Support Vector Machine Based Method for Automatic Detection of Diabetic Eye Disease using Thermal Images

Diabetic Eye Disease

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Abstract: **Diabetic eye disease is one of the major problems worldwide. Early detection of eye diseases increases the survival rate by successful treatment. The proposed methodology is to explore machine learning technique to detect diabetic diseased using thermography images of an eye and to introduce the effect of thermal variation of abnormality in the eye structure as a diagnosis imaging modality which are useful for ophthalmologists to do the clinical diagnosis. Thermal images are pre-processed, and then Gray Level Cooccurrence Matrix (GLCM) based texture features from gray images, statistical features from RGB and HSI images are extracted and classified using classifier with various combination of features. To detect diabetic diseased eye, here Support Vector Machine classifier is used for classification and their performance are compared. A 5-fold cross validation scheme is used to enhance the generalization capability of the proposed method. Experimental results obtained for various feature combinations gives maximum accuracy of 86. 22%, sensitivity of 94. 07% and specificity of 79. 17% using SVM classifier with five-fold validation.**

Index Terms*: *Diabetic eye disease, Infrared Thermography, GLCM, Support Vector Machine

I. Introduction

Accurate diagnosis has attained in medical procedure by identifying the symptoms using emerging imaging modalities. There are different diagnostic modalities including fluorescein angiography and optical coherence tomography. Fundus Photography is mostly used for the evaluation of diabetic patient eye diseases. The present modalities of medical imaging are invasive and painful for patients as well. Infrared thermography is emerging non-ionizing technique which is non-invasive method and is successfully accepted for diagnosis. Thermal imaging modality recently used in breast cancer detection, diabetic foot and various eye diseases such as dry eye, glaucoma, Meibomian gland dysfunction and thyroid eye diseases. Diabetic eye disease is a chronic disease affects various organs of human body including the eye. Infrared thermography offers a digitized thermal distribution called thermograph. It indicates the observation are with a thermal variation of the surface temperature. Various color is used to describe variations in temperature because color is a powerful descriptor [1]. Padmapriya Nammalwar et al. [2] proposed non-invasive procedure to estimate the presence of diseases using thermography images of an eye. Euclidean distance-based segmentation algorithm is used to threshold the IR image to obtain the region of interest, where the appearance of eye disease is dominant. Infrared thermography is an efficient tool not only to capture temperatures of corneal surface, but also to detect and visualize any changes on the Ocular surface temperature [3].

Rajendra Acharya et al. [4] suggested a prospective approach for evaluating treatments clinical consequence to identity the symptom responders and non-respondents to the treatments by means of the response analysis. Meibomian gland syndrome (MGD) patients has higher margin temperature in eyelid part. The temperature ratio is calculated by the 8 regions of interest in the margin of eyelid. Above methods are highly uncomfortable for patients when compared with thermography, finally they accomplish that the participants with MGD have a higher eyelid margin temperature than the controls because of eyelid inflammation [5]. A non-invasive infrared thermal image system was proposed by Tai Yuan Su et al. [6] to measure the spatial and temporal variation in the eye surface temperature. Ankush A Kawali analyzed eye thermal imaging using diagnostic tool that distinguish inflammatory eye conditions from noninflammatory conditions [7]. Thermography images not only suitable for eye but also used breast cancer detection for early diagnosis. Handcrafted features are used by a Neural Network classifier in order to classify the breast as normal or suspected cancer. Thermo grams based on color analys is done for abnormality detection using K-Means Clustering [8].

Priya Hankare et al. [9] proposed approach using K-means clustering technique for segmenting hot region using three clusters denote is able to accurately segment the hot regions in the image. In order to obtain the required region of interest (ROI), the breast infrared thermography images are segmented by gradient operator and canny operator. Extraction of features is performed on the segmented images of the breast. Multilayer neural perceptron network based on supervised technique of machine learning is used to classify breast thermo grams as normal, benign and malignant [10]. The thermography has been based on higher metabolic activity and blood flow in the cancerous tissue region rather than normal tissue region. Infrared thermography is promising and growing technology for breast cancer detection [11].

The imaging modality also suitable for the detection of diabetes using foot images. Textural features are extracted from the segmented region for further analysis. SVM, PNN and KNN classifier are used for verifying the accuracy detection [12].

Abdulshahed AM et al. [13] established the effectiveness of the artificial intelligence tools for early detection of diseases. Thermo graphic valuation of temperature variation within the observed skin assists a quick, non-contact, noninvasive comparative measurement of their temperature variations. It used an Artificial Neural Network (ANN) model and thermal camera for early analysis of diabetic foot. This work shows that the output predicted using the ANN based on thermography, used for early detection of foot diabetes [14-15].

