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### FEATURE EXTRACTION OF CERVICAL CANCEROUS AND NON-CANCEROUS CELLS BASED ON EDGES, REGIONS AND COLOR-INTENSITY USING FUZZY LOGIC

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### ABSTRACT

**Objective** – This paper proposed feature extraction of Pap smear slide images and present an automated method for extracting the features from the input images (cancerous and non-cancerous cells). Fuzzy logic technique gives better results in improving the image parameters and provides a better diagnosis of cervical cancer.

**Methods-** In this work, there are 3 stages. In first stage, preprocessed images were detecting the edges using fuzzy logic. The detected edges are converted into gray-level co-occurrence matrix for extracting texture features. In second stage, the filtered images were selecting the particular region of nuclei and segment with threshold technique for extracting region features. In third stage, the filtered images were segmented with colors using Fuzzy C-means clustering method for color-intensity features.

**Results** – There are 228 slides of different 7 classes are used to extract the features for classifying cancerous and non-cancerous cells are present in the Pap smear slides. There are 22 features are extracted from the input slides of different stages of classes.

**Conclusion** – Feature extraction techniques provide the statistical measures for further implementation of feature selection and classification for classifying cancerous and non-cancerous cells are present in Pap smear image.

Keywords: Feature Extraction, Edge Detection, Fuzzy Logic, Fuzzy C-Means Clustering, Threshold Technique.

### **1. INTRODUCTION**

Cervical cancer is caused by a virus called Human Papilloma Virus (HPV). A Pap test is used to find changes in cervical cells before they turn into cancer. The Pap smear slide image is the input of this paper and extracts the features of cancerous and non-cancerous cells<sup>1</sup>. In this paper deals with various feature extraction techniques based on size, shape, texture and color-intensity features of pap smear slides. Feature extraction is an important step, which is a form for developing dimensionality reduction and classification. Feature extraction is the process of transforming the inputs into a set of features. There are 228 Pap smear slides are used to extract features are present in different stage of 7 classes.

In this stage, there are 2 steps are used to extract features are as follows:

Pre-Processing: The input image is filtered by unwanted noise and segmentation.

Feature extraction: Extracting features based on edges, regions and color-intensity information.

Edge-based techniques used to detect the edges of cancerous and non-cancerous cells of Pap smear images. Fuzzy logic was used to detect the edges; the detecting edges are transformed into gray cooccurrence matrix (GLCM) for extracting the texture features of cells. Texture information extracted from GLCM of edges is contrast, correlation, energy, homogeneity, entropy, skewness, and kurtosis<sup>2</sup>.

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Region-based techniques used to detect the particular region of the inputs. First, select the nucleus of the pap smear slides using imfreehand() function in MATLAB. After selecting the nucleus, it was converted to binary image using threshold method. Threshold is used to convert the original image into binary image<sup>3</sup>. The binary image of the particular region is measured by region properties using regionprops() method in MATLAB. Region informations are area, majoraxislength, minoraxislength, eccentricity, orientation, convexarea, equivdiameter, solidity, extent, and perimeter.

Color-intensity based techniques are used to extract the intensity information of different colors are present in the input image. Fuzzy Cmeans clustering (FCM) technique is used to find the intensity of colors. FCM is used to convert the original image into different colors using more than clusters<sup>4</sup>. After conversion, the colorintensity image was measured by related information are mean, median, standard deviation, covariance and range.

Automating the cancer diagnosis process can play a very significant role in reducing the number of cancer diagnosis is semiautomatic and is prone to human error and time consuming. A computer system that performs automatic grading can assist pathologists by providing second opinions, reducing their workload, and altering them to cases that require closer attention, allowing them to focus on diagnosis and prognosis. This paper discussed the recent advances and future perspectives in relation to cervical cancer detection

