RESEARCH ARTICLE

RSP Science Hub

International Research Journal on Advanced Science Hub
2582-4376
www.rspsciencehub.com
Vol. 07, Issue 01 January

Check for updates

http://dx.doi.org/10.47392/IRJASH.2025.004

Automated Detection of Conjunctiva Nevus and Choroidal Nevus Using Colour Models and Fundus Mask Generation Technique

Mr. Madhusudhan S[1], *Dr. Anitha S*[2]

[1]*Assistant professor, Department of Electronics and Communication Engineering, AIEMS, Bidadi, Bengaluru, Research scholar- Research center: ACS College of Engineering, Bengaluru, Visvesvaraya technology university, Belagavi, Karnataka, India.*

[2]*Professor, Department of Bio-medical Engineering, ACS College of Engineering, Bengaluru, Visvesvaraya technology university, Belagavi, Karnataka, India.*

Emails: *madhusudhan617@gmail.com*[1], *dranithasammilan@gmail.com*[2]

Article history

Received: 13 December 2024
Accepted: 31 December 2024
Published: 29 January 2025

Keywords:
Conjunctiva nevus, Choroidal nevus, Diabetic Retinopathy Screening, Data base.

Abstract

Diabetics and eye related diseases are becoming a global cause for eye related problems from infants to the old age persons, eye diseases are more intense in case of diabetics in urban and rural parts. The number of ophthalmologist to the number of raising patient's ratio suggest that an automated technique needed to screen patients, especially present in remote location or rural areas for fast and accurate diagnose of eye related problems. This includes conjunctiva nevus which is a freckle or mole-like spot around iris and need to be diagnosed before it becomes type of cancer called melanoma, Choroidal nevus which is present inside eye under retinal tissue called the choroid will be of multiple colour and need to be examine before it can become small choroidal melanoma. This paper presents an automatic technique to screen conjunctiva nevus and choroidal nevus for diabetic retinopathy screening by automated mask generation technique.

1. Introduction

Eye related problems increases as the person suffers from diabetic for more than 5 to 10 years and continue to increase if diabetic is not in control, many conjunctivitis [1-2] appears like allergic and non allerigic, viral, bacterial [3] which leads to swelling and tearing of conjunctiva, in this paper the conjunctiva nevus and choroidal nevus [1-2] are considered to detect automatically using mask generation technique. The major optic globe covered with conjunctiva it covers the anterior portion of optic globe which comprises of continuous mucous membrane from palpebral [3] portion present in back side of eyelid to the forniceal portion or fornix and from bulbar portion surface of globe to the limbal portion [3]. In conjunctiva nevus, nevus is the common growth in the eye which is also called as freckle of the eye and made up of cells called as melanocytes [2], with color yellow to brown and darken or lighten over time, the nevi may appear in any part of the front eye on conjunctiva. The nevus inside the eye is called choroidal nevus [1-2] which is found under the tissue in choroid, it may be of gray, yellow, and brown or also can have multiple color or orange color and need to be detected before it become choroidal melanoma [1-2]. The conventional physical examination by expert using reading chart, lamp slit test and eye dilation which are the time consuming process. Various other detection methods uses KNN [6], region based approach [6], SVM [7-8] and other classifier using fundus images, this paper focus on a mask generation technique by using the characteristics of conjunctiva nevus and choroidal nevus by improving efficiency and algorithms are implemented using OpenCV library in python platform. Section 1 provides the introduction, section 2 gives Literature review section 3 the complete information about proposed method, and section 4 shows the result and discussion and section 5 shows conclusion and feature work.

2. Literature Review

Kumar Saurabh [1] applied Conventional color fundus photography (CFP) which is normally used in detection of lesion and multicolor imaging (MCI) available spectral domain optical coherence tomography system is increasingly been tested vis-à-vis conventional CFP in various retinal diseases. Kele Xu [16] uses deep convolutional neural networks deep convolutional neural network methodology for the automatic classification of Conjunctiva Nevus and Choroidal Nevus. Zafer Yavuz and Cemal Köse [17] Algorithm is applied with four satges 1. Dataset segmentation is done by preprocessing stage. 2. image enhancement by Gabor, Frangi, and Gauss filters. 3. clustering stage to get binary vessel map includes K-means and Fuzzy C-means (FCM). 4. To remove falsely segmented isolated regions a post-processing is applied K. Malathi, R. Kavitha [18] The evaluation of the performance is done by various segmentation algorithms and fuzzy c-means clustering, naïve Bayesian classifier, support vector machine classifier.