In this work, the thermal images of an eye is obtained from IGCAR Kalpakkam, Tamilnadu. Various algorithms are implemented for the extraction of the thermal characteristics features and image analysis. Gray-Level Co-occurrence Matrix based texture features are extracted from gray images and color based statistical features are extracted from HSI and RGB color images. These features are given to the Support Vector Machine (SVM) Classifier for classification of an eye as normal or diabetic diseased eye. The Proposed work is tested with 283 thermal images using the performance measures such as accuracy, sensitivity and specificity. This paper's structure is arranged as follow

s. Section 2 describes the materials and methods of proposed work Section 3 discusses the results obtained. The work is concluded in Chapter 4.

II. MATERIALS AND METHODS

The proposed system uses supervised machine learning techniques to classify the thermal images of an eye into "Normal" or "Diabetic Diseased Eye" as shown in Fig. 1.

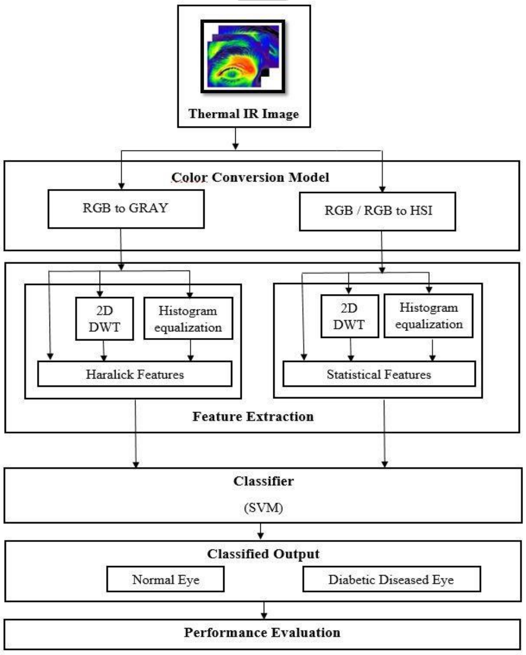

Fig. 1. Proposed Methodology

A. Thermal Images

All objects with zero Kelvin above emit infrared radiation. Infrared radiation emitted by skin can be converted to temperature according to StefanBoltzmann law. The thermal images with only diabetes patients and normal person of an eye images are used as input. FLIR T400 thermal camera captures the thermal images. This dataset consists of 283 eye images with dimension of 640*480 pixels in which 149 images corresponds to eyes of only diabetes patients and remaining 134 images corresponds to eye of normal persons.

B. PRE-PROCESSING Techniques

- The color conversion model is very important to extract the required features. In this work, two conversion such as RGB to Gray and RGB to HSI are done and RGB, Gray and HSI color model are used as an input images for feature extraction module.

- Two pre-processing techniques such as Histogram Equalization (HE) and Discrete Wavelet Transform (DWT) are performed.

- Histogram equalization maps the input intensity to all available intensities.

DWT transforms a discrete time to time-Scale representation, which provides efficient multiresolution in medical images. Haar wavelets can be used to analyses the localized feature of signals.

C. Feature Extraction

Feature Extraction is the most important step in the analysis of images. It is a process of gathering distinguishable information from the image itself from an object or group of objects. On the basis of this information, the classification of the objects with different features are implemented. In this work two different features types are extracted for classification of thermal images which are explained as follows.

1) Texture Feature Extraction:

Texture feature measure the relationship among the pixels in local area, reflecting the changes of image gray levels. GLCM based handcrafted texture features are extracted which is the representation of several pixel intensities mixture in an image. From this GLCM matrix, 14 different haralick features are obtained.

Haralick Features: The feasibility of using Haralick Features to discriminate between "Normal" and "Diseased" by selecting the most discriminating parameters. There are 14 features are extracted from GLCM matrixes of 0 degree with one distance. These measurements are applied to designate the overall texture feature of an image using measures. Haralick Features are calculated by using the following 1 to 14 equations:

Energy = ∑ ∑ p(i, j) (1)

Contrast = ∑ ∑ (−) (,) (2)

( ) ( )

Correlation = ∑ ∑ (3)

Variance = ∑ − ( ) (4)

Inverse Difference = ∑ ∑ (,) (5)

| |

Sum Average = ∑ kp (k) (6)

Sum Variance = ∑ k − μ p (k) (7)

Sum Entropy = − ∑ p (8)

(9)

Diff Entropy = − ∑ p (k)log p (k) (10)

Diff Variance = k − μ p (k) (11)

IMC 1 = (12)

(,)

IMC 2 = 1 − exp −2(HXY2 − HXY) (13)

Maximum Probability = max p(i, j) (14)

,

Where , are the Standard deviation and mean of p and p are the partial. Instead of using all 14 features reducing computational complexity randomly selected the most discriminating 7 and 4 features used as a features for analysis that is given in Table I.