### 2. LITERATURE REVIEW

Edge detection method<sup>5</sup> was applied to smooth and noisy clinical images. The proposed method guided by fuzzy rule set. It detected very few false edge pixels, compared to Sobel, Prewitt, LOG, Roberts and Canny false edge pixels. Fuzzy entropy based approach<sup>6</sup> presents a multi-level image threshold approach based on fuzzy partition of the image histogram and entropy theory. This method used to entropy measure is then optimized to obtain the thresholds of the image. This approach delivers satisfactory results in case of visual comparison. Edge detection<sup>7</sup> use parametric functions in the transformation of the gradient images into fuzzy sets. Beddeley's Delta Metric (BDM) has been selected for the comparison of binary results. To analyzed the generation of membership degrees to the edges from the magnitude of the gradients associated with each pixel. Edge detection<sup>8</sup> which aims at identifying points in a image. Fuzzy edge filter technique is to stimulate at a mathematical level the compensatory behavior in process of decision making or subjective evaluation. This approach detects different classes of image pixels corresponding to gray level variation in the various directions. Edge detection technique<sup>9</sup> used to reduce data without disturbing important features of the image. Fuzzy logic inference system used to detect the edges of the image on the basics of output membership function. This method preserved nearly 90% of edge information. Texture information<sup>10</sup> used in classifying the regions of interest in an image. Texture feature extracted by Gray-Level Cooccurrence Matrix (GLCM) which contains statistical information of neighboring pixels of an image. This paper discussed about the importance of direction and distance parameters while GLCM processing. Edge detection of digital images based on Tsallis entropy and Shannon entropy using split and merge technique<sup>11</sup>. The objective of this paper is to find the best edge representation and minimize the computation time. Fuzzy C-means algorithm<sup>12</sup> used for image segmentation and detect the tumor objects that are found in the MR brain image. This algorithm is widely allows pixels to belong to multiple classes with varying degrees of membership. The implementation of FCM is obtained average speed-ups of as much as 80 times of traditional technique. Fuzzy C-means clustering<sup>13</sup> unsupervised algorithm used for enhancement of color separation of satellite image using de-correlation stretching is carried out and then the regions are grouped into a set of five classes. In this approach, to reduce the computational cost avoiding features calculation for every pixel in the image. Fuzzy C-means approach<sup>14</sup> used to analyze and compare the gray level texture feature technique. This algorithm used to assign the different clusters with center data points which belong to individual clusters instead of belonging to particular clusters.

### **3. MATERIALS AND METHODS**

There are 22 features are extracted from Pap smear slide images which are cancerous ad non-cancerous cells are present in the input

image. There are 3 methods are used to extract the features are: edge-based, region-based, and color-intensity based techniques (Fig.1).



Figure 1: Process of Feature Extraction

### 3.1. Preprocessing of Pap smear Images

The Pap smear images are acquired by skilled cytotechnicians. The publically available database is given by Herlev University Hospital, Denmark. In this database, several Pap smear images with seven stages of cancer and cell images were captured with a resolution of  $0.201 \frac{\mu m}{pixel}$  shown in Table.1. The collected images are enhanced by filtering techniques for removing noise reduction and segmenting the cell nucleus and cytoplasm.

Table.1 Summary of Datasets

Datasets (Pap smear slides)	Number of instances	Feature types
Normal superficial	54	
Normal intermediate	37	
Normal columnar	36	Integer
Light dysplastic	37	real
Moderate dysplastic	21	categorical
Severe dysplastic	23	
Carcinoma_in_situ	20	

Total number of extracted features= 22(7 classes) Total number of input slides= 228 images

### **3.2. Feature Extraction Methods**

It involves 3 types of extraction methods: edge-based using Fuzzy logic, regionbased using threshold, and color-intensity based using Fuzzy C-means (FCM) clustering methods.

### 3.2. 1. Edge-Based Using Fuzzy Logic

Edge detection is the important feature of the inputs. It reduces the unwanted information of data and gives the structural properties of the original image<sup>15</sup>. Fuzzy logic is used to detect the edges of the inputs on the basics of membership function. Fuzzy logic detects the boundaries of the particular regions are present in the original image. The result of edge detection indicates the boundaries of surface present in the Pap smear slides. The edge detection process involves are:

Step 1: Load the pre-processed input image.

Step 2: Implement the Fuzzy Logic method for detecting edges.

Step 3: Detected edges are converted into gray cooccurrence matrices.

