

# Investigation of Abnormal Skin Lesion Analysis System for Melanoma Early Detection Using Image Processing

\*<sup>1</sup>M.Sheriff, <sup>2</sup>K.Dinakaran, <sup>3</sup>M.Kumaran, <sup>4</sup>B.Saikiran, <sup>5</sup>I.Vikram

<sup>1</sup>Asst.Professor , <sup>2,3,4,5</sup>UG Students Electronics and Communication Engineering, VEL TECH, Avadi, Chennai-600062,

\*Email: kumaran6398@gmail.com

## Abstract:

In this paper, acquisition of lesion image is carried out and compared using three different segmentation algorithm. Otsu’s method based thresholding technique is used to minimize variance of the background and foreground pixels. Here tone detection and exclusion, three ROI segmentation models (K-means, Fuzzy-C means, Chan Vese model) followed by hybrid feature extraction, and classification methods are carried out. Accuracy, sensitivity, precision , F measure of the acquired lesion image are obtained by using the above segmentation methods and the best method is examined.

**Keywords:** K-Means, Fuzzy-C, Chan Vese, ROI (Region Of Interest), accuracy , sensitivity , precision ,F measure Ada boost ,GLCM( gray-level co-occurrence matrix) Melanoma, Lesion.

## 1. Introduction:

Skin is the largest organ in an exceedingly figure, which helps to cover the muscles, bones and all parts of the body. Skin is exposed to outer surroundings so the sickness and infection happens additional to skin. So, we’ve to convey a bigger attention to skin disorder. The spot on skin that is infected is named a lesion space. Skin lesions are the primary clinical signs of sickness like varicella, Melanoma, etc. Early detection of skin disease is more complex. By incorporating digital image process for carcinoma detection, it is possible to do the diagnosis without any physical contact with skin[7].

## 2. Proposed System

K means – Fuzzy C – Chan vese level means based multi level ROI segmentation model is used for ROI skin lesion isolation. Robust rotational invariant texture analyze is carried out to explore spatial relationship within skin lesion along side with color feature attributes. The above description can be seen in the figure. 1.

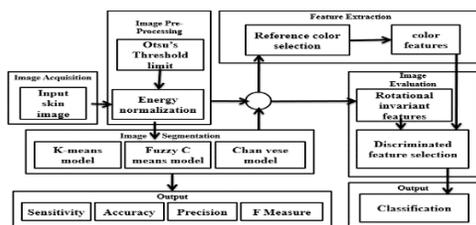


Fig. 1: Block Diagram

## 3. ROI Models (Region of Interest)

K means model is used to cluster the abnormal skin regions into various groups. Fuzzy C means model is used to isolate lesions with uneven boundary conditions[8,9]. The chan vese model is to evolve the contour in such a way that it stops on the boundaries of the foreground region.

## 4. Image Acquisition

The general aim of Image Acquisition is to transform an optical image into an array of numerical data which could be later manipulated on a computer, before any video or image processing can commence an image must be captured by camera and converted into a manageable entity. Image Acquisition is achieved by suitable camera. The clarity of image will also play a huge role in the finding the parameter such as Accuracy, sensitivity, precision F measures. The above description can be seen in the figure. 2.



Fig.2: Input Image

## 5. Image Pre-Processing

The input image given to the system will be obtained in any lighting condition or by victimization any camera like mobile camera. Hence it needs to be pre-processed[10,11]. The aim of pre-processing is associate improvement of the image information that suppresses unwanted distortions or enhances some image options vital for more process.

- a) **Thresholding:** The basic principle of thresholding method is converting the gray scale image into binary image by comparing pixel value with the predefined threshold limit[13].
- b) **Ground Truth :** This done as an reference image. This image is will be compared with images that were processed using the above mentioned algorithm. The ground truth image of the above input image is shown in fig 3.

