IJCTA, 9(10), 2016, pp. 4339-4346

Detecting Abnormality in Retinal Images Using Combined Haar Wavelet and GLCM Features

***Shantala Giraddi **Dr P.S.Hiremath ***Dr Jagadeesh Pujari ****Savita Gadwal**

Abstract : Diabetic Retinopathy has become a major cause of blindness. Many automated mechanisms have been developed to reduce the burden on ophthalmologists. All these mechanisms follow an elaborate mechanism of performing segmentation and then classifying these regions into exudates and non-exudates. Real time image analysis, which can quickly classify the image as Healthy or Diseased one is the need of the day. In this paper attempt has been made to develop novel system for the whole image classification based on the application of haar wavelet and second order texture features from the detailed coefficients obtained. The authors have conducted study using Diaretdb0 and Diaretdb1 and performed a comparative study of Decision tree classifier and Knn classier based on second order features and obtained encouraging results with classification accuracy of 95 % with Decision tree classifier and 79% accuracy with Knn classifier.

Keywords : HaarWavelet, Diabetic Retinopathy, Classification GLCM.

1. INTRODUCTION

The most challenging public health problem of 21st century is Diabetes mellitus. It is estimated that worldwide there are 387 million (8.3%) people affected with Diabetes and predicted to be 592 million by 2035. The patients, who have had Diabetes for more than 10 years, are likely to be affected by Diabetic retinopathy (DR). Diabetic retinopathy is a major cause of blindness among the working age group. [1][2] Regular retinal screening and effective DR management are very important to prevent any vision loss. According to a study, regular screening for diabetic retinopathy could reduce the number of people getting affected at least by 90%.

In several patients, the only visible symptoms of DR are exudates. The main obstacle in exudates detection is extreme variability of color and contrast in retinal images that depends on the degree of pigmentation, size of the pupil and illumination. These factors affect the appearance of exudates in the retinal images. Many techniques such as clustering, morphological operations, classification, and segmentation using texture features have been used for the exudates detection. All these techniques have high computational requirement.

Akara Sopharak et.al [1] proposed an automatic method to detect exudates based on Fuzzy c means clustering and the number of clusters is selected based on a quantitative experiment. Based on sensitivity and specificity the number of clusters was varied from two to eight. Hussain F. Jaafar, Asoke K. Nandi and Waleed Al-Nuaimy et al. [2], used a split-and-merge algorithm based on image features and a statistical hypothesis which occasionally fails to exclude some non- exudates objects having features similar to real exudates. Ivo soars et.al [3] proposed a method based on computation of the noise map distribution, the use of morphological operators and adaptive

* Dept of Computer Science and Engineering B.V.B College of Engineering and Technology Hubli, India shantala@bvb.edu
** Dept of Computer Applications (MCA) B.V.B College of Engineering and Technology Hubli, India pshiremath@bvb.edu
*** Dept of Information Science and Engineering S.D.M College of Engineering and Technology Dharwad, India jaggudp@gmail.com
**** Dept of Computer Science and Engineering B.V.B College of Engineering and Technology Hubli,India savita.gadwal@gmail.com

thresholding. The authors claim that proposed method results in a correct detection of exudates. Ramesh Shahin et.al [4] proposed a system for automated classification of normal, and abnormal retinal images by making measurements such as blood vessels area, exudates area, micro aneurysms area, entropy and homogeneity from the processed retinal images. These objective measurements are used to train artificial neural network (ANN) classifier for the automatic classification. Osareh [5] segmented retinal images using fuzzy c-means clustering. The entire segmented images establish a dataset of regions. A set of features such as color, size, edge strength, and texture are extracted to further classify these segmented regions. Giancarlo, Luca et.al [6] in their work used new methods based on Kirsch's Edges and Stationary Wavelets for the detection of exudates. The methods do not require lesion training set so the need to ground-truth data is avoided with significant time savings and independence from human error. Quality of retinal image plays an important role in the reliable detection of abnormality in retinal images [7][8].