Step 4: GLCM of edges used to extracts texture information.

Step 5: Extracted features are converted into table.

### 3.2.2. Fuzzy Inference system

A fuzzy rule was used to determine the pixels of the edges in the output image. Fuzzy inference system using MATLAB software (R2015a) for detect the edges<sup>16</sup>. It provides mapping to formulate the given input using Fuzzy logic. The image gradient is to locate the breaks present in the uniform region. The Gaussian membership function is used to specify for each input. The triangular membership function is specified for output<sup>17</sup>. There are 3 steps: Fuzzification: To convert the original data into

Fuzzification: To convert the original data into fuzzy data or membership function<sup>18</sup>.

Fuzzy Inference System: Membership functions are processed by fuzzy rules and derive the output.

Defuzzification: To calculate the outputs are converted into lookup table.

Fuzzy Rules: There are 2 rules are used to detects the edge points

If (Ix is zero) and (Iy is zero) then (Iout is white)

If (Ix is not zero) or (Iy is not zero) then (Iout is black)



Figure 2: Steps for Implementing Fuzzy Logic

### 3.2.3. Fuzzy logic operators

These operators are used to write logic combinations between fuzzy notions, i.e. to perform computations on degrees of truth. Just as for classical logic, AND, OR and NOT operators can be defined. The logic operator corresponding to the intersection of sets is AND. The degree of truth of the proposal "A AND B" is the minimum value of the degrees of truth of A and B:

$$\mu(A AND B) = MIN(\mu(A), \mu(B))$$
(1)

The logic operator corresponding to the union of sets is OR. The degree of truth of the proposal "A OR B" is the maximum value of the degrees of truth of A and B:

$$\mu(A \ OR \ B) = MAX(\mu(A), \mu(B))$$
(2)

The logic operator corresponding to the complement of a set is the negation.

$$\mu(NOT A) = 1 - \mu(A) \tag{3}$$

Step 1: Load the pre-processed Pap smear slide images and converted into threshold image (Fig.3).

Step 2: To convert the Pap smear image into double precision [0, 1].

Step 3: To determine the x-axis and y-axis by image gradient (Fig.4).

Step 4: To derive the output, FIS performed with given input.

Step 5: Fuzzy rules are used to determine the regions are white or black (Fig.5).

Step 6: The input is evaluated by horizontal and vertical wise.

Step 7: To display the Fuzzy output (Fig.6).



Figure 3: Input Image



Figure 4: Input of Ix and Iy

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Figure 5: Gaussian Membership Function



*Figure 6: Output of Fuzzy Logic (Edges)* 

### 3.2.5. Gray co-occurrence matrix (GLCM)

After detecting the edges, the edges are converted into gray co-occurrence matrices<sup>19</sup>. GLCM is used to analyze, extract the textural features of the input image and it specifies the combinations of gray-level occurs in an image. It gives the measurement of pixel-intensity variations are present in the input image. GLCM used to extract the textures are present in the gray-level distribution of the input image<sup>20</sup>. There are 7 texture features are extracted from the edges of the Pap smear slides.

Contrast: It returns the measurement of the intensity between a pixel and its neighbor over the original image.

$$\sum_{i\,i} |i-j|^2 P(i,j) \tag{4}$$

Correlation: It returns the measurement of how correlated a pixel is to its neighbor over the original image.

$$\sum_{ij} \frac{(i-\mu_i)(j-\mu_j)P(ij)}{\sigma_i \sigma_j} \tag{5}$$

Energy: It returns the sum of squared element in the gray-level co-occurrence matrix (GLCM).

$$\sum_{ij} P(i,j)^2 \tag{6}$$

Homogeneity: It returns the value that measures the closeness of the distribution of elements in the gray-level co-occurrence matrix to the GLCM diagonal.

$$\sum_{ij} \frac{P(ij)}{1+|i-j|} \tag{7}$$

Entropy: It returns the measurement of randomness that can be used to characterize the texture of th input image<sup>21</sup>.

$$\sum P_{ij} \log P_{ij} \tag{8}$$

Skewness: It returns the measurement of the asymmetry of gray. If the output is negative, the data are spread out more to the left of the mean than to the right. If the output is positive, the data are spread out more to the right.

$$S = \frac{E(x-\mu)^3}{\sigma^3} \tag{9}$$

 $\mu = mean of x$ ,

 $\sigma$  is the standard deviation of x, and E(t) represent the expected value of the quantity t.