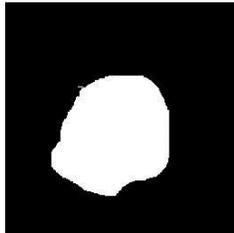


Fig 3: Ground Truth Image

## 6. Image Segmentation

Image segmentation is performed by victimization our projected automatic thresholding and masking operation in R, G and B planes. First, automatic thresholding proposed by Otsu is applied in each plane. Binary masks for every plane are obtained and so combined to supply a final lesion mask. Then edge detection is applied to further segmentation. The main purpose for extracting the features is that the lesion must be separated from the surrounding normal skin.

## 7. Types of Segmentation Process Used

- a) **K-Mean Clustering:** The objective of K means clustering is to partition an image into mutually exclusive clusters by minimizing the distance metric between the pixel and the cluster centroid.
- b) **Fuzzy C Mens:** FCM is an effective clustering technique, the resulting membership values do not always correspond well to the degree of belonging of the data, and it may be inaccurate in noisy environment.
- c) **Chan Vese Model:** Chan Vese model, a special case of Mumford Shah segmentation technique is an iterative algorithm to detect smooth and discontinuous edges.

## 8. Skin Lesion Segmentation:

The objective of the skin lesion segmentation step is to seek out the border of the skin lesion. It is vital that this step is performed accurately as a result of several options accustomed assess the chance of malignant melanoma are derived supported the lesion border. Our approach to finding the lesion border may be a texture distinctiveness-based lesion segmentation. In the second stage, the pixels in the image are classified as being part of the normal skin or lesion class. To do this, the image is split into variety of regions.

These regions are combined with the feel distinctiveness map to seek out the skin lesion.

### 8.1. K-Mean

**Color Conversion:** A pixel color in an image is a combination of three colors Red, Green, and Blue (RGB). The conversion of a color image into a grayscale image is converting the RGB values (24 bit) into grayscale value (8 bit.). The segmented image for K-mean is shown in Figure 4.

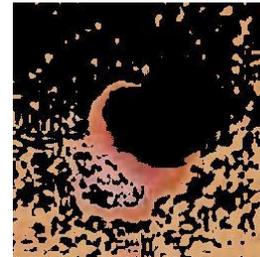


Fig. 4: Segmented Image using K-mean

### 8.2. Fuzzy-C

**Energy Normalization:** Normalization is a process that changes the range of pixel intensity values. Normalization is sometimes called contrast stretching. The segmented image for Fuzzy-C is shown in Figure 5.



Fig. 5: Segmented Image using Fuzzy-C

### 8.3. Chan Vese

**Histogram equalization:** This is a computer image processing technique used to improve contrast in images. It accomplishes this by effectively spreading out the foremost frequent intensity values, i.e. stretching out the intensity range of the image. This methodology sometimes will increase the world distinction of pictures once its usable information is delineated by shut distinction values. The segmented image for Chan Vese is shown in Figure 6.



Fig. 6: Segmented Image using Chan Vese

### Feature Extraction:

In order to use classification techniques, the image should be reworked specified it delineate a degree in some n-dimensional feature house. The axes during this feature house represent calculations that area unit relevant to describing the determined development (e.g., malignancy). A set of what we call high-level intuitive features (HLIFS). A HLIF is defined as follows:

High-Level Intuitive Feature (HLIF): A mathematical model that has been carefully designed to describe some human-observable characteristic, and whose score can be intuited by both color ,texture & spectral contents.

- a) **Cell Energy:** additionally called the live of uniformity, it's the various science lab image parts. We define feature "δ" to be where  $x=n \ i=1 \ x_i/n$ ,  $P(i, j)$  represents the normalized GLCM element for the  $i$ th row and  $j$ th column, and  $ij \ P2(i, j)$  represents the ASM indicates the margin by which this feature differentiates cancer from noncancerous images .cancer from noncancerous images.