Over the last decade wavelet representation has emerged as a more solid, formal mathematical framework for texture analysis [9]. The application of Haar wavelet low pass and high pass filters produces four sub-bands. The four sub-bands are LL1, HL1, LH1, and HH1. The low-frequency sub-band LL1 can be further decomposed into four sub-bands LL2, HL2, LH2, and HH2 at the next coarser scale. LLi is a reduced resolution corresponding to the low frequency part of the image. The other sub-bands HLi, LHi and Hhi are the high frequency parts in the vertical, horizontal, and diagonal directions, respectively [10]. First and second order statistics from the wavelet detailed coefficients provide texture descriptors that can discriminate contrasting intensity properties.

In this paper an attempt has been made to build a robust system for the classification of image as Diseased or Normal one. The system is based on application of HAAR wavelets and second order features extracted from the coefficients obtained from the first level decomposition of image.

This rest of the paper is organized as follows. Section 2 presents the material and methods. Results are discussed and presented Section 3. Finally conclusion and future scope are discussed in section 4.

2. MATERIALS AND METHODS

A. Database

Two well known publicly available databases Diaretdb0 and Diaretdb1 are used for the study. The number of images in each of the databases is given in the Table 1. The images from Diaretdb0 and Diaretdb1 are of size 1500X1152 in png format. For the study 20 Healthy images and 40 images having diabetic retinopathy from Diaretdb0 and Diaretdb1 are selected. Fig. 1. Shows Healthy retinal image and Fig. 2 shows mild DR and Fig. 3. Show severe DR images.

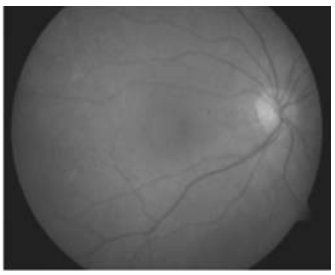

Fig. 1. Healthy retinal image

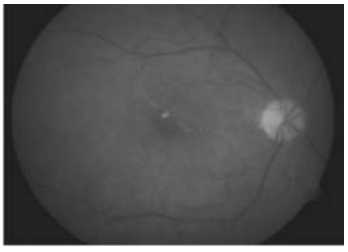

Fig. 2. Retinal image having mild DR

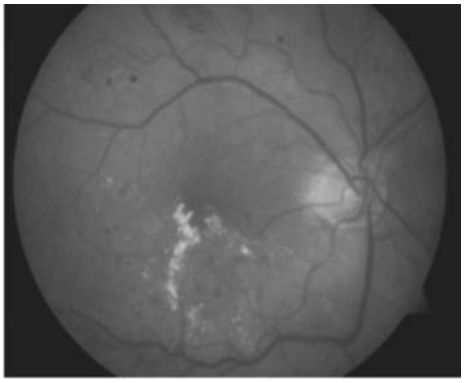

Fig. 3. Retinal image having severe DR.

The experiments are carried out in MATLAB 7 on a Windows XP machine with a 3.00 GHz Intel Pentium 4 processor and 1 GB of RAM. .

B. Pre-processing

The images are of varying contrast. The image is contrast enhanced by converting to HIS color space and after enhancing converted back to RGB color space. The red, green and blue components are separated.

C. Application of HAAR wavelet

Each of the colour components red, green and blue is considered. To each colour channel, 2D Haar Wavelet is applied; coefficients are computed from the decomposition matrices. Fig 4. Shows approximation, horizontal, vertical and diagonal components after the first level decomposition of HAAR wavelet.