TABLE I. HARALICK FEATURES

Count	Features
14	Energy, Contrast, Correlation, Variance Inverse Difference Moment, Maximal Correlation Coefficient, Sum Average, Sum Variance, Sum Entropy, Entropy, Difference Variance, Difference Entropy, Information Measures of Correlation (IMC) I, and IMC II.
7	Sum Average, Energy, Difference Variance, Correlation, Variance, Sum Variance and Contrast.
4	Contrast, Energy, Homogeneity and Correlation.

2) Statistical Feature Extraction: Color moments are scaling and rotation invariant used as features in image processing applications. Since color moments encode data about both shapes and colors that is worthy features to use under changing lighting conditions. There are five statistical features are extracted from the RGB and HSI image:

Mean (μ) = ∑ ( ) (15)

Std Deviation (σ) = (16)

Skewness = ∑ (x − μ) ( ) (17)

Kurtosis = ∑ (x − μ) ( ) (18)

Entropy = ∑ ( ) log ( ) (19)

Where ( ) denotes the normalized histogram of an image.

D. Support Vector Machine Classification

The emerging technique of machine learning is preferred currently for classification task. Support Vector Machine (SVM) is supervised model of learning with related algorithm that analyses statistics used for classification. An SVM training algorithm forms a model that creates new examples for one or the other category, making it a no probabilistic binary linear classifier, given a set of training examples, each marked as suitable for one of the two groups.

K – Fold Validation Technique: Cross validation is an important tool which gives an honest assessment of the true accuracy of classifier. In cross-validation, the dataset is divided into a sets of large training set and a smaller validation set, then train done on the training set and use the validation set to measure performance analysis. This methodology involves randomly dividing the dataset into k folds, of almost equal size. The first fold is treated as a validation set, and the method is fit on the other k − 1 folds.

E. Performance Analysis

1) Accuracy: Accuracy reflects the overall correctness of the classification and it is calculated by adding the true positive and negative together and dividing by the entire number of images.

$$Accuracy = \frac{TP \quad TN}{TP \quad TN \quad FP \quad FN}$$

2) Sensitivity: Sensitivity measures the accuracy among positive instances. It indicates the accuracy of diabetic diseased eye.

$$Sensitivity = \frac{TP}{TP \quad FN}$$

3) Specificity: Specificity measure the accuracy among negative instances. It indicates the accuracy of Normal eye.

$$Specificity = \frac{TN}{TN \quad FP}$$

III. RESULT AND DISCUSSION

Infrared thermal images of eye are used as input images. The dataset with 283 eye thermal images both normal and diabetes patients are used for training and testing process. The method of 5 fold cross validation is used to validate the performance of the classifier. The 283 images are divided into 5 fold each with 30 diseased and 27 normal images approximately. The training is done with 4 folds and testing with remaining 1 fold, in this manner all the folds are tested with trained classifier. Database Sample images are shown in Fig. 2.

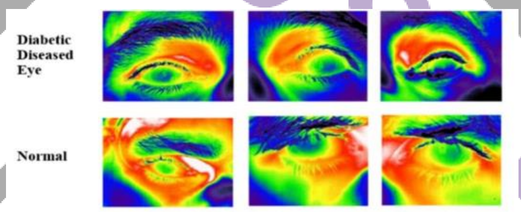

Fig. 2. Sample Images from Database

1) Color Conversion Results

The database RGB thermal images are converted into Gray and HSI images for required feature extraction. The sample color converted images are shown in Fig. 3.

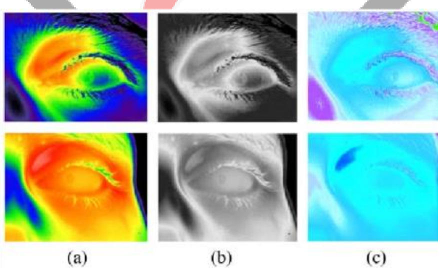

Fig. 3. Color Converted Images.

