# GTCM Based Skin Lesion Melanoma Disease Detection Approach for Optimal Classification of Medical Images

**K. Muthukumar, P. Gowthaman, M. Venkatachalam, M. Saroja, N. Pradheep**

***Abstract: The medical image classification plays vital role in the detection of various diseases. Number of approaches available for the detection of skin lesion melanoma but suffers to achieve higher performance. Towards this issue, a GTCM (Gray-Texture-Covariance-measure) based melanoma detection approach is presented in this paper. The method reads the input skin image and enhances by applying multi level gray filters. From the enhanced image, the method extracts gray features and texture features. The texture features of the lesion have been extracted based on the gray covariance matrix generated. Extracted features has been converted into GTC matrix and based on the values of GTC, the method estimates the GTCM measure towards the available training set. Finally based on the similarity of GTCM, the method estimates the GTC lesion strength to perform detection of melanoma. The method improves the performance of melanoma detection and reduces the false classification ratio.***

***Key Terms: Skin Lesion, Melanoma, Medical Imaging, Image Classification, GTC.***

## I.INTRODUCTION

The human society has higher threat of being affected by cancer. The disease shows its upcoming through the changes in the skin. The skin lesion is the initial symptom of cancer which can be diagnosed and eradicated from the human. In general the skin images would contain lesion and can be investigated by any medical practitioner. The detection of lesion and classifying it as melanoma cannot be done in a single view. Even the experienced medical practitioner would struggle to take decision about the presence of melanoma. The skin lesion is considered as the part of skin being changed in its color. The change in color would be due to many reasons which have been controlled by the melanin present in the human body. When the skin color changes it has been considered as skin lesion but cannot be classified as melanoma directly. This requires some scientific approaches in the classification.

**Revised Manuscript Received on April 10, 2019**

**K. Muthukumar,**Research Scholar, Department of Electronics, Erode Arts and Science College, Erode

**P.Gowthaman,**Assistant Professor, Department of Electronics, Erode Arts and Science College

**L.Venkatachalam,** Associate Professor, Department of Electronics, Erode Arts and Science College

**M. Saroja,** Associate Professor, Department of Electronics, Erode Arts and Science College

**N. Pradheep,**Research Scholar, Department of Electronics, Erode Arts and Science College, Erode

The medical image processing techniques can be adapted to many problems of medical domains. However, the image processing techniques has variety of applications. In the problem of lesion based melanoma detection, there are number of approaches has been discussed which uses various features of the image. The color based approaches are available to classify the image as melanoma or genuine. Identifying malignant image is highly a challenging issue. However the color based approaches are used in several techniques, the shape and texture of the lesion cannot be omitted and does not considered in any of the articles. The skins lesions are appear in different shapes and have no specific shape but vary with the color. So it is necessary to consider the shape and other features. The texture of the lesion is another feature being considered in this article. When the skin lesions are considered, it varies in shape but it is necessary to consider the texture of lesion. The texture of melanoma has certain similarity but would vary with the size. So by considering the texture of the skin melanoma, the detection process can be performed in efficient way. Similarly, the gray value of the skin lesion would play vital role in the classification and detection of melanoma. By considering the gray scale values of image, the appropriate color values of the lesion can be selected. By selecting the lesion pixels, the gray covariance can be generated. The generated covariance matrix can be used to extract the texture features. The GTC is the feature which combines both gray and texture features of the input lesion image. By extracting gray scale and texture features of the input image, the classification of the image can be performed. Based on the extracted features the GTCM (gray texture covariance measure) can be estimated. This would support the detection of melanoma from the skin lesion images. This paper presents such a technique to improve the performance in melanoma detection. The detailed approach is discussed in detail in the upcoming section.