3. Proposed Method

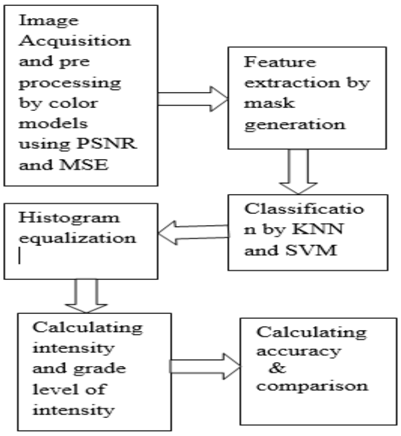

Figure 1 **Block Diagram of Proposed Method**

3.1. Image Acquisition

The first step in the process is image acquisition, this is done using different open source data base like ARIA database [9-10], DRIVE [11]-digital retinal images for vessel extraction data set, Messidor data base [12], REVIEW [13] data base from which 20 to 30 images are considered respectively Figure 1 shows Block Diagram of Proposed Method

3.2. Image Pre Processing

This step includes the transformation of color fundus image into green channel image by which any changes in the fundus image can be found as compare to normal fundus image followed by resizing [5] in dimension if necessary is to be done. The feature extraction also includes image enhancement for reduction of noise and filter out the image completely, for this the median value of 5 is considered

3.3. Feature Extraction by Mask Generation

In this step a mask generation by Hough circle detection and morphological processing [12, 14] is employed by considering the characteristics of the diseases, the mask has been developed according to size, shape, texture and colour [1]. The colour images are converted to grey scale images for conjunctiva detection and then the image will be masked

4. Pixel Level Mask Generation Using colour Spaces

The fundus color image contains three color channels namely red, green and blue channel, for vessel extraction normally green channel is used, in this paper green channel is used to generate mask using bit level operation. Using python opencv the color format is BGR then it is converted to RGB , the typical values used for RGB are 0, 255, 0 for green, 255,0,0 for red and 0, 0, 255 for blue. For orange 255, 128, 0 and for pink 255,153,255 [3]

4.1. Conjunctiva nevus

First the area frontal portion of the conjunctiva is given as an input. The key step is to detect any color change in the fundus considering green channel image. The detected area may be of any size and shape. Hough transform [2] is modified to detect the area with morphological processing

4.2. Algorithm 1

Step1: start
Step2: compute the colour change
lightest orange= (1, 190, 200)

darkest orange= (18, 255, 255)
Step3: spot the area by MHT- Modified hough transform
MHTmask=cv2.inRange(bgr, lightest orange, darkest_orange)
Step4: record co-ordinates x,y and radius
Circle_o = np.zeros((300, 300), datatype="uint8")
cv2.circle_o(circle, (150, 150), 150, 255,-1)
cv2.imshow("Circle : ", circle)
Step5: End

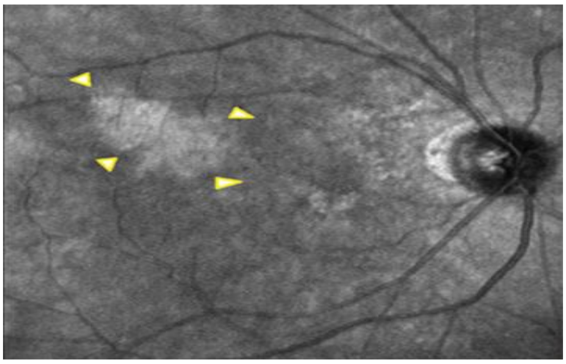

Figure 2 Grey Scale Converted Image

4.3. Choroidal nevus

First the inner portion of the fundus image is considered as input, also called as back portion of fundus or choroid [4]. Search for any changes in the fundus considering green channel image. The detected area may be of any size and shape. Hough transform is modified to detect the area with morphological processing Figure 2 shows Grey Scale Converted Image Figure 3,4 shows Fundus Images Showing the Area of Choroidal Nevus Figure 5 shows Mask Generation for Choroidal Nevus Detection (Darkest Part)