## 9. Texture Classification Model

The LBPP,R operator produces 2P totally different output values, appreciate the 2P totally different binary patterns which will be shaped by the P pixels within the neighbor set. When the image is rotated, the gray values will correspondingly rotate. Since first pixel of the circle is always assigned to be the gray value of element LBP which is to the right of the center pixel. But when the image is rotated a particular binary pattern naturally results in a different LBP value. So the pattern is not unique. To remove the impact of rotation, i.e., to assign a novel symbol to every rotation invariant native binary pattern we tend to define: ROR(x,i) performs a circular bit-wise right shift on the P-bit number  $x_i$  times. In terms of image pixels we rotate the LBP pattern P times in a circular fashion and among all the different LBP pattern lowest value (binary P bit value) is chosen. Each grayscale pixel P of an image is used as a center of a circle with radius  $R = 1$  or  $2$  (radius R is usually kept very small). Since the types of local pattern transitions are determined by the binary coding function for the LDP operator, it may lose the ability to distinguish the patterns derived from the neighboring pixels with equal gray levels which occur frequently in the median-filtered images from the "turning point" and "gradient turning" patterns.

## 10. ROI Segmented Image

### 10.1. K-Means Clustering For Image Segmentation

The objective of K means clustering is to partition an image into mutually exclusive clusters by minimizing the distance metric between the pixel and the cluster centroid . For the input image I with  $X = \{x_1, x_2, \dots, x_N\}$  pixels  $K = \{k_1, k_2, \dots, k_K\}$  number of clusters.

#### Methodology:

**Step 1:** Randomly assign each pixel to any of the clusters.

**Step 2:** Compute the distance between the pixel and all centroids  $C = \{c_1, \dots, c_K\}$  as ,

$$\sum_{i=1}^k \sum_{X_j} \|X_j - C_k\|^2 ; X_j \in k_i$$

where  $\|\cdot\|$  denotes the Euclidean norm ,

$c_k$  = mean of all pixels in  $k$ th cluster

Reassign the pixel  $x_j$  to the cluster  $c_i$

$$\text{If } \|X_j - C_i\|^2 \leq \|X_j - C_k\|^2 ; 1 \leq k \leq K$$

(1)

**Step 3:** Repeat above steps until there is no further reassignment.

## 10.2. Fuzzy C-Means E Model For Image Segmentation

A fuzzy c-means (FCM) formula that comes with abstraction info into the membership perform for agglomeration. The spatial function is the summation of the membership function in the neighborhood of each pixel under In this paper, they present a fuzzy c-means (FCM) algorithm that incorporates spatial information consideration. This technique could be a powerful methodology for uproarious image segmentation and works for each single and multiple-feature knowledge with abstraction info.

**Step 1:** Read the image. Read the image from mother source which is in .JPEG format, which is a fused image.

**Step 2:** For color separation of an image apply the De-correlation stretching.

**Step 3:** Convert Image from RGB Color Space to  $L^*a^*b^*$  Color Space. How many colors do we see in the image if we ignore variations in brightness? There are three colors: white, blue, and pink. We can easily visually distinguish these colors from one another. The  $L^*a^*b^*$  color space (also known as CIELAB or CIE  $L^*a^*b^*$ ) enables us to quantify these visual differences. The  $L^*a^*b^*$  color space is derived from the CIE XYZ tristimulus values. The  $L^*a^*b^*$  space consists of a luminosity layer 'L\*', chromaticity-layer 'a\*' indicating where color falls along the red-green axis, and chromaticity-layer 'b\*' indicating where the color falls along the blue-yellow axis. All of the color information is in the 'a\*' and 'b\*' layers. We can measure the difference between two colors using the Euclidean distance metric. Convert the image to  $L^*a^*b^*$  color space.

