

DETECTION OF HARD EXUDATES IN FUNDUS IMAGES USING CASCADED CORRELATION NEURAL NETWORK CLASSIFIER

¹S.Antelin Vijila, ²R.S.Rajesh

¹Assistant Professor, ²Professor,

Department of Computer Science and Engineering

Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India

¹antelinvijila@gmail.com, ²rs_rajesh1@yahoo.co.in

Abstract: This paper presents a novel approach for classification of hard exudates in fundus image. Hard Exudate is one of the important indication of Diabetic Retinopathy(DR) in human eye. The diagnosis of hard exudate at early stage can protect a person from DR. This paper presents an expert decision making system designed using a Cascaded Correlation Neural Network (CCNN) to detect hard exudates in fundus images. The unique feature of CCNN is, it does not use a predefined set of hidden units, but the hidden units gets added up one by one until the error is minimized. By making use of this feature of CCNN, we have developed a computationally efficient computerized detection algorithm that is accurate in detecting hard exudates. To discriminate between the exudates and the non-exudates pixels, texture features are extracted from the fundus images and are given as input to the CCNN classifier. The performance of this scheme is evaluated using a database of 300 retinal images collected from diabetic retinopathy screening programs. The result shows that the proposed CCNN based classifier has good performance.

Keywords: Diabetic Retinopathy, Color Fundus images, Hard Exudates, Laws texture energy measures, Cascaded Correlation Neural Network.

1. Introduction

Diabetic Retinopathy (DR) is a complication of diabetes that is caused by damage to the small blood vessels of the retina. Blindness is an outcome of Diabetic retinopathy and it occurs in 80% of all diabetic patients. Epidemiologic studies and randomized clinical trials show that one of the cause for type 2 diabetes is diet and lifestyle modifications(Hu, 2011). When a person got affected by diabetes and got no medical assistance then this will affect the retinal nerves of the person and result in diabetic retinopathy. Recent studies says that, "in 2010 among the global population out of overall 32.4 million blind and 191 million visually impaired people, 0.8 million were blind and 3.7 million

were visually impaired because of DR"(Leasher *et al.*, 2016). DR is the leading cause of blindness is people between the age of 20 and 60. However, early detection and prompt treatment could prevent the vision loss caused by DR. Premature detection of DR is a challenging task because patients with DR will have no symptoms until vision loss develops. DR is a progressive disease; it becomes Proliferative Diabetic retinopathy (PDR) from Non-Proliferative Diabetic retinopathy (NPDR). NPDR is the earliest stage of DR while PDR is an advanced stage. This can be identified in the screening process which is done yearly for the diabetic patients looking for any signs of NPDR. It has been shown that fundus photography is the most accurate means of screening for retinopathy. In most of the developing countries, the rural side will not have enough specialists to examine diabetic patients by ophthalmologists in screening programmes.

NPDR commonly known as background retinopathy, is an early detection of DR. The DR starts with a mild NPDR, which usually does not affect the vision. When lipoproteins/other proteins leaking from retinal blood vessels it affects the vision and it is called as Exudates (EXs). Exudates can be hard exudates (yellow spots seen in the retina) and soft exudates (pale yellow or white areas with ill defined edges). (Niemeijer *et al.*, 2007) proposed a pixel based method for differentiating exudates, drusen and cotton wool spots and tested with 300 retinal images achieving a sensitivity of 95.5% for exudates detection. The probability of each pixel is calculated and the pixel with higher probability is taken as a lesion pixel. Based on the cluster characteristics, clusters were classified as exudates, drusen and cotton wool spots.

