = x_i^T x_j \quad (5)$$

Polynomial:

$$K(x_i,x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0. \quad (6)$$

Where, γ, r are the kernel parameters and d is the degree of the polynomial

Radial Basis Function:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (7)$$

Where, σ is the kernel parameter

2.7.2.K nearest neighbor (KNN)

K-nearest neighbor classifier is a simple, supervised classifier proposed by Fix & Hodges in 1951. This classifier also requires data to be divided into training set and testing se. Nevertheless, the Training data based model formed by the KNN will include the entire training data set. When test data features are given to KNN classifier, it searches through the entire training set to find K most similar instances called neighbors [20]. Different types of distance measures like Euclidean distance, Cityblock distance, Manhattan distance, etc. can be used for finding similarities. Class of that K number of nearest neighbors will be assigned to the test data.

2.8. Performance evaluation

A total of 224 features that have been extracted from a data set of 70 fundus images are given to two types of classifiers namely SVM and KNN. Performances of these two classifiers are tested using 10-fold cross validation technique. Cross validation is an

important step in performance evaluation when a limited number of data set is used. In 10-fold cross validation, the data set is randomly divided into 10 equal sized subsets.Out of 10 subsets, 9 subsets are used for training and the remaining one subset used for testing. This process is repeated 10 times by taking each of the subset for testing once. Results of all the 10 evaluations are averaged to get the final result. Performance's measures are calculated based on the following values.

True Negative (TN): Number of normal images predicted as normal.

True Positive (TP): Number of abnormal images predicted as abnormal.

False Positive (FP): Number of normal images predicted as abnormal.

False Negative (FN): Number of abnormal images predicted as normal.

Performance measures used are sensitivity, specificity, accuracy, misclassification rate, Positive Predictive Value Negative Predictive Value and Youden's Index. Details are as given below.

Sensitivity (Sn): Measure of correct predictions of presence of abnormality in the image out of total number of images with abnormality. It is also called as True Positive Rate or Recall.

$$\text{Sn} = \frac{\text{TP}}{(\text{TP+FN})} \text{ X } 100 \quad (8)$$

Specificity (Sp): Measure of correct predictions of absence of abnormality in the image out of total number of images without abnormality. It is also called as True Negative Rate.

$$\text{Sp} = \frac{\text{TN}}{(\text{FP+TN})} \text{ X } 100 \quad (9)$$

Accuracy (A): Measure of correct predictions of presence or absence of the abnormality in the image out of total number of images.

$$\text{Acc} = \frac{\text{TP+TN}}{(\text{TP+FN+FP+TN})} \text{ X } 100 \quad (10)$$

Misclassification Rate (MCR): Measure of wrong predictions.

$$\text{MCR} = \frac{\text{FP+FN}}{(\text{TP+FN+FP+TN})} \text{ X } 100 \quad (11)$$

Positive Prediction Rate (PPV): Measure of correct predictions of presence of abnormality in the image out of total number of positive predictions. It is also called as Precision.

$$\text{PPV} = \frac{\text{TP}}{(\text{TP+FP})} \text{ X } 100 \quad (12)$$

Negative Prediction Rate (NPV): Measure of correct predictions of absence of abnormality in the image out of total number of negative predictions.

$$\text{NPV} = \frac{\text{TN}}{(\text{TN+FN})} \text{ X } 100 \quad (13)$$

Youden's index (J): This index gives a summarized value of classifier performance. Its value ranges from -1 to +1. Values towards +1 indicate good performance.

$$\text{J} = \frac{\text{TP}}{(\text{TP+FN})} + \frac{\text{TN}}{(\text{FP+TN})} - 1 \quad (14)$$

Features extracted are classified by using different classifiers. Performance of variants of SVM is tabulated in Table 2, and a plot of it is shown in Fig 2. It can be seen that SVM with Polynomial of order 1 gives best results of an accuracy of 96.7%, Sensitivity of 94.29%, Specificity of 100% and Misclassification rate of 3.3%, Youden's index is a good indication of both positive as well as negative predictions, and this value are also nearer to 1 than other forms of SVMs. In order to overcome "Curse of Dimensionality", PCA is applied to feature set. Results of SVM classification after applications of PCA to the data are given in Table 3, and the related plot is given in Fig 3. Results indicate that there is a reduction in the performance. As mentioned earlier, the features extracted in this work are Haralick features of Gabor Images and Haralick et al., [16] in their paper have mentioned that some of the features suggested by them are correlated. Hence, reduction in the performance of the classifier in case of PCA might be due to redundancy in the feature extracted.