2) Histogram Equalisation Results

Fig. 4 shows the resulting images and their corresponding histograms after equalization as applied. After that features are extracted from histogram equalized image.

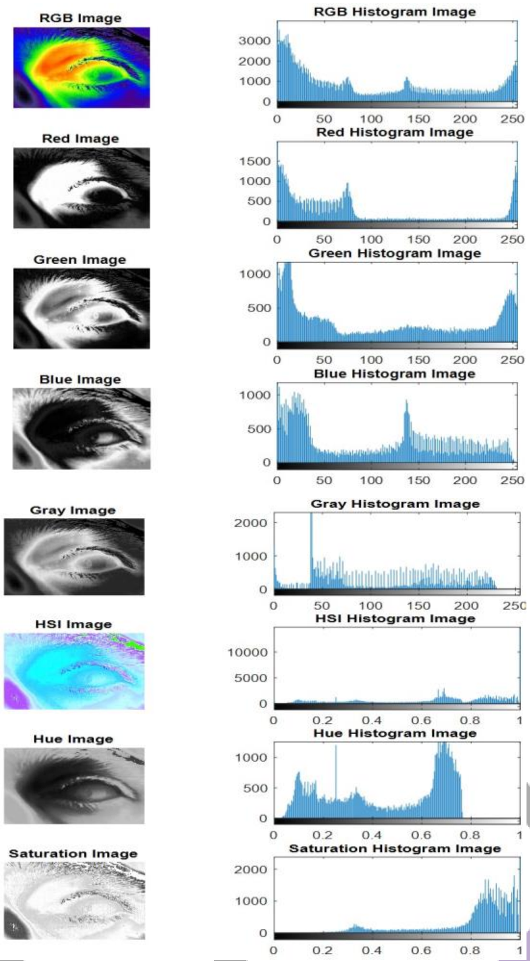

Fig. 4. Histogram Equalization Results

3) 2D DWT Results

First level decomposition taken from image and features are extracted from all sub bands. Fig. 5 shows the discrete wavelet transformed sample images from various color model.

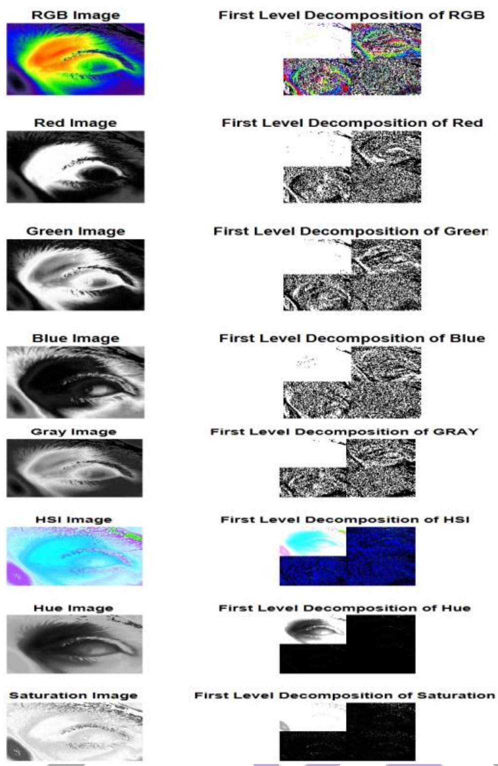

Fig. 5. 2D DWT Results

4) Image Classification Result

The performance of SVM classifier has been evaluated in terms of accuracy, sensitivity and specificity. The following Table II-IV gives the classification result of various combination of features.

TABLE II. CLASSIFICATION RESULT – TEXTURE FEATUURES OF GRAY IMAGES

NO	**Features**	**SVM** *Sensitivity (%)*	*Specificity (%)*	*Accuracy (%)*
Haralick Features				
1	14 Features	86. 60	79. 77	83. 00
2	**7 Features**	**87. 29**	**79. 86**	**83. 38**
3	4 Features	38. 91	89. 19	65. 38
Discrete Wavelet Transformed Haralick Features (all bands)				
1	14 Features	91. 73	72. 43	81. 57
2	7 Features	86. 60	70. 39	78. 06
3	4 Features	78. 97	78. 52	78. 74
Histogram Equalized Haralick Features				
1	14 Features	29. 03	70. 50	50. 87
2	7 Features	8. 88	88. 64	50. 88
3	4 Features	0	100	52. 65