(Nayak *et al.*, 2008) have proposed a computer based approach for the detection of diabetic retinopathy stage using fundus images. Image preprocessing, morphological processing techniques and texture analysis methods are applied on the fundus images to detect the features such as area of hard exudates, area of the blood vessels and the contrast. The extracted features are applied to an ANN for an automatic

classification. They achieve a classification accuracy of 93% and sensitivity of 90%

(Welfer, Scharcanski and Marinho, 2010) present a new method based on mathematical morphology for detecting exudates in color eye fundus images. They did the evaluation of the proposed method performance on a known public database, namely DIARETDB1, and achieved an average sensitivity of 70.48%, and an average specificity of 98.84%. (Ranamuka and Meegama, 2013) propose a technique based on morphological image processing and fuzzy logic to detect hard exudates from DR retinal images. They used mathematical morphology after eliminating the optic disc to find the exudates. Subsequently, hard exudates are extracted using an adaptive fuzzy logic algorithm that uses values in the RGB colour space of retinal image to form fuzzy sets and membership functions. The fuzzy output for all the pixels in every exudate is calculated for a given input set corresponding to red, green and blue channels of a pixel in an exudate. This work shows 75.43% sensitivity and 99.99% specificity for hard exudates detection.

(Reza, Eswaran and Dimyati, 2011) provides an on marker-controlled watershed segmentation method. Initially input images are subjected to average filtering and contrast adjustment. The concept of the markers is used to modify the gradient before the watershed transformation is applied. The performance of the proposed algorithm is evaluated using the test images of STARE and DRIVE databases. It gives a value for sensitivity (95%) when compares to the already known methods.

(Paper, 2012) propose a computer aided system for the early detection of DR. It is a generalized system which can detect various lesions in fundus images. This work provides algorithms for retinal image preprocessing, blood vessel enhancement and segmentation and optic disk localization. It leads to detection of different DR lesions using the proposed hybrid fuzzy classifier. (Geethanjali and Meegama, 1994) propose a technique based on morphological image processing and fuzzy logic to detect hard exudates from DR retinal images. They use morphological operations and also remove the optic disc in preprocessing stage. Then, fuzzy sets and membership functions are formed from the RGB color space values and used in adaptive fuzzy logic algorithm to extract the exudates. This work shows a sensitivity and specificity of 75.43% and 99.99%, respectively.

(Youssef and Solouma, 2012) developed a new method for the detection of blood vessels which improves the detection of exudates in fundus photographs. Edge detection algorithm is applied to get the segmented image. Also optic disc is eliminated using Hough transformation technique. Finally exudates

are obtained by morphological reconstruction. It shows a sensitivity and specificity of exudates detection to 80% and 100% respectively.

(Rajput and Patil, 2014) presented a method to identify and classify the exudates as hard and soft exudates. CIELAB color space of the retinal image is used for pre-processing which result in noise elimination. Next, blood vessels network is eliminated to facilitate detection and elimination of optic disc. Hough transform technique is used to eliminate Optic disc. The candidate exudates are then detected using k-means clustering technique. Finally, the hard and soft exudates are classified based on their energy and threshold.

From the above, we can see that previous methods either have a less classification accuracy for hard exudate detection or that they are not a fully automated system. The previous methods did not consider texture features as an important feature on hard exudates while the complexity of hard exudate detection requires us to identify them more accurately by considering multiple feature characteristics.

DR may cause several abnormalities in the retina like microaneurysms, (MAs), Haemorrhages (HMs), Hard Exudates and Soft Exudates (Cotton Wool Spots). Among these pathologies exudates are the prime markers of DR causing vision. Hence the main goal of this article is to develop an intelligent decision making system that automatically detects the hard exudates in the retinal images. The hard exudates detection is formulated into three stages. First, the retinal images are subjected to preprocessing. Then the textures feature are extracted from the histogram equalized image. Finally these features are given to the CCNN classifier to classify the exudates and non-exudates pixel with high accuracy.

2. Materials And Methods

A. Image Acquisition

A large dataset was constructed with manually labeled images for both training and testing of this method. This dataset consists of 300 images taken from a DR screening program. The images were acquired using a Cannon non-mydratic CR6-45NM camera. The images selected are of 2240×1488 dimensions with resolution of 96 dpi. Of the 300 images in the dataset, 150 are of patients with no pathologies (normal) and the rest of the images are abnormal (contain pathologies such as exudates, cotton wool spots, micro aneurysm and hemorrhages). Examples of fundus images are shown in Fig. 1.