4.4. Algorithm 2

Step1: start
Step2: compute the color change in choroid fundus
lightest_pink=(190, 1, 200)
darkest_pink=(255, 153, 255)
Step3: spot the area by MHT- Modified hough transform
MHTmask=cv2.inRange(bgr, lightest_pink, darkest_pink)
cv2.circle_c(MHTmask, (145, 200),100,255,-1)cv2.imshow("MHTMask", mask)
Step4: record co-ordinates x,y and radius
Circle_o = np.zeros((300, 300), datatype="uint8")
cv2.circle_o(circle, (150, 150), 150, 255,-1)
cv2.imshow("Circle : ", circle)
Step5: End

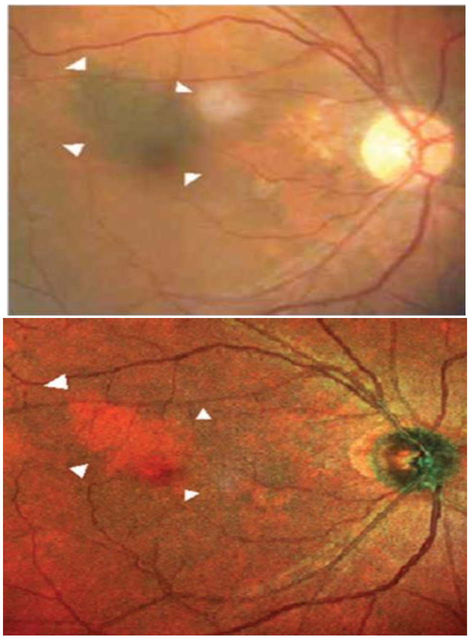

Figure 3,4 Fundus Images Showing the Area of Choroidal Nevus

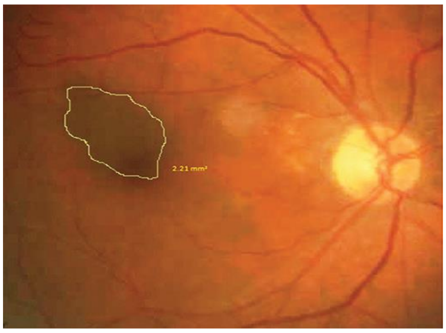

Figure 5 Mask Generation for Choroidal Nevus Detection (Darkest Part)

4.5. Classification

For classification KNN classifier [15] is employed
Algorithm3
Step1: start
Step2: if frontal fundus with mask using gray scale image on cornea then Conjunctiva nevus
plt.imshow(MHTmask, MHTmask="gray")Step3 if not choroidal nevus
Step4: list the image into two groups
(minimumVal, maximumVal, minimumLoc, maximumLoc) = cv2.minMaxLoc(gray)
cv2.circle_o(image, maxLoc, 5, (255, 0, 0), 2)
Maximum brightest value indicates nevus
Step5: End

4.6. Histogram equalization

It is done for intensity of the area of interest for frontal and back portion of fundus, the end result is the intensity histogram [14]

Algorithm4

Step1: Start

Step2: Consider frontal fundus

Step3: Calculate Histogram Equalization

Step4: Analyze the intensity values

Step5: End

4.7. Algorithm5

Step1: Start

Step2: Consider back portion of fundus

Step3: Calculate Histogram Equalization

Step4: Analyse the intensity values

Step5: End

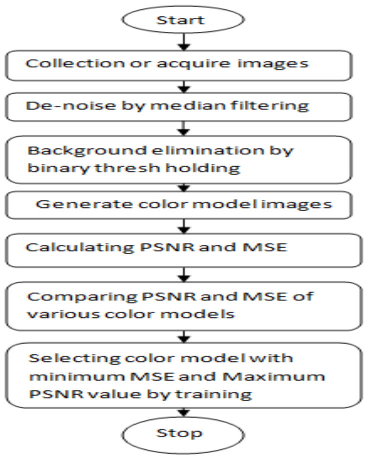

Figure 6 To Calculate PSNR and MSE for Colour Model Selection

5. Result and Discussion

With the training set of 100 fundus images the algorithm has been examined. The images are obtained from ARIA database, DRIVE data set, Messidor data base, REVIEW data base with sufficient variation in colour. The images are classified according to conjunctiva nevus, choroidal nevus by an ophthalmologist for training set, among 100 images 30 images are normal and 70 images has abnormalities. The algorithm is executed on python3 opencv platform on a 64-bit intel i5 system with 8gb internal RAM, 2.40ghz, for 10 secs for each image. The PSNR and MSE are compared to select best visible colour model for automatic detection in pre-processing. Figure 6 shows to Calculate PSNR and MSE for Colour Model Selection Figure 7 shows The Darkest Part Showing Conjunctiva Nevus. Table1 shows Comparison of PSNR Values for Selection of Best Color Model for Automatic Detection of Conjunctiva Nevus and Choroidal Nevus