In order to overcome this problem feature selection using Genetic Algorithm is applied. The SVM classification results of this are tabulated in Table 4, and the plot is given in Fig 4. The results show good improvement on the performance. Again, best results are achieved by SVM with polynomial of order 1 with an accuracy of 98.7%, Sensitivity of 98.61% and Specificity of 100%. It also shows lowest Misclassification rate of 1.3% as well as the best Youden's index of 0.9861, which is nearest of all to 1.

Table 2: Performance of SVM (in %)

SVM	Acc	Sn	Sp	MCR	PPV	NPV	J
Linear	94.89	91.06	100	5.11	100	89.72	91.06
Poly 1	96.7	94.29	100	3.3	100	92.92	94.29
Poly 2	96.55	95.03	98.58	3.45	98.91	93.72	93.58
Poly 3	95.71	95.42	96.10	4.29	97.03	94.02	91.52
RBF	94.34	95.59	92.68	5.66	94.6	94.04	88.27

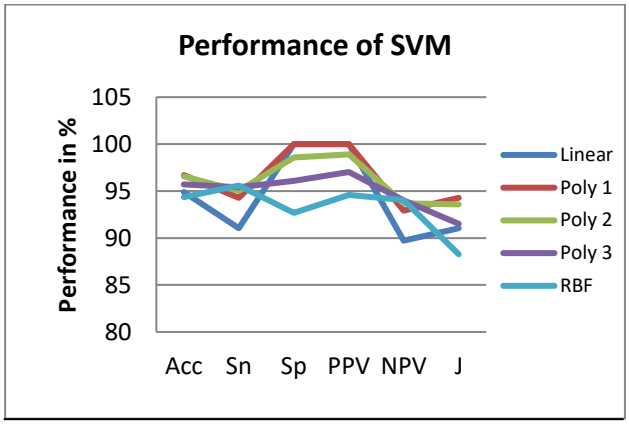

Fig. 2: Performance of SVM.

Table 3: Performance of SVM with PCA (in %)

SVM	Acc	Sn	Sp	MCR	PPV	NPV	J
Linear	93.17	95.72	89.76	6.83	92.58	94.02	85.48
Poly 1	93.78	95.61	91.33	6.22	93.63	93.98	86.94
Poly 2	93.76	95.17	91.88	6.24	93.99	93.46	87.05
Poly 3	93.45	94.8	91.66	6.55	93.81	92.96	86.46
RBF	93.64	94.63	92.31	6.36	94.26	92.80	86.94

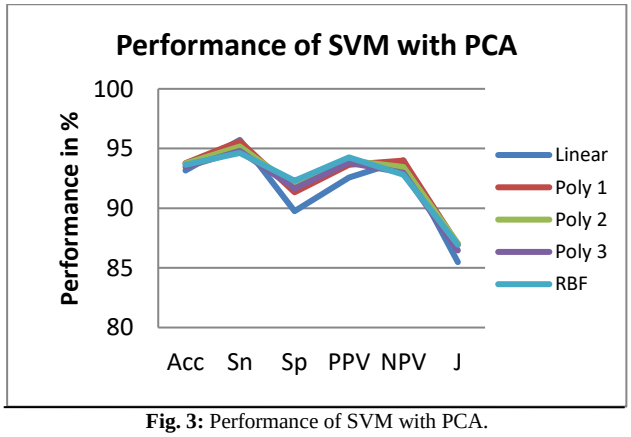

Fig. 3: Performance of SVM with PCA.

Table 4: Performance of SVM with GA (in %)

SVM	Acc	Sn	Sp	MCR	PPV	NPV	J
Linear	97.14	95.72	100	2.86	99.58	98.02	95.72
Poly 1	98.7	98.61	100	1.3	99.63	98.98	98.61
Poly 2	98.5	97.17	99.88	1.5	98.99	97.46	97.05
Poly 3	98.7	97.8	99.66	1.3	98.81	97.96	97.46
RBF	96.2	97.63	94.31	3.8	96.26	96.80	91.94

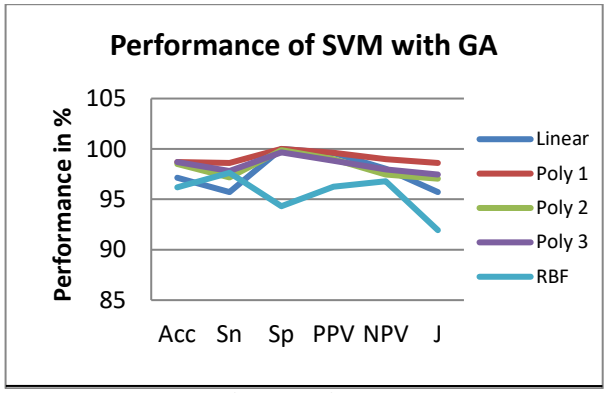

Fig. 4: Performance of SVM with GA.