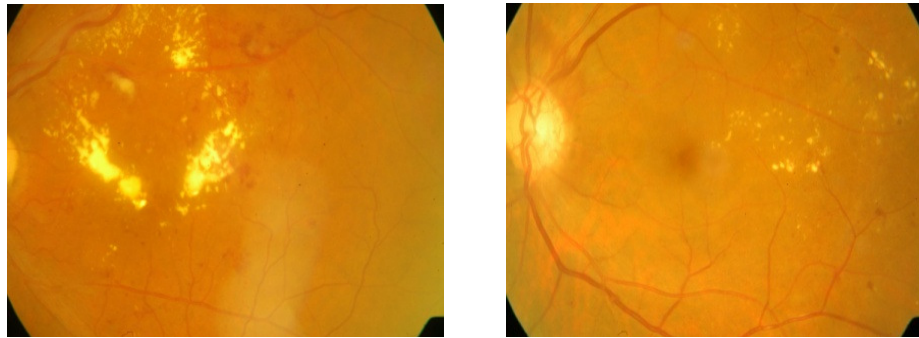


Figure 1. Examples of DR images.

Fig 2. Shows the block diagram of the hard exudates detection method.

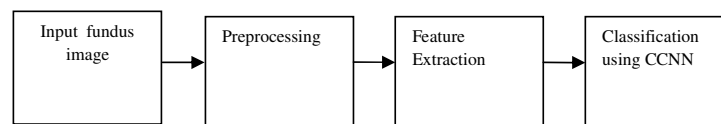


Figure 2. Block diagram of Hard Exudate detection

B. Preprocessing

In general, the color of the fundus for patients will vary as they are strongly connected to the person's race and iris color. Therefore, the input fundus image is subjected to two preprocessing steps before starting the detection of exudates. The first step is to normalize the

color of the retinal images across the dataset. We selected a retinal image as a reference [Fig. 3(a)], and then applied histogram equalization to modify the values of each image in the database to get an image with good contrast [for example, Fig. 3(b)] such that its frequency histogram matched the reference image distribution.

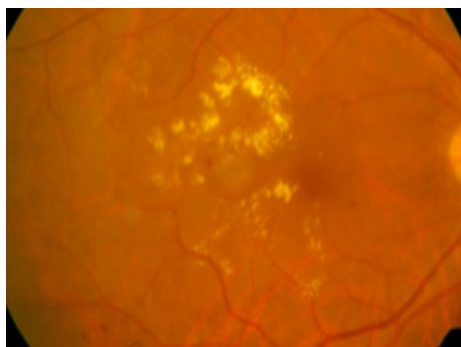
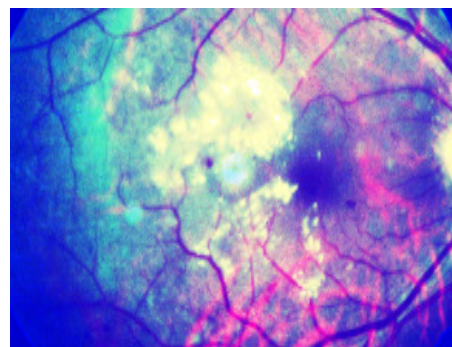


Figure 3.(a) Fundus Image



(b) Histogram equalized Image.

The histogram specification technique was independently applied to each individual RGB channel to match the shapes of three specific histograms of the reference image. Here, the reference histograms were taken from an image, which represents a frequent retinal pigmentation color among our image dataset. This image was chosen in agreement with the expert ophthalmologist.

C. Feature Extraction

The Texture Energy Measures (TEM) developed by Kenneth Ivan Laws (Laws, 1979) at the University of Southern California presented his approach to texture analysis. Texture features are a set of metrics that is designed to quantify the extracted texture of an image. The textures extracted from the fundus image gives information about the spatial arrangement of intensities and statistical properties of the ROI. Laws texture energy measures are a powerful texture feature extractor that quantify the texture properties of the image. The textures are quantified using small convolution kernels of length 5. The kernels includes texture descriptors level (L), edge (E), spot (S), wave (W) and ripple (R). These measures are computed by first applying small convolution kernels to the ROI and then performing a windowing operation. The texture features are computed from vectors of length 5, $L5 = (1, 4, 6, 4, 1)$, $E5 = (-1, -2, 0, 2, 1)$, $S5 = (-1, 0, 2, 0, -1)$, $W5 = (-1, 2, 0, -2, 1)$, $R5 = (1, -4, 6, -4, 1)$. These are the one dimensional convolution kernels, where its length is 5.