**Step 4:** Classify the Colors in 'a\*b\*' Space Using K-Means Clustering. Clustering is a way to separate groups of objects. K-means clustering treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means clustering requires that you specify the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other. Since the color information exists in the 'a\*b\*' space, your objects are pixels with 'a\*' and 'b\*' values. Use K-means to cluster the objects into three clusters using the Euclidean distance metric.

**Step 5:** Label Every Pixel in the Image using the results from K-MEANS. For every object in our input, K-means returns an index corresponding to a cluster . Label every pixel in the image with its cluster index.

**Step 6:** Create Images that Segment the Image by Color. Using pixel labels, we have to separate objects in image by Color.

**Step 7:** Segment the Nuclei into a Separate Image.

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & \text{if } U(LBP_{P,R}) \leq 2 \\ P + 1, & \text{Otherwise} \end{cases} \quad (2)$$

#### Chan Vese Model for Image Segmentation

Chan Vese model, a special case of Mumford Shah segmentation technique is an iterative algorithm to detect smooth and discontinuous edges. Its main objective is to minimize the energy functional given as ,

$$F(c_1, c_2, C) = \mu L(C) + \nu A(im(C)) + \lambda_1 \int_{in(C)} |u_0(x, y) - c_1|^2 dx dy + \lambda_2 \int_{out(C)} |u_0(x, y) - c_2|^2 dx dy \quad (3)$$

where,  $\mu, \nu \geq 0$ ;  $\lambda_1 = \lambda_2 = 1$  are the positive weighting parameters  
 $u_0(x, y)$  - input image  
 $c_1, c_2$  - average inside and outside the contour respectively

$\mu L(C) + \nu A(in(C))$  - Regularizing term

$$F_1(C) + F_2(C) = \lambda_1 \int_{in(C)} |u_0(x,y) - c_1|^2 dx dy + \lambda_2 \int_{out(C)} |u_0(x,y) - c_2|^2 dx dy \tag{4}$$

F1(C), F2(C)-fitting terms

The values of  $c_1$  and  $c_2$  are calculated using the Heaviside function  $H(\varphi)$ .

**Methodology:**

**Step 1:** Initialize mask for contour,  $\phi$ , 0.

**Step 2:** Calculate  $c_1$  and  $c_2$ .

**Step 3:** Compute the Fitting term  $F_1(C) + F_2(C)$  and the energy

functional  $\frac{\partial \phi}{\partial t}$ .

**Step 4:** Iterate until  $\frac{\partial \phi}{\partial t}$  is minimum

**11. Ada boost classifier**

It focuses on classification problems and aims to convert a set of weak classifiers into a strong one. Ada boost classifier allocate group for different color feature using color marker. When an unknown image is feed , they get segmented , grouped and compared to form different classes. Data present in directory and processed image were correlated by any of the class and the type of skin disease can be displayed as output.

**12. Factor concerning the segmentation**

Various factors that have an effect on the segmentation of carcinoma pictures square measure as follows:

- The skin lesions have advanced structure, large variations in size as well as complex colors in the skin.
- The lesion is distinction to the encompassing skin.
- The borders of lesions are not always well defined.
- The influence of little structures, hairs, bubbles, light reflection, and other artifacts.
- The influence of the skin lesions within the close regions. These factors make the segmentation more complex. To analyze skin lesions, it is necessary to accurately locate and isolate the lesions. The description of the border side seems to be a very important feature for clinical judgment . Some border descriptors, such as border irregularity and the presence of abrupt border cutters have been considered as predictors of malignancy. Also, the variation in color signifies the malignancy of the lesion. Hence effective discrimination of the skin lesions was supported the distribution of texture and color options during this study. A pre-processing step was adopted to get rid of the influence of skin lesions within the close regions and additionally the influence of little structures, hairs, bubbles etc.