Table 5: Comparison of SVM Performance in Terms of Accuracy

SVM Used	SVM	SVM with PCA	SVM with GA
Linear	94.89	93.17	97.14
Polynomial 1	96.7	93.78	98.7
Polynomial 2	96.55	93.76	98.5
Polynomial 3	95.71	93.45	98.7
RBF	94.34	93.64	96.2

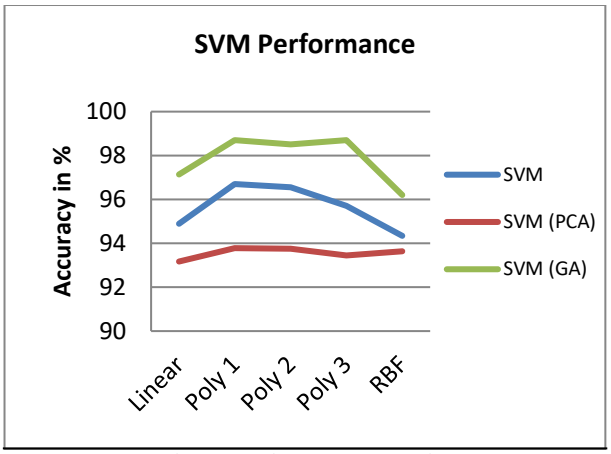

Fig. 5: Performance of SVM in Terms of Accuracy.

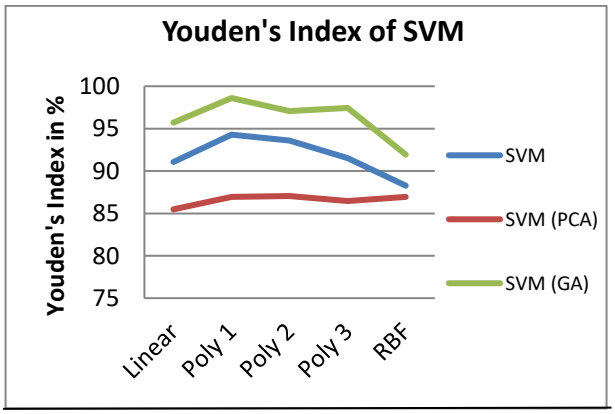

Fig. 6: Youden's Index of SVM.

Table 6: Comparison of KNN Performance in terms of Accuracy

Distance Used	KNN	KNN with PCA	KNN with GA
Euclidean	94.28	94.45	95.25
Mahalanobis	94.3	94.43	95.6
City Block	94.25	94.35	95.3

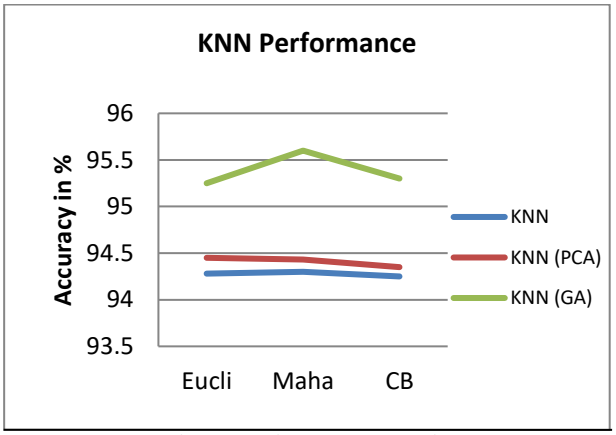

Fig. 7: Performance of KNN in Terms of Accuracy

Table 7: Drusen Detection Techniques Used by Different Authors

	Author (Year of Publication)	Feature Extraction	Classification	Accuracy
1.	M R K Mookiah et al., [12] (2014)	Wavelet Transform with KLD	SVM	93.7%
2.	M R K Mookiah et al., [13] (2014)	Entropies, HOS and Gabor Filter.	SVM	90.19%
3.	Saima Waseem et al. [14] (2014)	Color and Gabor Filter	KNN	96%
4.	Damon W.K. Wong et al. [21] (2013)	Hierarchical Word Transform (HWI)	SVM	95.46%
5.	Proposed Method	Gabor Filter with GLCM and GA	SVM	98.7%

A comparison of performance of variants of SVM without PCA or GA, With PCA and With GA are summarized in Table 5, and it is also plotted in Fig 5. A Plot of Youden's Index is given in Fig 6. It can be seen that feature selection using GA performs the best.