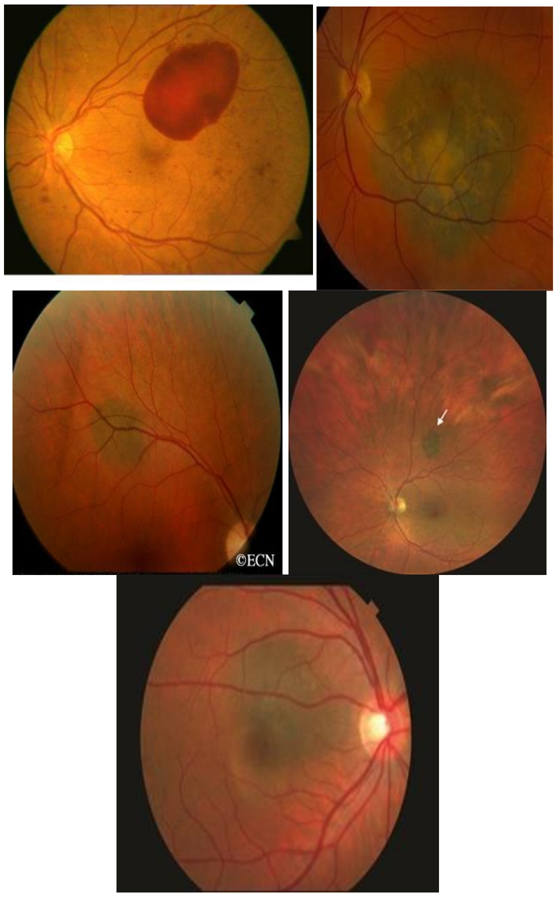

Figure 7 The Darkest Part Showing Conjunctiva Nevus

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

TP: True Positives: Correctly classified conjunctiva pixels.

FP, False Positives: Wrongly classified conjunctiva pixels as non-conjunctiva pixels.

TN: True Negatives: non conjunctiva pixels which are correctly classified.

FN: False Negatives: conjunctiva pixels which are wrongly classified as non-conjunctiva pixels.

Accuracy: Extent to which algorithm works correctly. Figure 8 shows Conjunctiva Nevus Detection Table 2 shows Comparison of MSE Values for Selection of Best Colour Model for Automatic Detection

Figure 8 Conjunctiva Nevus Detection

Table1 Comparison of PSNR Values for Selection of Best Color Model for Automatic Detection of Conjunctiva Nevus and Choroidal Nevus

Image	HSI	YIQ	YUV	RGB R	RGB G	RGB B
1	113.85	100.78	110.81	101.88	56.94	95.30
2	115.88	113.01	113.33	110.84	82.38	102.19
3	125.43	108.56	112.34	111.40	100.21	89.82
4	117.58	91.075	108.63	105.33	21.220	89.62
5	118.91	115.38	98.65	115.11	77.865	75.74

Table 2 Comparison of MSE Values for Selection of Best Colour Model for Automatic Detection

Image	HSI	YIQ	YUV	RGB R	RGB G	RGB B
1	27.55	28.09	27.68	28.04	30.57	28.33
2	27.48	27.60	27.58	27.69	28.96	28.03
3	27.13	27.77	27.62	27.66	28.12	28.59
4	27.41	28.53	27.77	27.90	34.86	28.60
5	27.36	27.50	28.18	27.51	29.21	29.33