Texture features are extracted for each pixel in the image. The classifier will identify whether each pixel belong to a normal or an abnormal pixel value. The steps involved in Laws texture energy measures are as follows,

Step 1: 25 masks are constructed by convoluting a Vertical 1-D 5x1 matrix with 1x5 horizontal 1-D matrix masks. From this process 25 different 2-D kernels are obtained. They are shown below.

L5L5 E5L5 S5L5 W5L5 R5L5 L5E5 E5E5 S5E5
W5E5 R5E5
L5S5 E5S5 S5S5 W5S5 R5S5 L5W5 E5W5 S5W5
W5W5 R5W5
L5R5 E5R5 S5R5 W5R5 R5R5

Step 2: The 2-D mask is applied to the preprocessed image to get $F(i, j)$, where $F(i, j)$ is a set of 25 $N \times M$ features.

Step 3: An absolute mean filter is applied to generate TEM at each pixel. Using this process each pixel in the image is smoothened. A 15×15 square matrix is taken to doing this operation. The filter is mentioned below (1).

$$E(x, y) = \sum_{i=-7}^7 \sum_{j=-7}^7 |F(x + i, y + j)| \quad (1)$$

Step 4: The texture features obtained from step 2 is normalized for the zero - mean.

The output is a single image with a vector of 25 texture attributes at each pixel from the preprocessed Image. The wave, ripple and the local average of the Laws texture energy measures corresponds to pixel variations. The other features, spot and edge along with wave, ripple and local average is used for detecting the abnormalities in fundus images.

D. Classification using Cascaded correlation Neural Network

Cascaded Correlation Neural Network (CCNN) was developed by Fahlman and Libiere in the year 1990. Cascade correlation neural networks are "self organizing" networks and are similar to traditional networks in which the neuron is the most basic unit. Training the neurons however is novel. The CCNN is a supervised learning architecture that builds a near-minimal multilayer network topology in the course of training. Initially the network contains only inputs, output units, and the connections between them. This single layer of connections is trained using the Quickprop algorithm (S. E. Fahlman, 1988; Fahlman and Lebiere, 1990) to minimize the error. Cascade-correlation eliminates the need for the user to guess in advance the network's size, depth, and topology. A reasonably small (though not minimal) network is built automatically. The main drawback in artificial neural network is the rate of convergence and the manual fixation of network architecture (hidden units) throughout training. These problems are addressed by cascaded correlation neural network. Moreover it uses simple training rules since only one layer of weights is being trained at a time.

A cascaded correlation network possesses input units, hidden units and output units that are connected directly to output unit with adjustable weighted connections. Connection from input unit to the hidden unit is trained when the hidden unit is added to the net and then they are frozen. The connection from the hidden unit to the output unit is also adjustable.

The texture features were captured based on level, edge, spot, wave and ripple and a total of 25 texture features for each pixel were extracted from the ROI. For the purpose of training a total of 2050 patterns were taken from the ROI which has both normal and abnormal pixels. CCNN classifier is thus designed with 25 input neurons, one hidden layer and one neuron at the output layer. The output layer classifies the given input feature as normal and abnormal pattern. The

hidden layer neuron is optimally chosen by the CCNN network. The hidden layer uses a tansigmoid activation function. The learning rate and momentum constant was set to 0.01 and 0.9 respectively. The training was stopped when the root mean square error per training was less than 0.1 or when it reaches 500 epochs. After training, the network was evaluated with the test cases. Fig. 4 shows the cascaded correlation structure designed with 25 input neurons. The w is the weights connecting the neurons and b is the bias. As shown in the Fig. 4 the input layer neurons are connected to the hidden layer neurons and also the output layer neurons. This brings a cascaded structure to the neural network.