TABLE III. CLASSIFICATION RESULT STATISTICAL FEATUURES OF HSI IMAGES

NO	Features	SVM		
		Sensitivity (%)	*Specificity (%)*	*Accuracy (%)*
Statistical Features				
1	5 Features-H	72. 47	80. 57	76. 74
2	5 Features-S	92. 56	70. 50	80. 95
3	5 Features-HSI	87. 35	73. 83	80. 23
Discrete Wavelet Transformed Statistical Features				
1	5 Features-H	76. 89	80. 59	78. 84
2	5 Features-S	91. 05	91. 05	70. 97
3	**5 Features-HSI**	**82. 13**	**82. 13**	**81. 26**
Histogram Equalized Statistical Features				
1	5 Features-H	36. 60	77. 08	57. 91
2	5 Features-S	92. 56	69. 90	80. 63
3	5 Features-HSI	99. 23	50. 29	73. 46

TABLE IV. CLASSIFICATION RESULT – STATISTICAL FEATUURES OF RGB IMAGES

NO	Features	SVM		
		Sensitivity (%)	*Specificity (%)*	*Accuracy (%)*
Statistical Features				
1	5 Features-R	91. 79	77. 24	84. 13
2	5 Features-G	90. 34	70. 43	79. 85
3	5 Features-B	90. 31	68. 43	78. 79
4	5 Features-RGB	89. 48	75. 14	81. 93
Discrete Wavelet Transformed Statistical Features				
1	5 Features-R	90. 28	67. 03	78. 04
2	5 Features-G	88. 80	73. 74	80. 87
3	5 Features-B	92. 50	74. 48	83. 01

4	5 Features-RGB	92. 56	75. 81	83. 74
Histogram Equalized Statistical Features				
1	5 Features-R	87. 97	81. 93	84. 79
2	5 Features-G	91. 08	49. 67	69. 28
3	5 Features-B	93. 27	61. 74	76. 67
4	5 Features-RGB	**94. 78**	**75. 78**	**84. 79**

TABLE V. CLASSIFICATION RESULT – TEXTURE AND STATISTICAL FEATUURES

NO	**Features**	**SVM**		
		Sensitivity (%)	***Specificity (%)***	***Accuracy (%)***
Texture Haralick Features				
1	7 Features	87. 29	79. 86	83. 38
2	14 Features	86. 60	79. 77	83. 00
Statistical Features				
3	5 Features (HE - RGB)	94. 78	75. 78	84. 79
4	5 Features (DWT - HSI)	82. 13	82. 13	81. 26
Texture & Statistical Features				
5	**5 features (R)+5 features (G)+ 5 features(B)+7 features (Haralick)**	**94. 07**	**79. 17**	**86. 22**
6	5 features(HSI) +14 features (Haralick)	91. 79	79. 83	85. 49

Fig. 6 shows the graphical representation of the classifier result with various combination of features

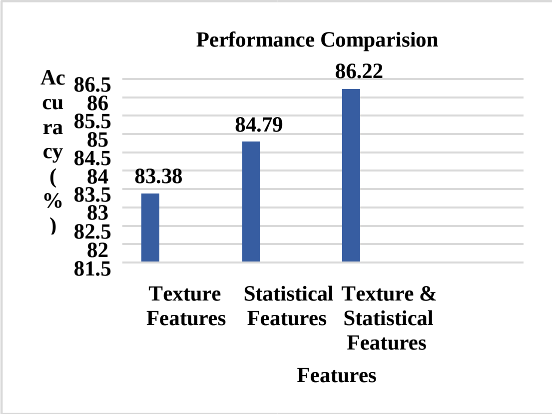

Fig. 6. Classifier Performance Comparison

Among the all combination while combining the statistical feature of each element of RGB and 7 haralick texture features gives better classification result.

IV. CONCLUSION

In the proposed work, a non-invasive procedure has been presented to evaluate the presence of diabetic diseases in the eye. The classification of diabetic diseased and normal eye IR images is done through Support Vector Machine classifier using various combination of texture and statistical features. The simulation results indicate that the classifier in the detection of diabetic diseased eye performed in the accepted level and provide accuracy, sensitivity, specificity of around 86. 22%, 91. 79% and 79. 83% using SVM classifier. This sort of methods will be useful in diagnostics as a suitable second opinion for the ophthalmologist. The approach can be employed in real time and with the help of the GUI implementation can support mass screening of diabetic eye disease patients. The results suggest that the custom designed IR thermal image system may be used as an effective modality for noninvasive and non-contact detection of diabetic diseased thermal eye.