## II.RELATED WORKS

There exist numerous techniques for the detection of skin lesion melanoma and this section describe set of methods towards the problem.Skin lesion classification from dermoscopic images using deep learning techniques



*Retrieval Number: F1046376S19/19©BEIESP*

*Published By:*
*Blue Eyes Intelligence Engineering*
*& Sciences Publication*

[1], focus on the problem of skin lesion classification, particularly early melanoma detection, and present a deep-learning based approach to solve the problem of classifying a dermoscopic image containing a skin lesion as malignant or benign. The proposed solution is built around the VGGNet convolutional neural network architecture and uses the transfer learning paradigm.Detection and Analysis of Skin Cancer from Skin Lesions [2], skin images are filtered to remove unwanted particles, then a new method for automatic segmentation of lesion area is carried out based on Markov and Laplace filter to detect lesion edge, followed by convert image to YUV color space, U channel will be processed to remove thick hair and extract lesion area. Diagnosis of melanoma achieved by using ABCD rules with new method for determine asymmetry based on rotation of lesion and divide lesion to two parts horizontally and vertically then count the number of pixels mismatched between the two parts based on union and intersection between the two parts. Automatic Detection of Melanoma Skin Cancer using Texture Analysis [3], presents an automated method for melanoma diagnosis applied on a set of dermoscopy images. Features extracted are based on gray level Co-occurrence matrix (GLCM) and Using Multilayer perceptron classifier (MLP) to classify between Melanocytic Nevi and Malignant melanoma. MLP classifier was proposed with two different techniques in training and testing process: Automatic MLP and Traditional MLP. Results indicated that texture analysis is a useful method for discrimination of melanocytic skin tumors with high accuracy. Very deep convolutional networks for large-scale image recognition [4], nvestigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3x3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16-19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second places in the localisation and classification tracks respectively. We also show that our representations generalise well to other datasets, where they achieve state-of-the-art results. Imagenet large scale visual recognition challenge [5], evaluates algorithms for object detection and image classification at large scale. One high level motivation is to allow researchers to compare progress in detection across a wider variety of objects -- taking advantage of the quite expensive labeling effort. Another motivation is to measure the progress of computer vision for large scale image indexing for retrieval and annotation. Deep learning ensembles for melanoma recognition in dermoscopy images [6], propose a system that combines recent developments in deep learning with established machine learning approaches, creating ensembles of methods that are capable of segmenting skin lesions, as well as analyzing the detected area and surrounding tissue for melanoma detection. Two systems for the detection of melanomas in dermoscopy images using texture and color features [7], addresses two different systems for the detection of melanomas in dermoscopy images. The first system uses global methods to classify skin lesions, whereas the second system uses local features and the bag-of-features classifier. This paper aims at determining the best system for skin lesion classification. The other objective is to compare the role of color and texture features in lesion classification and determine which set of features is more discriminative.Skin Lesion Analysis towards Melanoma Detection [8], Preprocessing To prepare the images for the network, each of the training images was resized to 192 pixels by 192 pixels. To create additional training images, each of the training images was elastically distorted. For each of the original training images, four randomly generated elastic distorted images were generated and then resized down to 192 by 192 pixels. In addition, each training image was also rotated 90 degrees and additional elastic distortions were applied to the rotated images.Detection of Melanoma Skin Cancer in Dermoscopy Images [9], present a novel method for the detection of melanoma skin cancer. To detect the hair and several noises from images, pre-processing step is carried out by applying a bank of directional filters. And therefore, Image inpainting method is implemented to fill in the unknown regions. Fuzzy C-Means and Markov Random Field methods are used to delineate the border of the lesion area in the images. The method was evaluated on a dataset of 200 dermoscopic images, and superior results were produced compared to alternative methods. Computer Aided Melanoma Skin Cancer Detection Using Image Processing [10], present a computer aided method for the detection of Melanoma Skin Cancer using Image Processing tools. The input to the system is the skin lesion image and then by applying novel image processing techniques, it analyses it to conclude about the presence of skin cancer. The Lesion Image analysis tools checks for the various Melanoma parameters Like Asymmetry, Border, Colour, Diameter,(ABCD) etc. by texture, size and shape analysis for image segmentation and feature stages. The extracted feature parameters are used to classify the image as Normal skin and Melanoma cancer lesion. Skin Lesion Detection using Automatic Neural Network Segmentation [11], image is subjected to pre-processing for removing the noise and enhancing the image. Brightness Preserving Dynamic Fuzzy Histogram Equalisation is an attractive method to enhance the image considering the local histogram method. This method is employed to provide crisper image by increasing the number of pixels between the interval. Then the image is segmented using Artificial Neural Network. Border detection in dermoscopy images using statistical region merging [12], present a fast and unsupervised approach to border detection in dermoscopy images of pigmented skin lesions based on the statistical region merging algorithm. Pigmented skin