D. Extraction of GLCM features

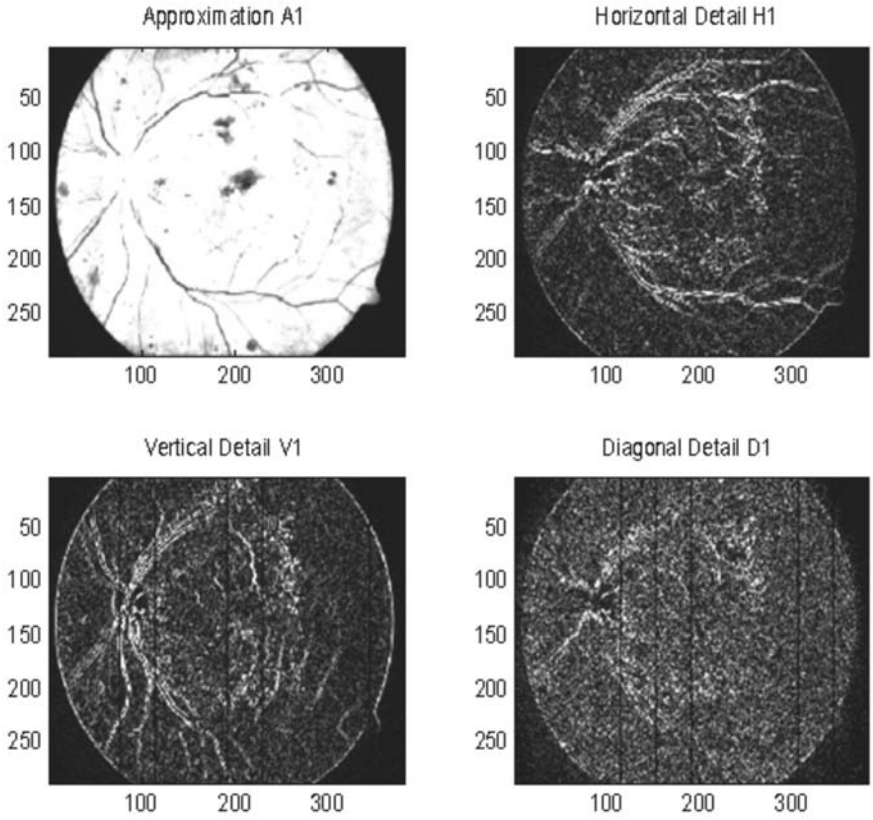

Fig. 4. Horizontal, Vertical and Diagonal coefficients produced after application of Haar wavelet.

The GLCM functions represent the texture of an image. They characterize texture by calculating how often pairs of pixel with specific values occur in a specified spatial relationship. GLCM Features have been used in many image processing applications. GLCM features are used in Retinal Haemorrhage Detection [11] after dividing the image into non overlapping regions. They are also used for the detection of skin cancer, GLCM texture features are extracted from clusters obtained from K-means clustering. GLCM features such as Contrast, Entropy, Energy, Homogeneity and Correlation are used to classify clusters into cancerous regions. Ranjan Parekh[12] used a combination GLCM and Haar wavelet on texture samples like bark, brick, bubbles, grass, leather and shown that recognition accuracy can be improved by the combined approach. In [13] a system based on hybrid feature set of wavelet and GLCM features used for IRIS based biometric method of authenticating users.

Fig. 5. Shows the creation of GLCM matrix in the direction of 0^0, 45^0, 90^0 and 135^0 at four different distances 1, 2, 3 and 4.