**13. Theoretical Formulae**

**Sensitivity :**

$$Sensitivity = TP / (TP + FN)$$

**Precision :**

$$Precision = TP / (TP + FP)$$

**Accuracy :**

$$Accuracy = (TP + TN) / (TP + FP + TN + FN)$$

**F measure :**

$$F \text{ measure} = \text{Finishing time} - \text{Starting time.}$$

where,

**True positive (TP) :** pixels correctly segmented as foreground.

**False positive (FP) :** pixels falsely segmented as foreground.

**True negative (TN) :** pixels correctly detected as background.

**False negative (FN) :** pixels falsely detected as background.

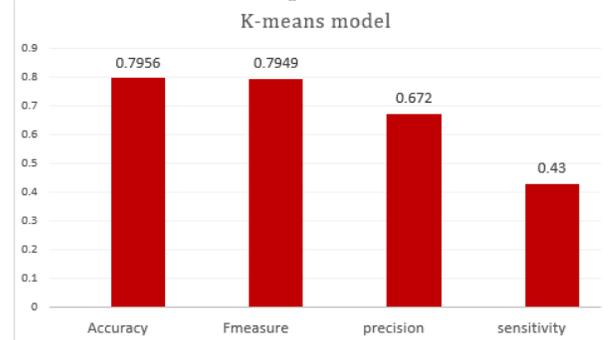
**14. Results**

K means ROI Segmented image



ROI Segmented Image Fig 7

K means Segmentation results



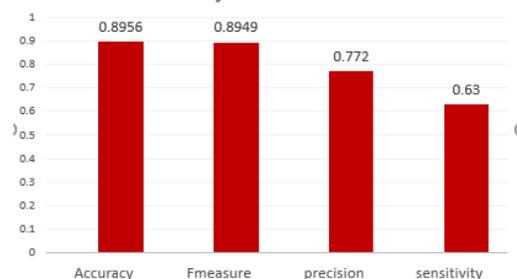
K-mean Performance Chart Fig 8

Fuzzy C means ROI Segmented image

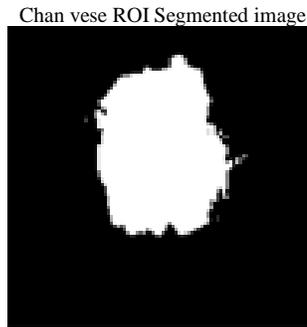


ROI Segmented Image Fig 9

Fuzzy C means Segmentation results

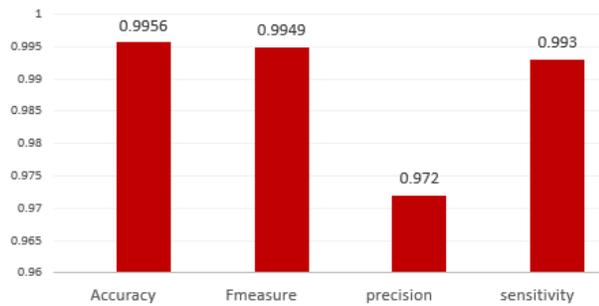


Fuzzy-C Performance Chart Fig 10



ROI Segmented Image Fig. 11

Chan vese Segmentation results  
Chan vese model



Chan Vese Performance Chart Fig. 12

Comparison of Accuracy, F measure, Precision and Sensitivity of K-mean, Fuzzy-C and Chan VeseAlgorithm	Accuracy	F measure	Precision	Sensitivity
<b>K-Mean</b>	0.7956	0.7944	0.672	0.43
<b>Fuzzy-C</b>	0.8956	0.8956	0.772	0.63
<b>Chan Vese</b>	0.9956	0.9949	0.972	0.993

Fig.13

### 15. Discussion

The segmented output of the algorithm implemented in matlab is shown in above figures and the mean of the evaluation metrics is tabulated in fig 13. Thresholding provides better results only when there is significant color change between the skin and lesion. The overall efficiency of the algorithms with user interaction ,not only depends on the efficiency of the algorithm but also on the users expertise to give the input. Accuracy is the main parameter which is precisely focused. The overall results show that chan vese provides better results for the input images with comparatively more accurate in result. Even though there are two other segmentation process ,their accuracy level and other parameters are low compared to chan vese segmentation