lesion segmentation on macroscopic images [13], proposes a new method for segmenting pigmented skin lesions on macroscopic images acquired with standard cameras. Our method is simpler than comparable methods proposed for dermoscopy, and our experiments based on publicly available datasets of pigmented skin lesion images show promising results. An ICAbased method for the segmentation of pigmented skin lesions in macroscopic images [14], a new skin lesion segmentation method is proposed. This method uses Independent Component Analysis to locate skin lesions in the image, and this location information is further refined by a Level-set segmentation method. Comparison of segmentation methods for melanoma diagnosis in dermoscopy images [15], propose and evaluate six methods for the segmentation of skin lesions in dermoscopic images. This set includes some state of the art techniques which have been successfully used in many medical imaging problems (gradient vector flow (GVF) and the level set method of Chan et al.[(C-LS)]. It also includes a set of methods developed by the authors which were tailored to this particular application (adaptive thresholding (AT), adaptive snake (AS), EM level set (EM-LS), and fuzzy-based split-and-merge algorithm (FBSM)]. The segmentation methods were applied to 100 dermoscopic images and evaluated with four different metrics, using the segmentation result obtained by an experienced dermatologist as the ground truth. All the above discussed methods suffer to achieve higher performance in the classification and produces higher false ratio.

## III.GTCM BASED SKIN LESION MELANOMA DETECTION:

The proposed skin lesion based melanoma detection algorithm reads the input image and preprocess to remove the noisy pixels and enhances with histogram equalization technique. From the enhanced image gray and texture features are extracted. The extracted features has been used to generate GTC matrix and to estimate GTCM measures. Based on the GTCM measures, the GTC melanoma strength has been measured to perform classification. Each stage has been discussed in detail in this section.

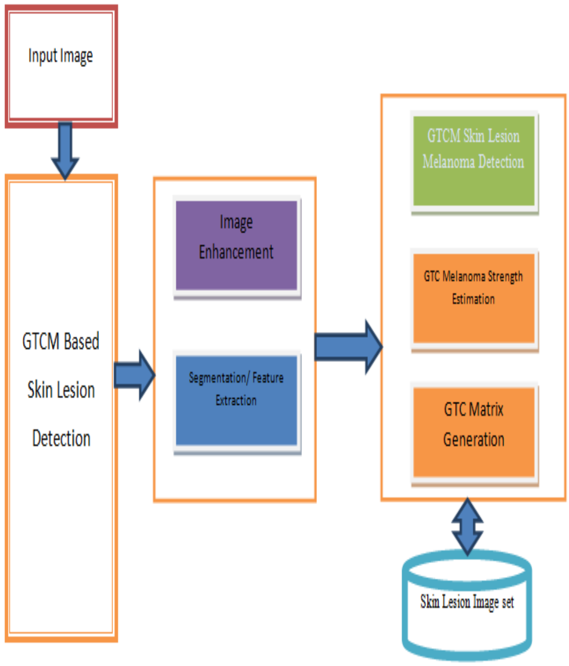


***Figure 1: Architecture of proposed GTCM Based Melanoma Detection***

The Figure 1, represent the architecture of proposed GTCM based melanoma detection approach and shows various stages of algorithm.