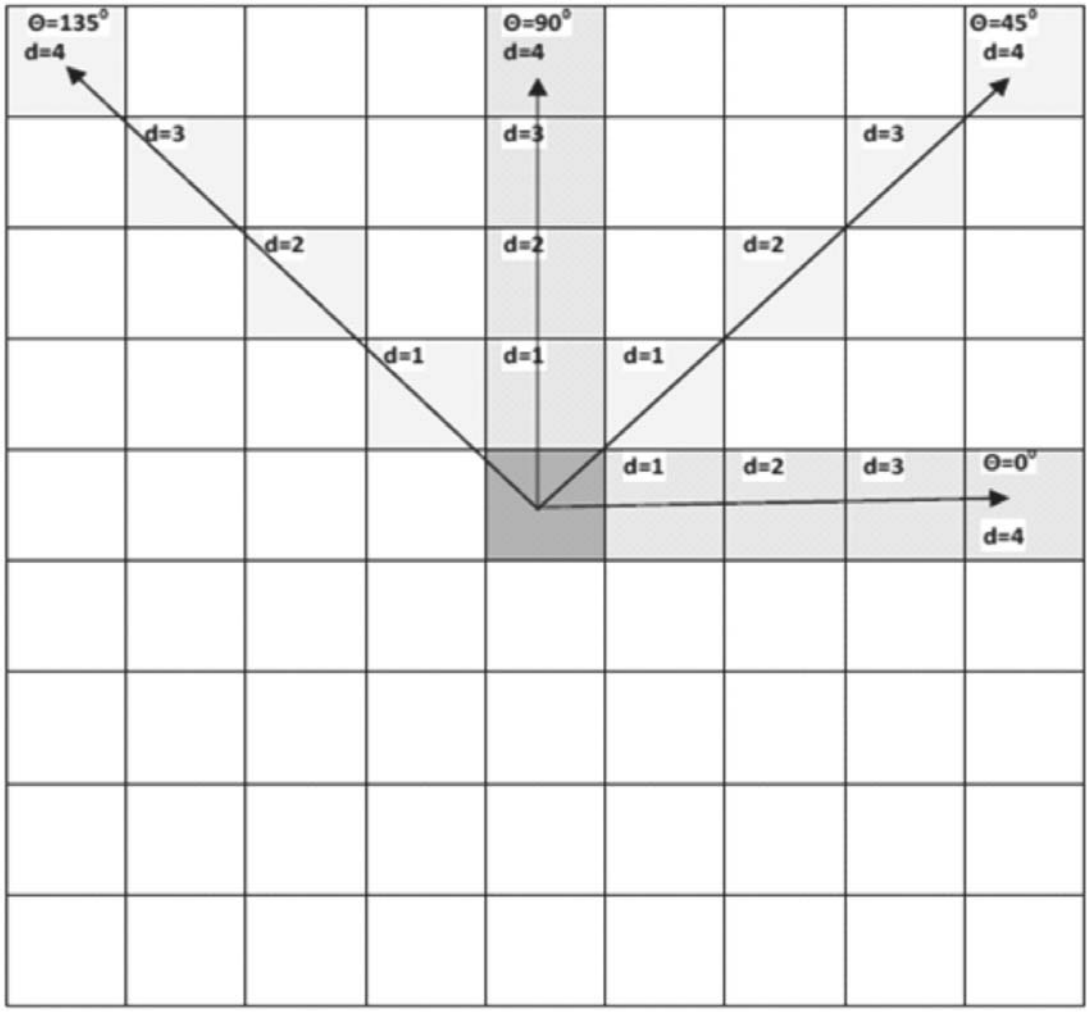

Fig. 5. Construction of GLCM in the direction of 0^0, 45^0, 90^0 and 135^0.

Authors have considered two directions 0^0 and 90^0 and distance of 1 pixel. From the horizontal, vertical and diagonal coefficients obtained for each color channel, gray level co-occurrence matrices (GLCM) have been constructed in the direction of 0^0 and 90^0 at a distance of 1 pixels. Totally 18 GLCM have been constructed. From each of these 18 matrices, 4 texture features namely Contrast, Correlation, Energy, and Homogeneity are computed. Our feature vector consists of 72 texture features. Table I shows the GLCM feature vector constructed from horizontal, vertical and diagonal components. The features are to be interpreted in the following manner.

Ex X1 feature: CH_ZeroContrast - Red channel horizontal component -GLCM constructed in zero degree -Contrast feature.

Table 1 : GLCM feature vector from horizontal, vertical and diagonal components.