Extracted features were classified by using KNN classifier with Euclidean, Mahalanobis and Cityblock distance measures. Performance of KNN did not show much improvement as compared to SVM. The accuracies obtained by KNN are tabulated in Table 6, and related plots are given in Fig 7. Even though best accuracy is obtained when KNN with the Mahalanobis distance measures was applied to features selected by GA, performance of SVM is found to be much better.

Different combination of features and classifiers has been suggested by various authors for the detection of drusen from fundus images as shown in Table 7. Even though the proposed method has achieved higher accuracy, the performance cannot be directly compared since the methods have been applied on different databases.

3. Conclusion

In this work, 224 textural features have been extracted from Gabor images with 8 orientations and 2 scales. Performance of different forms of SVM and KNN with different types of distance measure has been evaluated. A Comparative study has been made by applying these classifiers directly to the features extracted, features reduced using Principle Component Analysis and features selected using Genetic Algorithm. Results obtained indicate that SVM with Polynomial of order 1 applied to features selected using Genetic algorithm gives best results with accuracy of 98.7%. Youden's

Index which is a measure of how well the classifier performs for detection of both presence and absence of any abnormality is also found to be best in this case and it is 0.9861. The results obtained in this work indicates that taking this work further can go a long way in aiding automated detection of drusen there by leading to detection of Age Related Macular Degeneration (AMD).

Acknowledgement

The Fundus images required for the proposed work have been collected from Sushrutha Eye Hospital, Mysuru, Karnataka, India. We would like to thank Dr. PallaviPrabhu and Mr. Arun Kumar of Sushrutha Eye Hospital, Mysuru, Karnataka, India for providing us the required images.

References

[1] Rama D. Jager, M.D., William F. Mieler, M.D., and Joan W. Miller, M.D., "Age Related Macular Degeneration: Review Article", the New England Journal of Medicine. 2008; 358:2606-17.

[2] Catherine Bowes Rickman, SinaFarsiu, Cynthia A. Toth, and Mikael Klingeborn, "Dry Age-Related Macular Degeneration: Mechanisms, Therapeutic Targets, and Imaging". Investigative Ophthalmology & Visual Science, Vol.54, (2013), pp. ORSF68-ORSF80. https://doi.org/10.1167/iovs.13-12757.

[3] Wan Ling Wong, Xinyi Su, Xiang Li, Chui Ming G Cheung, Ronald Klein, Ching-Yu Cheng, Tien Yin Wong, "Global prevalence of age-related macular degeneration and disease burden projection for 2020 and 2040: a systematic review and meta-analysis", The Lancet Global Health, Vol 2, No. 2, (2014), pp. e106-e116, https://doi.org/10.1016/S2214-109X(13)70145-1.

[4] Mark J. J. P. van Grinsven, Yara T. E. Lechanteur, Johannes P. H. van de Ven, Bram van Ginneken, Carel B. Hoyng, Thomas Theelen, and Clara. S´anchez, "Automatic Drusen Quantification and Risk Assessment of Age-Related Macular Degeneration on Color Fundus Images", Investigative Ophthalmology & Visual Science,Vol.54, (2013), pp. 3019-3027. https://doi.org/10.1167/iovs.12-11449.

[5] AlauddinBhuiyan, Ryo Kawasaki, Mariko Sasaki, EcosseLamoureux, KotagiriRamamohanarao, Robyn Guymer, Tien Y Wong and KanagasingamYogesan, "Drusen Detection and Quantification for Early Identification of Age Related Macular Degeneration using Color Fundus Imaging", Journal of Clinical and Experimental Ophthalmology, Vol. 4, No. 5, (2013), https://doi.org/10.4172/2155-9570.1000305.

[6] Mora A., Vieira P., Fonseca J., "Advances in Image Processing Techniques for DrusensDetection and Quantification in Fundus Images". Emerging Trends in Technological Innovation. DoCEIS, IFIP Advances in Information and Communication Technology, vol 314. Springer. (2010). https://doi.org/10.1007/978-3-642-11628-5_32.

[7] Rama Prasath.A, M.M.Ramya, " Automated Drusen Grading System In Fundus Image Using Fuzzy C-Means Clustering", International Journal of Engineering Technology, Vol 6, No 2, (2014).