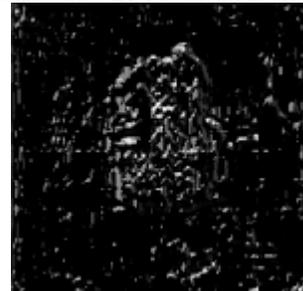
#### Rotation Invariant Variance Measures Of The Contrast Of Local Image Texture

The 1st operator is a gray-scale invariant measure, i.e., its output is not affected by any monotonic transformation of the gray scale value. It is an excellent measure of the spatial pattern, but by definition, it discards contrast. If gray-scale changelessness isn't needed and that we wished to include the distinction of native image texture furthermore, we will live it with a rotation invariant live of local variance.

We can change the values of P and R like {P=8,R=1}; {P=16,R=2}; {P=24,R= 3} ; to get different feature.

There are several facilities if anyone uses LBP method for feature extraction. Firstly, every human skin are not same colored and any skin diseases affected skin does not form same color. So in case of using the previous methods are not good enough for feature extraction from different skin. But in case of LBP it measure feature for an image which is gray scale invariant[4]. By applying methodologies one can make LBP feature rotation invariant[4]. Secondly this method can be combined with other methodologies like gabor image transform method. The texture measurement of rotational invariant model is done as two sets Set 1 (Figure 14) and Set 2 (Figure 15)

Texture measures SET-1 rotational invariant model



Rotational Invariant Set-1 Fig 14

Texture measures SET-2 scale invariant model



Rotational Invariant Set-2 Fig 15

#### GLCM Texture Measures

Data base GLCM feaure values

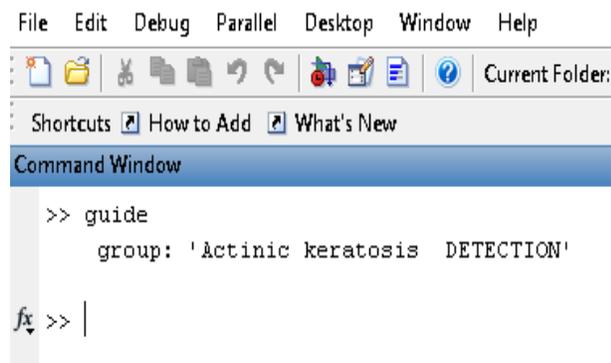
```

Autocorrelation: 2.302016178641732e+01
Contrast: 9.622693159448817e+00
Correlation: 5.982670202581664e-01
Correlation1: 5.982670202581664e-01
Prominence: 1.967573151786778e+03
Shade: 6.937244747816388e+01
Dissimilarity: 1.376107283464567e+00
Energy: 3.519140193035025e-01
Entropy: 1.188344156985764e+00
Homogeneity: 8.274403626792745e-01
Homogeneity1: 8.068113395137264e-01
probability: 4.749938484251969e-01
Variance: 2.770961875615157e+01
sumaverage: 7.963674950787402e+00
sumvariance: 8.606499006112861e+01
sumentropy: 1.051239166072348e+00
Diffvariance: 9.622693159448819e+00
Diffentropy: 5.078081434256719e-01
infmeasurecorrelation1: -2.749979887454913e-01
infmeasurecorrelation2: 5.616118365999172e-01
Diffnormalized: 9.081898942319709e-01
momentnormalized: 9.148217400087369e-01
    
```

GLCM Measurement Fig. 16

## 16. Lesion Classification

This is the final result where the affect diseases will be display in the console if there is no such disease detect is will show no disease message this is show in the figure 17.



```
File Edit Debug Parallel Desktop Window Help
Shortcuts How to Add What's New
Command Window
>> guide
    group: 'Actinic keratosis DETECTION'
fx >> |
```

Fig. 17

## 17. Conclusion

Here in this work system performance against variability of skin lesion shapes and complexity of determining the lesion location, size and texture. Here the efficiency of fully automated segmentation and classification of skin tonal analyzes is validated. Finally ROI image is pre-processed using tonal preserved invariant texture classification models which evolve using orientation driven spatial operations. Finally intensity normalized GLCM feature set is forwarded to the classification model, which explore the skin abnormality types. Here only thorough texture feature attributes auto classification is performed using Adaboost classification.