Red		Green		Blue	
X1	CH_ZeroContrast	X25	CH_ZeroContrast	X49	CH_ZeroContrast
X2	CH_ZeroCorrelation	X26	CH_ZeroCorrelation	X50	CH_ZeroCorrelation
X3	CH_ZeroEnergy	X27	CH_ZeroEnergy	X51	CH_ZeroEnergy
X4	CH_ZeroHomogeneity	X28	CH_ZeroHomogeneity	X52	CH_ZeroHomogeneity
X5	CH_NinetyContrast	X29	CH_NinetyContrast	X53	CH_NinetyContrast
X6	CH_NinetyCorrelation	X30	CH_NinetyCorrelation	X54	CH_NinetyCorrelation
X7	CH_NinetyEnergy	X31	CH_NinetyEnergy	X55	CH_NinetyEnergy
X8	CH_NinetyHomogeneity	X32	CH_NinetyHomogeneity	X56	CH_Ninety Homogeneity
X9	CV_ZeroContrast	X33	CV_ZeroContrast	X57	CV_ZeroContrast
X10	CV_ZeroCorrelation	X34	CV_ZeroCorrelation	X58	CV_ZeroCorrelation
X11	CV_ZeroEnergy	X35	CV_ZeroEnergy	X59	CV_ZeroEnergy
X12	CV_ZeroHomogeneity	X36	CV_ZeroHomogeneity	X60	CV_ZeroHomogeneity
X13	CV_NinetyContrast	X37	CV_NinetyContrast	X61	CV_NinetyContrast
X14	CV_NinetyCorrelation	X38	CV_NinetyCorrelation	X62	CV_NinetyCorrelation
X15	CV_NinetyEnergy	X39	CV_NinetyEnergy	X63	CV_NinetyEnergy
X16	CV_NinetyHomogeneity	X40	CV_NinetyHomogeneity	X64	CV_NinetyHomogeneity
X17	CD_ZeroContrast	X41	CD_ZeroContrast	X65	CD_ZeroContrast
X18	CD_ZeroCorrelation	X42	CD_ZeroCorrelation	X66	CD_ZeroCorrelation
X19	CD_ZeroEnergy	X43	CD_ZeroEnergy	X67	CD_ZeroEnergy
X20	CD_ZeroHomogeneity	X44	CD_Zero Homogeneity	X68	CD_ZeroHomogeneity
X21	CD_NinetyContrast	X45	CD_NinetyContrast	X69	CD_NinetyContrast
X22	CD_Ninety Correlation	X46	CD_NinetyCorrelation	X70	CD_NinetyCorrelation
X23	CD_Ninety Energy	X47	CD_NinetyEnergy	X71	CD_NinetyEnergy
X24	CD_NinetyHomogeneity	X48	CD_NinetyHomogeneity	X72	CD_NinetyHomogeneity

E. Classification using Decision tree

Decision tree is a set of simple rules. They are nonparametric in nature. They are simple, flexible and efficient. The decision tree method has been used to classify the medical images for diagnosis. These systems enhance the classification process to be more accurate. Usage of decision trees for the classification is reported by Hunt et al. [14]. P. Rajendran, and M.Madheswaran [15] have used decision tree mechanism for classifying CT-Scan brain images into Normal, benign, and malignant. Three different image features namely Haralick, Tamura and Wolds's texture features are explored with two classification models namely random forest and decision tree to classify CT scan brain images. The authors have used decision tree for the classification of retinal images into Diseased or Normal.

The decision tree was constructed using Classregtree function in the Matlab (CART implementation). Classification tree generated using GLCM features on all three components Ch, Cv and Cd is shown in the Fig. 6 below. The data set consisted of 72 features and 60 samples. 20 images are Healthy images and the remaining 20 are mild DR and 20 are severe DR.