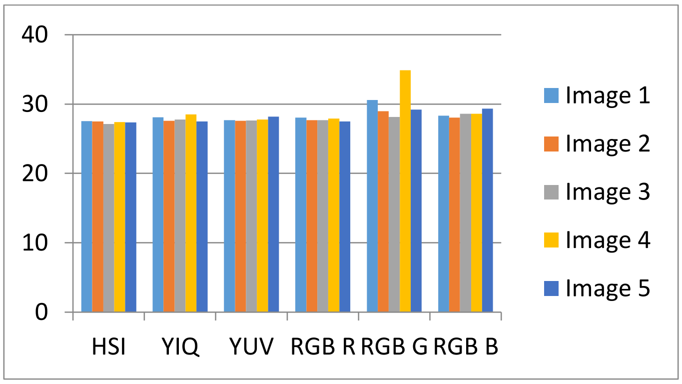

Figure 9 Comparison of PSNR for Automatic Detection of Conjunctiva Nevus and Choroidal Nevus

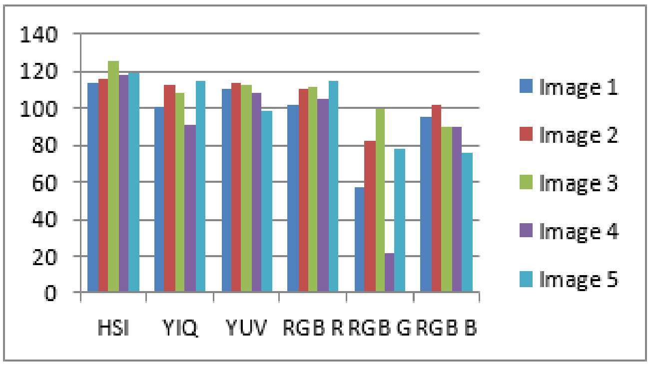

Figure 10 Comparison of MSE for Automatic Detection of Conjunctiva Nevus and Choroidal Nevus

Conclusion

The proposed method for detecting conjunctiva nevus and choroidal nevus uses python OpenCV library as the tool for the implementation of algorithm. In this work the color fundus images are considered to detect the infected eye and to differentiate the conjunctiva nevus and choroidal nevus using BGR color patterns and tested for different data sets. The test result uses PSNR and MSE for preprocessing images and reflects an accuracy of 93% over images of data set 100 for conjunctiva nevus detection and 85% for choroidal nevus detection using the proposed method. The accuracy depends on image quality, position, degree and further accuracy can be increased if more fundus images are considered for test, also this algorithm can be extend to detect many other major conjunctiva diseases.

References

[1]. Amith asish bhadra,manu jain, sushila shidnal,"automated detection of eye diseases, IEEE WiSPNET 2016 conference

[2]. Kumar Saurabh, Rupak Roy1, Subham Sinharoy2,Dhaivat Shah2, Purna Nangia1 Measurement of size of pigmented c h o r o i d a l n e v u s : S u p e r i o r i t y of multicolor imaging compared t o c o n ve n t i o n a l c o l o r f u n d u s photography Indian Journal of Ophthalmology Volume

66 Issue 10

[3]. Dr. Anitha S1 Mr. Madhusudhan S2 Validating Retinal Color Fundus Data Bases and Methods for Diabetic Retinopathy Screening

[4]. Jayesh Vazirani, Pragnya R Donthineni1, Sahil Goel2, Sayali S Sane3, Sheetal Mahuvakar4, Purvasha Narang5,Swapna S Shanbhag1, Sayan Basu1Chronic cicatrizing conjunctivitis: A review of the differential diagnosis and an algorithmic approach to management© 2020 Indian Journal of Ophthalmology | Published by Wolters Kluwer – Medknow

[5]. Pushpanjali R Ojha, Archana Hemant Deshpande, Chitrawati Bal Gargade, Jitendra Singh NigamEpipalpebral conjunctival chondroid choristoma: Interesting developmental anomaly presenting in an adult Indian Journal of Ophthalmology Volume 65 Issue 7

[6]. Hardeep Singh Mudhar Update on conjunctival pathology Indian Journal of Ophthalmology Volume 65 Issue 9

[7]. Edward A. Ashton, Michel J. Bergt, Kevin J. Parker, Jegrey Weisberg, Chang Wen Chen and Leena Ketonent Segmentation And Features Extraction Techniques, With Applications To Biomedical IMAGESDepartment of Electrical Engineering tDepartment of Neurology *Department of Radiology University of Rochester Rochester, NY 14627 IEEE transaction 1994