## References:

- [1] S. Suer, S. Kockara, and M. Mete, "An improved border detection in dermoscopy images for density based clustering," *BMC Bioinformat.*, vol. 12, no. 10, p. S12, 2011.
- [2] M. Rademaker and A. Oakley, "Digital monitoring by whole body photography and sequential digital dermoscopy detects thinner melanomas," *J. Primary Health Care*, vol. 2, no. 4, pp. 268–272, 2010.
- [3] O. Abuzagheh, B. D. Barkana, and M. Faezipour, "SKINeure: A real time image analysis system to aid in the malignant melanoma prevention and early detection," in *Proc. IEEE Southwest Symp. Image Anal. Interpretation (SSIAI)*, Apr. 2014, pp. 85–88.
- [4] O. Abuzagheh, B. D. Barkana, and M. Faezipour, "Automated skin lesion analysis based on color and shape geometry feature set for melanoma early detection and prevention," in *Proc. IEEE Long Island Syst., Appl. Technol. Conf. (LISAT)*, May 2014, pp. 1–6.
- [5] (Mar. 27, 2014). American Cancer Society, *Cancer Facts & Figures*. [Online]. Available: <http://www.cancer.org/research/cancerfactsstatistics/cancerfactsfigures2014/index>
- [6] R. P. Braun, H. Rabinovitz, J. E. Tzu, and A. A. Marghoob, "Dermoscopy research—An update," *Seminars Cutaneous Med. Surgery*, vol. 28, no. 3, pp. 165–171, 2009.
- [7] Dr. AntoBennet, M, Sankar Babu G, Natarajan S, "Reverse Room Techniques for Irreversible Data Hiding", *Journal of Chemical and Pharmaceutical Sciences* 08(03): 469-475, September 2015.
- [8] Dr. AntoBennet, M , Sankaranarayanan S, Sankar Babu G, "Performance & Analysis of Effective Iris Recognition System Using Independent Component Analysis", *Journal of Chemical and Pharmaceutical Sciences* 08(03): 571-576, August 2015.
- [9] Dr. AntoBennet, M, Suresh R, Mohamed Sulaiman S, "Performance & analysis of automated removal of head movement artifacts in EEG using brain computer interface", *Journal of Chemical and Pharmaceutical Research* 07(08): 291-299, August 2015.
- [10] .Dr. AntoBennet, M "A Novel Effective Refined Histogram For Supervised Texture Classification", *International Journal of Computer & Modern Technology* , Issue 01 ,Volume02 ,pp 67-73, June 2015.
- [11] Dr. AntoBennet, M, Srinath R, Raisha Banu A, "Development of Deblocking Architectures for block artifact reduction in videos", *International Journal of Applied Engineering Research*, Volume 10, Number 09 (2015) pp. 6985-6991, April 2015.
- [12] AntoBennet, M & JacobRaglend, "Performance Analysis Of Filtering Schedule Using Deblocking Filter For The Reduction Of Block Artifacts From MPEQ Compressed Document Images", *Journal of Computer Science*, vol. 8, no. 9, pp. 1447-1454, 2012.
- [13] AntoBennet, M & JacobRaglend, "Performance Analysis of Block Artifact Reduction Scheme Using Pseudo Random Noise Mask Filtering", *European Journal of Scientific Research*, vol. 66 no.1, pp.120-129, 2011.