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REFERENCES

[1] N. Selvarasu, Alamelu Nachiappan and N. M. Nandhitha. ,International Journal of Computer Theory and Engineering, Vol 2, No. 4, pp. 514 – 516, August 2010.

[2] Padmapriya Nammalwar, Venkateswaran Narasimhan, Toshita Kannan and SindhuMadhuri Morapakala, “Noninvasive Glaucoma Screening Using Ocular Thermal Image Classification”, CIT. Journal of Computing and Information Technology, Vol. 25, No. 3, pp. 227–236, September 2017.

[3] Harshvardhan G,Venkateswaran N and Padmapriya N, “Assessment of Glaucoma with Ocular Thermal Images using GLCM Techniques and Logistic Regression classifier”, IEEE WiSPNET 2016 conference, pp. 15341537, June 2006.

[4] U. Rajendra Acharya, Jen Hong Tan, Vidya S, Sharon Yeo, Cheah oon Too, Wei Jie Eugene Lim, Kuang Chua Chua, Louis Tong, “Diagnosis of response and non-response to Dry Eye 67, pp. 497503, September 2014.

[5] Tai-Tuan Su,Wei-Ting Ho, Shu-Chiung Chiang, Chien-Yi Lu, Kuihua Kenny Chiang, Shu-Wen Chang, “Infrared Thermography in the Evaluation of Meibomian Gland Dysfunction”, Journal of the Formosan Medical Association, Vol. 116, pp. 554-559, July 2017.

[6] Tai Yuan Su, Chen Kerh Hwa, Po Hsuan Liu, Ming Hong Wu, David O. Chang, Po Fang Su, Shu Wen Chang, and Huihua Kenny Chianga, “Noncontact detection of Dry Eye using a custom designed infrared thermal image system”, Journal of Biomedical Optics, Vol. 16, No. 4, pp. 0460092 to 046009-6, April 2011.

[7] Ankush A Kawali Uvea Clinic, Aravind Eye Hospital, Avinashi Road, Coimbatore, Tamil Nadu, India, “Thermography in ocular inflammation”, Indian Journal of Radiology and Imaging, Vol. 23, No. 3, pp. 281-283, August 2013.

[8] Nader Abd El-Rahman Mohamed, “Breast Cancer Risk Detection Using Digital Infrared Thermal Images”, International Journal of Bioinformatics and Biomedical Engineering, Vol. 1, No. 2, pp. 185-194, August 2015.

[9] Prof. Priya Hankare, Kesha Shah, Deepthy Nair, Divya Nair, “Breast Cancer Detection Using Thermography”, International Research Journal of Engineering and Technology, Vol. 03, No. 4, pp. 2395-0072, April 2016. [

10] Pragati Kapoor, Dr. S. V. A. V. Prasad, Dr. Seema Patni, “Automatic Analysis of Breast Thermo grams for Tumor Detection based on Bio statistical feature extraction and ANN”, International Journal of Emerging trends in Engineering and Development, Vol. 07, No. 2, pp. 245255, November 2012.

[11] Amir Ehsan Lashkari, Mohammad Firouzmand, “Early Breast Cancer Detection in Thermo gram Images using AdaBoost Classifier and Fuzzy C-Means Clustering Algorithm”, Middle East Journal of Cancer, Vol. 7, No. 3, pp. 113-124, July 2016.

[12] S. Purnima, Shiny Angelin P, Priyanka R, Subasri G, Venkatesh R, “Automated Detection of Diabetic Foot Using Thermal Images by Neural Network Classifiers”, International Journal of Emerging Trends in Science and Technology, Vol. 04, No. 05; pp. 5183-5188, July 2018.

[13] Abdulshahed AM, Alabyad FM , Goohe HA , Saed MA “Early Detection of Diabetes using Thermography and artificial Neural Networks”, International Journal of Computational & Neural Engineering, Vol. 4, No. 2, pp. 71-75, September 2017.

[14] Costanzo Di Maria, John Allen, Jane Dickinson, Christopher Neoh, and Petros Perros ,“Novel Thermal Imaging Analysis Technique for Detecting Inflammation in Thyroid Eye Disease”, J Clin Endocrinol Metab, Vol. 99, No. 12, pp. 4600–460, December 2014.

[15] Deepak Ranjan Nayak n , Ratnakar Dash, Banshidhar Majhi, “Brain MR image classification using twodimensional discrete wavelet transform and AdaBoost with random forests”, Elsevier, Neurocomputing, Vol. 177, pp. 188–197, December 2015.