**Image Enhancement:**

The input lesion image would have lot of noise intruded by the capturing device. To support higher rate of classification, the method first reads the input image. The input image has been applied with the multi levelgabor filter. The gabor filter applies at each level and remove the noise from input image. In the second stage, the method applies histogram equalization to enhance the input image. The enhanced image has been used to proceed with classification.

*Intake: Lesion image Limg*

*Output: Enhanced image Eimg.*

*Start*

*Read lesion image Limg.*

*Initialize gabor filter GF = GF(Filter F, No of level Nl)*

*For each level l*

*Eimg = GF(F,l,Limg)*

*End*



Retrieval Number: F1046376S19/19©BEIESP

*Published By:*
*Blue Eyes Intelligence Engineering*
*& Sciences Publication*

*Eimg = Histogram Equalization (Eimg)*

*Stop*

The above discussed algorithm enhances the input lesion image by removing the noise and improves the quality of the image.

**Segmentation and Feature Extraction:**

The segmentation is the process of grouping the pixels of the image. The lesion image contains lot of genuine skin pixels and the pixels with varying colors. So it is necessary to identify the region of interest. To perform this, the method identifies the list of gray values and estimates the gray median value. Second, for each gray value identified, the method estimate the distance with the median value and if it is far from the higher gray value, it has been added to a interest group and other has been added to another group. This produces the segmentation of the pixels of the image. The group of pixels from the interest group has been considered for the further processing. From the interest group of pixels, the method extracts the gray features and texture features as the result.

**Algorithm:**

*Input: enhanced image Eimg.*

*Output: Feature Set GF and TF.*

*Start*

*Step1: Read Eimg.*

*Step2: Read available gray values GrFs* = $\int_{i=1}^{size(Eimg)} \sum(values \in GrFs) \cup Eimg(i).gray$

*Step3: Compute median Gm* = $\frac{\int_{i=1}^{size(GrFs)} Max(GrFs(i))}{2}$

*Step4: Compute least gray value Lg* = $\int_{i=1}^{size(GrFs)} Min(GrFs(i))$

*Step5: Compute max gray value Mg* = $\int_{i=1}^{size(GrFs)} Max(GrFs(i))$

*Step6: For each gray value Gv from GrFs*

*Compute distance with max gray value Mgd = Dist(gv,mg)*

*If Mgd<Gm then*

*Add to interested group Ig* = $\sum(gf \in lg(i)) \cup gv$

*End*

*End*

*Step 7: while no of gray movements greater than 1*

*Gf=lg*

*Go to step 3.*

*End*

*Step 8: extract coordinates of values from Lg.*

*Step 9: extract textures of Lg.*

*Step 10: stop*

The above discussed algorithm extracts the features and has been used to perform lesion based melanoma detection.

**GTC MATRIX GENERATION:**

The gray texture covariance matrix has been generated for each training sample available towards the test sample. For each test sample available with the training set, the method computes gray variance measure and texture variance measure based on the coordinate points. Estimated values has been added to the GTC matrix. The GTC matrix represent the variance in the gray values and texture variance. Generated GTC matrix has been used to perform classification.

**Algorithm:**

*Intake: Interested Gray Feature Ig, Interested Texture Feature IT, Training Set Ts*

*Output: GTC matrix Gcm,Tcm*

*Start*

*For each sample s from Ts*

*Estimate gray covariance measure Gcvm* = $\frac{\sum_{i=1}^{size(Ig)} Ig(i)==s(Ig(i)}{size(Ig)}$

*Estimate texture covariance measure Tcvm* = $\frac{\sum_{i=1}^{size(IT)} IT(i)\in(IT(i)}{size(IT)}$

*Add to GCM* = $\sum(gvcm \in GCM) \cup Gvcm$

*Add to TCm* = $\sum(Tvcm \in TCM) \cup Tvcm$

*End*

*Stop*



Retrieval Number: F1046376S19/19©BEIESP

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The above discussed algorithm estimates the feature variance measures and store to concern covariance matrix which has been used for classification.