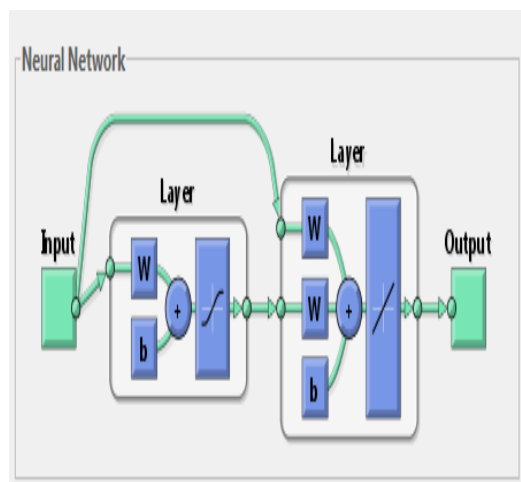


Figure 4. Proposed Design of Cascaded Correlation NN

The effectiveness of the proposed framework is investigated with an image dataset of 300 labeled retinal images including 150 normal and 150 abnormal images. Medical images are usually low resolution and high noise images. Moreover, color and intensity of the medical images are not as important as in photographs; whereas texture analysis becomes crucial in medical image. Texture also refers to visual patterns which have properties of homogeneity and cannot result from the presence of only a single color or intensity (S. . Fahlman, 1988). Texture perception plays an important role in the human visual system of recognition and interpretation. The texture features were captured for each pixel and were extracted from the DR and normal images. For the purpose of CCNN training a total of 2050 patterns were taken which has both normal and abnormal pixels. The designed CCNN classifier is a two class classifier that organizes all training sets into two classes, namely, 'Exudates present' and 'Exudates absent'. In Fig. 5 abnormal segments of hard exudates are detected using the CCNN classifier is shown.

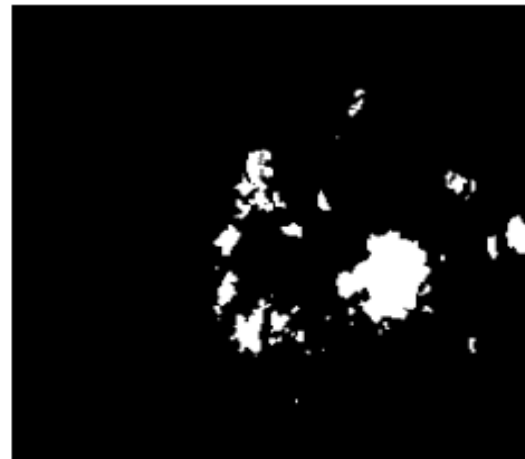


Figure 5. Detected hard exudate segments using CCNN classifier

3. Result Discussion

The proposed method's performance is measured using the various metrics Sensitivity, Specificity, Youden's index (J), AUC, Misclassification Rate and accuracy. Table I demonstrates the performance of the classifier using various summary measures. In order to evaluate the laws texture features on CCNN classifier additional metrics like sensitivity, specificity, classification accuracy, Youden's index and misclassification rate (Metz, 1986; Mark H. Zweig and Gregory Campbell, 1993) is considered. Youden's index (J) developed by Youden W.J is a single statistic that captures the performance of a diagnostic test is given as J and is calculated as,

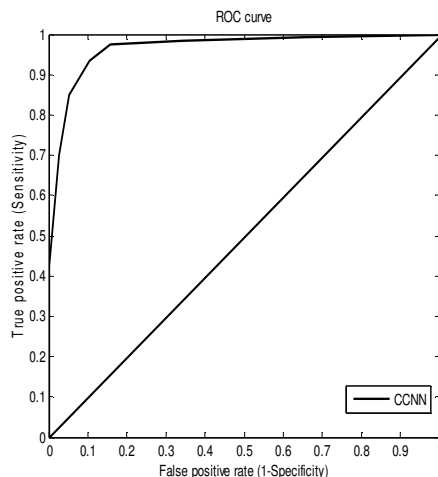
$$J = \text{sensitivity} + \text{specificity} - 1$$

The performance of the CCNN classifier with an accuracy of 92.405% is better than the conventional approaches applied with real images collected from mammogram screening laboratory. A sensitivity of 93.33% is achieved using the proposed method with the specificity of 89.474%. The CCNN classifier has a misclassification rate of 0.0759 which is less when compared to the other classifier models. It was of more interest to focus the experimentation on trying to improve the classification rate by focusing on CCNN parameters. Consequently, by using CCNN the classification accuracy is improved drastically. CCNN have a great potential to be applied in automatic detection of hard exudates in fundus images by reducing the misclassification rate.