[8] Thanh Vân Phan, Lama Seoud, HadiChakor, and Farida Cheriet, "Automatic Screening and Grading of Age-Related Macular Degeneration from Texture Analysis of Fundus Images", Journal of Ophthalmology, Volume 2016, Article ID 5893601, 11 pages, Hindawi Publishing Corporation, https://doi.org/10.1155/2016/5893601.

[9] Ziyang Liang, Damon W.K. Wong, Jiang Liu, KapLuk Chan, Tien Yin Wong, "Towards automatic detection of age-related macular degeneration in retinal fundus images", 32nd Annual International Conference of the IEEE EMBS, Buenos Aires, Argentina, Aug 31 - Sep 4, 2010.

[10] P. Burlina, D.E. Freund, B. Dupas, and N. Bressler, "Automatic Screening of Age-Related Macular Degeneration and Retinal Abnormalities", 33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, Aug 30 - Sep 3, 2011. https://doi.org/10.1109/IEMBS.2011.6090984.

[11] Xiangang Cheng, Damon Wing Kee Wong, Jiang Liu, Beng-Hai Lee, Ngan Meng Tan, Jielin Zhang, Ching Yu Cheng, Gemmy Cheung and Tien Yin Wong, "Automatic localization of retinal landmarks" 34th Annual International Conference of the IEEE EMBS San Diego, California USA, 28 Aug - 1 Sept, 2012.

[12] Muthu Rama Krishnan Mookiah, U. Rajendra Acharya, Joel E.W. Koh, Chua Kuang Chua, Jen Hong Tan, Vinod Chandran, Choo Min Lim, Kevin Noronha, Augustinus Laude, Louis Tong, "Decision support system for age-related macular degeneration using discrete wavelet transform", Medical & Biological Engineering & Computing, Vol 52, No. 9, (2014), pp 781–796, https://doi.org/10.1007/s11517-014-1180-8.

[13] Muthu Rama Krishnan Mookiah, U Rajendra Acharya, Joel E. W. Koh, Vinod Chandran, Chua Kuang Chua, Jen Hong Tan, Choo Min Lim, E. Y. K Ng, Kevin Noronha, Louis Tong, Augustinus Laude. "Automated diagnosis of Age-related Macular Degeneration using greyscale features from digital fundus images", Computers in Biology and Medicine, Volume 53, 2014, pp 55-64, https://doi.org/10.1016/j.compbiomed.2014.07.015.

[14] Saima Waseem, M. Usman Akram, Bilal Ashfaq Ahmed. "Drusen Detection From Colored Fundus Images for Diagnosis of Age Related Macular Degeneration", 7th IEEE International Conference on Information and Automation for Sustainability (ICIAfS), 2014. https://doi.org/10.1109/ICIAFS.2014.7069581.

[15] John G.Daugman, Two Dimensional Spectral Analysis of Cortical Receptive Field Profiles, Vision Group, Vol. 20, No. 10, (1980), pp 847-856, https://doi.org/10.1016/0042-6989(80)90065-6.

[16] Robert M. Haralick, K. Shanmugam, Its'hakDinstein. "Textural Features for Image Classification", IEEE Transactions on Systems, Man and Cybernetics, Vol SMC -3, No. 6, (1973), pp. 610-621.

[17] Dibyadeep Nandi; Amira S. Ashour; SouravSamanta; Sayan Chakraborty; Mohammed A.M. Salem; NilanjanDey "Principal Component Analysis in Medical Image Processing: A Study", International Journal of Image Mining, Vol 1, No. 1, (2015), pp 65 – 86, https://doi.org/10.1504/IJIM.2015.070024.

[18] J. H. Holland, "Adaptation in Natural and Artificial Systems", The University of Michigan Press, Ann Arbor, Michigan, USA, 1975

[19] Corinna Cortes, Vladimir Vapnik. "Support-Vector Networks", Machine Learning, Vol. 20, No 3, (1995), pp. 273-297. https://doi.org/10.1007/BF00994018.

[20] D.T.Larose, "Discovering Knowledge in Data; An Introduction to Data Mining", Wiley Interscience, (2004), pp. 90-109.https://doi.org/10.1002/0471687545.

[21] Damon W.K. Wong, Jiang Liu, Xiangang Cheng, Jielin Zhang, Fengshou Yin, Mayuri Bhargava, Gemmy C.M. Cheung, Tien Yin Wong, "THALIA - An automatic hierarchical analysis system to detect drusen lesion images for amd assessment", IEEE 10th International Symposium onBiomedical Imaging (ISBI), (2013), https://doi.org/10.1109/ISBI.2013.6556617.