**GTCM Skin Lesion Melanoma Detection:**

The proposed GTCM based skin lesion melanoma detection algorithm reads the input image and performs preprocessing initially to perform enhancement. The enhanced image has been used to extract the gray and texture features. With the extracted features, the method generates GT covariance matrix. The generated matrix has been used to estimate the GTC melanoma strength for the input image. If the estimated GTCMs value is higher than specific threshold, the image has been classified as malign.

**Algorithm:**

*Input: Lesion image limg, Training Set Ts*

*Outcome: Boolean*

*Start*

*Read lesion image limg*

*Eimg = Image Enhancement(limg)*

*[Gf,Tf]=Segmentation/Feature Extraction(Eimg)*

*Initialize GT covariance matrix Gcm, Tcm*

*[Gcm,Tcm] = Perform GCM generation (Gf,Tf,Ts)*

*For each sample s from Ts*

*Compute GTCM melanoma strength GTCMMs.*

$$GTCMMS = Gcm(s)\times Tcm(s)\frac{Gcm(s)\times Tcm(s)}{size(Eimg)}/_{3}$$

*If GTCMMS>MTh then //Mth-melanoma threshold*

*Return true*

*Else*

*Return false*

*End*

*End*

*Stop*

The above discussed algorithm estimates the GTCM melanoma strength measure for different training samples. Based on the value, the image has been classified [16].

**Results and Discussion:**

The proposed gray and texture covariance measure based lesion orient melanoma detection algorithm has been implemented using matlab. The algorithm has been evaluated for its performance in disease detection and classification using varying number of test samples. In all the classes, the method has produced higher performance in detection and classification. The result has been compared with other methods and has been presented below.

***Table 1: Evaluation Details***

| Property | Value |
|---|---|
| Tool | Matlab |
| Data Set | ISIC |
| No of lesion Images | 13786 |
| No of classes | 2 |

The details of evaluation being used to validate the performance has been given in the above Table 1. The performance of the method has been measured in various parameters and has been presented below.

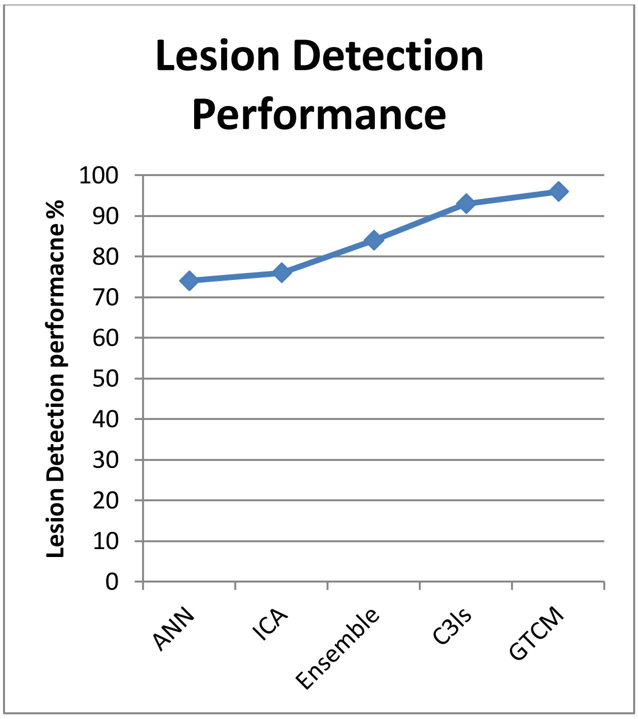


***Figure 2: Comparison on lesion detection performance***

The Figure 2, shows the comparative result on lesion detection performance produced by different methods. The proposed GTCM algorithm has produced higher detection accuracy than other methods.