Table 1. Performance Measures ForCCNN Classifier

Metrics	Performance Measures for Real Clinical Database
Sensitivity (%)	93.333
Specificity (%)	89.474
Accuracy (%)	92.405
AUC	0.95735
Youden's index	0.82807
Misclassification Rate	0.075949

From the ROC plot in Fig. 5 it is clear that the image performance is better than the other approaches found in literature. The accuracy of a diagnostic (or screening) test is characterized by the ROC curve which provides much more information about how the test performs than just a single estimate of the test's sensitivity and specificity.

**Figure 6.** Receiver Operator Characteristic Curve

The result emphasizes the potential of CCNN algorithm to be used as a classifier for hard exudates detection in fundus images.

4. Conclusion

In this paper, we investigated a novel method for the detection of hard exudates in colour fundus images. The pathology caused by diabetic retinopathy is detection using an intelligent decision support system using cascaded correlation neural network. The laws texture features are used as feature sets for discriminating between the exudates and non-exudates pixels. First, the optic disc is segmented using a morphological and edge detection process. Second, laws texture energy measures are applied to obtain texture features from the retinal area. Then, an

intelligent classifier - CCNN is used to detect the pathological regions in the colour fundus images. The proposed intelligent decision support system can be used by the ophthalmologists as a second reader which detects the subtle signs of hard exudates at early stage. The performance evaluation demonstrates that the result of the CCNN classifier is generally better than that of the conventional classifiers.

References

- [1] Fahlman, S. (1988) 'Faster-Learning Variations on Back-Propagation: An Empirical Study', in Proceedings of the 1988 Connectionist Models summer School, pp. 38–51.
- [2] Fahlman, S. E. (1988) 'Faster-Learning Variations on Back-Propagation: An Empirical Study', in Proceedings of the 1988 Connectionist Models summer School, Morgan Kaufmann, pp. 38–51.
- [3] Fahlman, S. E. and Lebiere, C. (1990) 'The Cascade-Correlation Learning Architecture', Advances in neural information processing systems, pp. 524–532. doi: 10.1190/1.1821929.
- [4] Geethanjali, N. and Meegama, R. G. N. (1994) IEE proceedings. Vision, image, and signal processing., IET Image Processing. [Institution of Electrical Engineers]. Available at: <http://digital-library.theiet.org/content/journals/10.1049/iet-ipr.2012.0134> (Accessed: 1 August 2017).
- [5] Hu, F. B. (2011) 'Globalization of Diabetes', Diabetes Care, 34(6), p. 1249 LP-1257. Available at: <http://care.diabetesjournals.org/content/34/6/1249.abstract>.
- [6] Laws, K. I. (1979) 'Texture Energy Measures', in Proceedings of DARPA Image Understanding Workshop, pp. 47–51.
- [7] Leasher, J. L. et al. (2016) 'Global Estimates on the Number of People Blind or Visually Impaired by Diabetic Retinopathy: A Meta-analysis From 1990 to 2010', Diabetes Care, 39(9), p. 1643 LP-1649. Available at: <http://care.diabetesjournals.org/content/39/9/1643.abstract>.
- [8] Mark H. Zweig and Gregory Campbell (1993) 'Receiver-Operating Characteristic (ROC) Plots: A Fundamental Evaluation Tool in Clinical MedicineNo Title', Clinical Chemistry, Vol. 39(4), pp. 561–577.
- [9] Metz, C. E. (1986) 'No TitleROC Methodology in Radiologic Imaging', Investigative Radiology, 21(9), pp. 720–733.