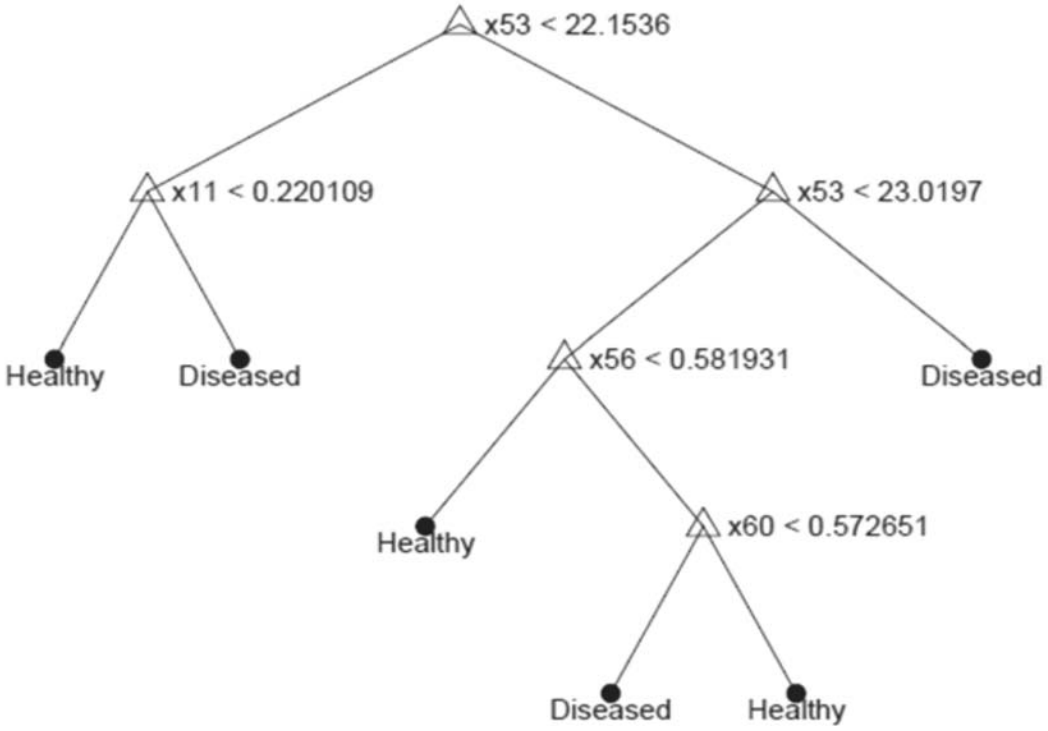

Fig. 6. Decision tree constructed using GLCM features

3. RESULTS AND DISCUSSIONS

A. Classification using decision tree

Testing has been performed using the database of 60 images. The sample consists of 20 Healthy images 20 mild DR images and 20 severe DR images. The confusion matrix for the decision tree is shown below in table 2. All the Healthy images have been classified as Healthy ones; only 10% of Diseased images have been classified as Healthy ones. Sensitivity obtained is 90% and specificity obtained is also 100%. 10% images having DR have been falsely classified as Healthy ones

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad ...(1)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad ...(2)$$

$$\text{Precision} = \frac{TP}{TP + PP} \quad ...(3)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad ...(4)$$

Table 2. Confusion matrix for Decision tree classifier

	Predicted Healthy	***Predicted Diseased***
Actual Healthy	100%	0%
Actual Diseased	10%	90%

True positive = 100%
False positive = 0%
True negative = 90%
False negative = 10%
Sensitivity = 90%
Specificity = 100%
Precision = 100%
Recall = 90%
Accuracy = 95%

B. Classification using Knn classifer

10-cross validation carried out using the same data set with Knn classifier has yielded the following confusion matrix. Sensitivity obtained is 76.85% and specificity obtained is also 75%. 17% images having DR have been falsely classified as Healthy ones. 25% Healthy images falsely classified as Diseased ones.

Table III.Confusion matrix for knn classifier

	Predicted Healthy	***Predicted Diseased***
Actual Healthy	75%	25%
Actual Diseased	17%	83%

True positive = 75%
False positive = 25%
True negative = 83%
False negative = 17%
Sensitivity = 76.85%
Specificity = 75%
Precision = 76.85%
Recall = 75%
Accuracy = 79%

4. CONCLUSION AND FUTURE SCOPE

In this paper, novel approach for the classification of retinal images has been developed. The system is based on the combined approach of Haar and GLCM features. The authors have obtained sensitivity of 90% and specificity of 100% using decision tree classifier which is better than Knn classifier. Combined approach based on Haar wavelet and GLCM features can be used effectively for the real time classification of bio-medical image.