*Retrieval Number: F1046376S19/19©BEIESP*

*Published By:*
*Blue Eyes Intelligence Engineering*
*& Sciences Publication*

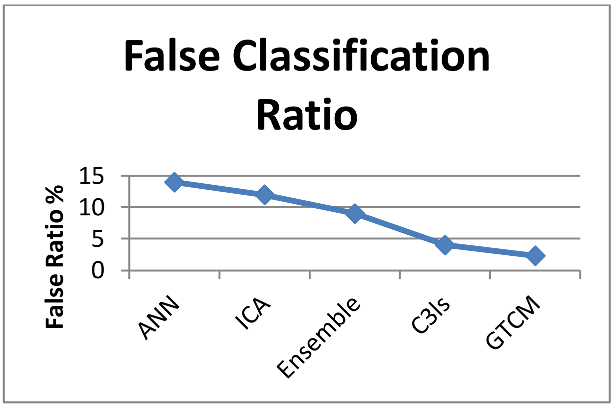


*Figure 3: Comparison on false classification ratio*

The Figure 3, shows the comparative result on false classification ratio being produced by various methods. The proposed GTCM algorithm has produced higher lower false ratio than other methods.

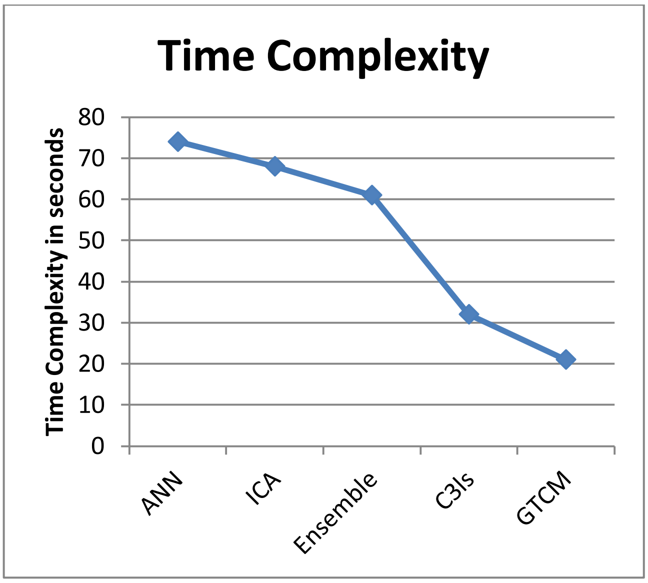


*Figure 4: Comparison on time complexity*

The Figure 4, shows the comparative result on time complexity produced by different methods. The proposed GTCM algorithm has produced less time complexity than other methods.

## IV.Conclusion

In this paper an efficient Gray-Texture-Covariance-Measure based melanoma detection has been presented. The method first read the skin lesion image and enhances by applying the gabor filter and histogram equalization. From the enhanced image, the method extracts gray and texture features. The extracted features has been used to generate covariance matrixes of gray and texture based on the similarity of values with the training set. Finally, using the covariance matrix, the method estimates the melanoma strength measure for each class based on which the disease detection has been performed. The method produces higher detection accuracy and reduces the false ratio with time complexity.