- [10] Nayak, J. et al. (2008) 'Automated Identification of Diabetic Retinopathy Stages Using Digital Fundus Images', *Journal of Medical Systems*, 32(2), pp. 107–115. doi: 10.1007/s10916-007-9113-9.
- [11] Niemeijer, M. et al. (2007) 'Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis', *Investigative Ophthalmology and Visual Science*, 48(5), pp. 2260–2267. doi: 10.1167/iops.06-0996.
- [12] Paper, O. (2012) 'Automated Detection of Dark and Bright Lesions in Retinal Images for Early Detection of Diabetic Retinopathy', pp. 3151–3162. doi: 10.1007/s10916-011-9802-2.
- [13] Rajput, G. G. and Patil, P. N. (2014) 'Detection and classification of exudates using k-means clustering in color retinal images', *Proceedings - 2014 5th International Conference on Signal and Image Processing, ICSIP 2014*, pp. 126–130. doi: 10.1109/ICSIP.2014.25.
- [14] Ranamuka, N. G. and Meegama, R. G. N. (2013) 'Detection of hard exudates from diabetic retinopathy images using fuzzy logic', *IET Image Processing*, 7(2), pp. 121–130. doi: 10.1049/iet-pr.2012.0134.
- [15] Reza, A. W., Eswaran, C. and Dimiyati, K. (2011) 'Diagnosis of diabetic retinopathy: Automatic extraction of optic disc and exudates from retinal images using marker-controlled watershed transformation', *Journal of Medical Systems*, 35(6), pp. 1491–1501. doi: 10.1007/s10916-009-9426-y.
- [16] Welfer, D., Scharcanski, J. and Marinho, D. R. (2010) 'A coarse-to-fine strategy for automatically detecting exudates in color eye fundus images', *Computerized Medical Imaging and Graphics*. Elsevier Ltd, 34(3), pp. 228–235. doi: 10.1016/j.compmedimag.2009.10.001.
- [17] Youssef, D. and Solouma, N. H. (2012) 'Accurate detection of blood vessels improves the detection of exudates in color fundus images', *Computer Methods and Programs in Biomedicine*. Elsevier Ireland Ltd, 108(3), pp. 1052–1061. doi: 10.1016/j.cmpb.2012.06.006.
- [18] S.V.Manikanthan and T.Padmapriya "Recent Trends In M2m Communications In 4g Networks And Evolution Towards 5g", *International Journal of Pure and Applied Mathematics*, ISSN NO:1314-3395, Vol-115, Issue -8, Sep 2017.
- [19] Rajesh, M., and J. M. Gnanasekar. "Path observation-based physical routing protocol for wireless ad hoc networks." *International Journal of Wireless and Mobile Computing* 11.3 (2016): 244-257.
- [20] T.Padmapriya, Ms. N. Dhivya, Ms U. Udhayamathi, "Minimizing Communication Cost In Wireless Sensor Networks To Avoid Packet Retransmission", *International Innovative Research Journal of Engineering and Technology*, Vol. 2, Special Issue, pp. 38-42.
- [21] S.V.Manikanthan and K.Baskaran "Low Cost VLSI Design Implementation of Sorting Network for ACSFD in Wireless Sensor Network", *CiiT International Journal of Programmable Device Circuits and Systems*, Print: ISSN 0974 – 973X & Online: ISSN 0974 – 9624, Issue :November 2011, PDCS112011008.
- [22] Rajesh, M., and J. M. Gnanasekar. "Path observation-based physical routing protocol for wireless ad hoc networks." *International Journal of Wireless and Mobile Computing* 11.3 (2016): 244-257.
- [23] T.Padmapriya, Ms. N. Dhivya, Ms U. Udhayamathi, "Minimizing Communication Cost In Wireless Sensor Networks To Avoid Packet Retransmission", *International Innovative Research Journal of Engineering and Technology*, Vol. 2, Special Issue, pp. 38-42.
- [24] S.V.Manikanthan and K.Baskaran "Low Cost VLSI Design Implementation of Sorting Network for ACSFD in Wireless Sensor Network", *CiiT International Journal of Programmable Device Circuits and Systems*, Print: ISSN 0974 – 973X & Online: ISSN 0974 – 9624, Issue :November 2011, PDCS112011008.