[8]. Prentašić, Pavle; Lončarić, Sven; Vatavuk, Zoran; Benčić, Goran; Subašić, Marko; Petković, Tomislav; Dujmović, Lana; Malenica-Ravlić, Maja; Budimlija, Nikolina; Tadić, Rašeljka. Diabetic Retinopathy Image Database(DRiDB): A new database for diabetic retinopathy screening programs research. Proceedings of 8th International Symposium on Image and Signal Processing and Analysis (ISPA 2013). Trieste, 2013, pp. 704-709

[9]. Automated Feature Extraction for Early detection of Diabetic Retinopathy in Fundus ImagesSaiprasad Ravishankar_, Arpit Jain_, Anurag Mittal University of Illinois at Urbana-Champaign, University of Maryland College Park , Indian Institute of Technology Madras, IEEE transaction 2009

[10]. Red Lesion Detection Using Dynamic Shape Features for Diabetic Retinopathy Screening, Lama Seoud*, Thomas Hurtut, Jihed Chelbi, Farida Cheriet, and J. M. Pierre Langlois, IEEE Transactions On Medical Imaging, VOL. 35, NO. 4, APRIL 2016

[11]. Kauppi, T., Kalesnykiene, V., Kamarainen, J.-K., Lensu, L., Sorri, I., Raninen A., Voutilainen R., Uusitalo, H., Kälviäinen, H., Pietilä, J., DIARETDB1 diabetic retinopathy database and evaluation protocol, Technical report (PDF).

[12]. DRISHTI-GS:retinal image data set for optic nerve head –ONH Segmentation Jayanthi Sivaswamyy S.R. Krishnadas, Gopal Dutt Joshiy Madhulika Jainy Ujjwaly Syed Tabish A.y y IIIT, Hyderabad, India, Arvind Eye Hospital, Madurai, India

[13]. Guidelines for the management of diabetic retinopathy [online]. Canberra, ACT: National Health and Medical Research Council; 2008 [cited 28 February 2011]. Available from: URL link Spurling G, Askew D, Jackson C. Retinopathy: Screening recommendations. Aust Fam Physician. 2009;38(10):780-3

[14]. Yalin Zheng; Mohd Hanafi Ahmad Hijazi; Frans Coenen Automated “Disease/No Disease” Grading of Age-Related Macular Degeneration by an Image Mining Approach Investigative Ophthalmology & Visual Science December 2012, Vol.53, 8310-8318. doi:https: //doi.org/ 10.1167/ iovs.12-9576

[15]. Prentašić, Pavle; Lončarić, Sven; Vatavuk, Zoran; Benčić, Goran; Subašić, Marko; Petković, Tomislav; Dujmović, Lana; Malenica-Ravlić, Maja; Budimlija, Nikolina; Tadić, Rašeljka. Diabetic Retinopathy Image Database(DRiDB): A new database for diabetic retinopathy screening programs research. Proceedings of 8th International Symposium on Image and Signal Processing and Analysis (ISPA 2013). Trieste, 2013, pp. 704-709

[16]. Kele Xu 1, Dawei Feng 2,* and Haibo Mi 2Deep Convolutional Neural Network-

Based Early Automated Detection of Diabetic Retinopathy Using Fundus Image1 School of Information and Communication, National University of Defense Technology, Wuhan 430019, China; kelele.xu@gmail.com 2 School of Computer, National University of Defense Technology, Changsha 410073, China; haibo_mihb@126.com * Correspondence: davyfeng.c@gmail.com; Tel.: +86-150-748-66526 Received: 10 November 2017; Accepted: 22 November 2017; Published: 23 November 2017

[17]. Zafer Yavuz and Cemal Köse Blood Vessel Extraction in Color Retinal Fundus Images with Enhancement Filtering and Unsupervised Classification Karadeniz Technical University, Trabzon, Turkey Correspondence should be addressed to Zafer Yavuz; zaferyavuz@ktu.edu.tr Received 6 April 2017; Revised 29 May 2017; Accepted 19 June 2017; Published 3 August 2017 Academic Editor: Anna Nowińska

[18]. K. Malathi, R. Kavitha Recognition and Classification of Diabetic Retinopathy utilizing Digital Fundus Image with Hybrid Algorithms International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-9 Issue-1, October 2019