## REFERENCES:

1. Adria Romero Lopez ; Xavier Giro-i-Nieto ; Jack Burdick ; OgeMarques,Skin lesion classification from dermoscopic images using deep learning techniques, IEEE Conference on Biomedical Engineering, 2017.
2. Nidhal K. EL Abbadi and Zahraa Faisal Detection and Analysis of Skin Cancer from Skin Lesions, International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 19 (2017) pp. 9046-9052.
3. M. A. Sheha, M.S.Mabrouk, A. Sharawy, “Automatic Detection of Melanoma Skin Cancer using Texture Analysis,” International Journal of Computer Applications, vol. 42, no. 20, pp. 22–26, 2012.
4. K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image recognition", arXiv preprint arXiv:1409.1556, 2014.
5. O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein et al., "Imagenet large scale visual recognition challenge", International Journal of Computer Vision, vol. 115, no. 3, pp. 211-252, 2015.
6. N. Codella, Q.-B. Nguyen, S. Pankanti, D. Gutman, B. Helba, A. Halpern, J. R. Smith, "Deep learning ensembles for melanoma recognition in dermoscopy images", arXiv preprint arXiv:1610.04662, 2016.
7. C. Barata, M. Ruela, M. Francisco, T. Mendonça, J. S. Marques, "Two systems for the detection of melanomas in dermoscopy images using texture and color features", IEEE Systems Journal, vol. 8, no. 3, pp. 965-979, 2014.
8. Matt Berseth, Skin Lesion Analysis Towards Melanoma Detection, Seantic Scholar, ISIC 2017.
9. Khalid Eltayef, Yongmin Li and Xiaohui Liu, Detection of Melanoma Skin Cancer in DermoscopyImages,IOP, Journal of Physics, Vol 787, 2017.
10. Shivangi Jain, Vandana jagtap Nitin Pise, Computer Aided Melanoma Skin Cancer Detection Using Image Processing, Elsevier, vol.28, pp:735-740, 2015.
11. D. Ramya1 , G. Sri Lakshmi2 and S. Prithi, Skin Lesion Detection using Automatic Neural Network Segmentation, SSRG International Journal of Electronics and Communication Engineering, 2017.
12. A. Marghoob, H. S. Rabinovitz, and S. W. Menzies, “Border detection in dermoscopy images using statistical region merging,” Skin Res. Technol., vol. 14, no. 3, pp. 347–353, 2008.
13. P. Cavalcanti, Y. Yari, and J. Scharcanski, “Pigmented skin lesion segmentation on macroscopic images,” in Proc. 25th Int. Conf. Image Vision Comput. New Zealand., 2010, pp. 1–7.
14. P. Cavalcanti, J. Scharcanski, L. Di Persia, and D.Milone, “An ICAbased method for the segmentation of pigmented skin lesions in macroscopic images,” in Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc., 2011,pp. 5993–5996.
15. M. Silveira, J. C. Nascimento, J. S. Marques, A. R. S. Marcal, T. Mendonca, S. Yamauchi, J. Maeda, and J. Rozeira,“Comparison of segmentation methods for melanoma diagnosis in dermoscopy images, ” IEEE J. Sel. Top. Signa., vol. 3, no. 1, pp: 35-45, 2009.
16. N. Pradheep, M. Venkatachalam, M. Saroja, S. Prakasam, “Implementing energy efficient and robust real-time data multicasting in mobile Ad Hoc networks” International Journal of Multidisciplinary Research and Development, Volume 3; Issue 3; March 2016; Page No. 263-266.

17. Rajesh, M., and J. M. Gnanasekar. "Path Observation Based Physical Routing Protocol for Wireless Ad Hoc Networks." Wireless Personal Communications 97.1 (2017): 1267-1289.
18. Rajesh, M., and J. M. Gnanasekar. "Sector Routing Protocol (SRP) in Ad-hoc Networks." Control Network and Complex Systems 5.7 (2015): 1-4.
19. Rajesh, M. "A Review on Excellence Analysis of Relationship Spur Advance in Wireless Ad Hoc Networks." International Journal of Pure and Applied Mathematics 118.9 (2018): 407-412.
20. Rajesh, M., et al. "SENSITIVE DATA SECURITY IN CLOUD COMPUTING AID OF DIFFERENT ENCRYPTION TECHNIQUES." Journal of Advanced Research in Dynamical and Control Systems 18.
21. Rajesh, M. "A signature based information security system for vitality proficient information accumulation in wireless sensor systems." International Journal of Pure and Applied Mathematics 118.9 (2018): 367-387.
22. Rajesh, M., K. Balasubramaniaswamy, and S. Aravindh. "MEBCK from Web using NLP Techniques." Computer Engineering and Intelligent Systems 6.8: 24-26.