Authors have also attempted to construct a system based on Haar wavelet and first order features and obtained encouraging results. The percentage of false positives can be reduced by finding robust and discriminating features before constructing the decision tree. The study can be conducted on other databases as well .

5. REFERENCES

1. Sopharak, Akara, Bunyarit Uyyanonvara, and Sarah Barman. “Automatic exudate detection from non-dilated diabetic retinopathy retinal images using fuzzy c-means clustering.” Sensors 9, no. 3 (2009): 2148-2161.
2. Jaafar, Hussain F., Asoke K. Nandi, and Waleed Al-Nuaimy. “Automated detection of exudates in retinal images using a split-and-merge algorithm.” InSignal Processing Conference, 2010 18th European, pp. 1622-1626. IEEE, 2010.

3. Soares, Ivo, Miguel Castelo-Branco, and António MG Pinheiro. "Exudates dynamic detection in retinal fundus images based on the noise map distribution." In Signal Processing Conference, 2011 19th European, pp. 46-50. IEEE, 2011.

4. Shahin, Eman M., T. Taha, Waleed Al-Nuaimy, S. El Rabaie, O. Zahran, and Fathi E. Abd El-Samie. "Automated detection of diabetic retinopathy in blurred digital fundus images." In Computer Engineering Conference (ICENCO), 2012 8th International, pp. 20-25. IEEE, 2012.

5. Osareh, Alireza, Bita Shadgar, and Richard Markham. "A computational-intelligence-based approach for detection of exudates in diabetic retinopathy images." Information Technology in Biomedicine, IEEE Transactions on 13, no. 4 (2009): 535-545.

6. Giancardo, Luca, Fabrice Meriaudeau, Thomas P. Karnowski, Yaquin Li, Kenneth William Tobin Jr, and Edward Chaum. "Automatic retina exudates segmentation without a manually labelled training set." In Biomedical Imaging: From Nano to Macro, 2011 IEEE International Symposium on, pp. 1396-1400. IEEE, 2011.

7. Shantala Giraddi, Jagadeesh Pujari and Savita Gadwal. " Quality Analysis of Retinal Image with Various Color spaces" International Journal of Applied Engineering Research, ISSN 0973-4562 Vol. 10 No.86 (2015)

8. Shantala Giraddi, Anoop Betageri, Chaitra Besthar"QUALITY ASSESSMENT AND GRADING OF DIABETIC RETINOPATHY"

9. International Journal of Recent Scientific Research Research Vol. 6, Issue, 4, pp.3259-3264, April, 2015

10. Van de Wouwer, Gert, Paul Scheunders, and Dirk Van Dyck. "Statistical texture characterization from discrete wavelet representations." Image Processing, IEEE Transactions on 8, no. 4 (1999): 592-598

11. M. Unser, "Texture classification and segmentation using wavelets frames", IEEE Transactions on Image Processing, vol. 4, pp. 1549–1560, November 1995.

12. Tang, Li, Meindert Niemeijer, Joseph M. Reinhardt, Mona Kathryn Garvin, and Michael D. Abràmoff. "Splat feature classification with application to retinal hemorrhage detection in fundus images." Medical Imaging, IEEE Transactions on 32, no. 2 (2013): 364-375.

13. Rajendran, P., and M. Madheswaran. "Hybrid medical image classification using association rule mining with decision tree algorithm." arXiv preprint arXiv: 1001.3503 (2010)

14. Tallapragada, VV Satyanarayana, and E. G. Rajan. "Iris recognition based on combined feature of GLCM and Wavelet transform." In Integrated Intelligent Computing (ICIIC), 2010 First International Conference on, pp. 205-210. IEEE, 2010.

15. Hunt, E.B, Marin, J., and Stone, P. J., 1966. Experiments in Induction, Academic Press

16. Rajendran, P., and M. Madheswaran. "An improved image mining technique for brain tumour classification using efficient classifier." arXiv preprint arXiv:1001.1988 (2010).