Kurtosis: It returns the measurement of how outliner-prone of distribution<sup>22</sup>. Normal distribution of kurtosis is 3. Measurement of more outlier-prone than the normal distribution is greater than 3. Measurement of less outlier-prone than the normal distribution is less than 3.

$$K = \frac{E(x-\mu)^4}{\sigma^4} \tag{10}$$

 $\mu = mean of x$ ,

 $\sigma$  is the standard deviation of x, and E(t) represent the expected value of the quantity t.

### 3.3. Region-Based Using Threshold

Region extraction is the process of measuring the size and shapes of nucleus are

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present in the Pap smear slides. The measured information is used to differentiate the cancerous and non-cancerous cells<sup>23</sup>. The processes of extracting particular regions are:

Step 1: Load the pre-processed input image.

Step 2: To select the nucleus of the particular region by imfreehand() function in MATLAB.

Step 3: The selected regions are converted into binary image using im2bw () function in MATLAB.

Step 4: The binary image is measured by regionprops() function in MATLAB.

Step 5: Extracted region information are converted into table.

### 3.3.1. Threshold with Otsu's method

Threshold process is to separate the light and dark region of images (Fig.7). It creates binary images from grey-level ones by turning all pixels below threshold to zero and all pixels about the threshold to one<sup>24</sup>. This method is used to measure the regions with high homogeneity and will have low variances. It selects the threshold by minimizing the within-class variance of the two groups of pixels and minimizes the combined spread<sup>25</sup>.

Within-class variance

$$\sigma^{2} \text{ within } (T)$$

$$= n_{B}(T)\sigma_{B}^{2}(T)$$

$$+ n_{o}(T)\sigma_{o}^{2}(T)$$
(11)

Where

$$n_B(T) = \sum_{i=0}^{T-1} p(i)$$
$$n_o(T) = \sum_{i=T}^{N-1} p(i)$$

 $\sigma_B^2(T)$  = the variance of the pixels in the background

 $\sigma_o^2(T)$  = the variance of the pixels in the foreground and [o, N - 1] is the range if intensifying levels.

Between - class variance

$$\sigma_{between}^{2}(T) = \sigma^{2} - \sigma_{within}^{2}$$
  
=  $n_{B}(T)[\mu_{B}(T) - \mu]^{2} + n_{o}(T)[\mu_{o}(T) - \mu]^{2}$  (12)

 $\sigma^2 = combined variance,$ 

 $\sigma^2 = combined mean$ 

T we

- (i) Separate the pixels into two clusters according to the threshold.
- (ii) Find the mean of each cluster.
- (iii) Square the difference between the means.
- (iv) Multiply by the number of pixels in one cluster times the number in the other.



Figure 7: Input image and Output of threshold image

After threshold image, the image is measured the particular regions using by region properties function in MATLAB. There are 10 features are extracted from the particular region are: area, eccentricity, convex area, eqivdiameter, extent, majoraxislength, minoraxislength, orientation, solidity and perimeter<sup>26</sup>.

Area- It returns the scalar value of pixels in the particular region.

$$A(R) \approx \frac{1}{2} \left| \sum_{i=0}^{M-1} (u_i v_{(i+1)} \mod M - u_{(i+1)} \mod M v_i) \right|$$
(13)

Eccentricity-It returns the scalar value of the eccentricity of ellipse. The scalar value off eccentricity is between 0 and 1. The eccentricity



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off ellipse is 0 means is actually a circle<sup>27</sup>. The eccentricity of ellipse value is 1 means is a line segment.

$$Ecc(R) = \frac{\alpha_1}{\alpha_2} = \frac{\mu_{20} + \mu_{02} + \sqrt{((\mu_{20} - \mu_{02})^2) + 4\mu_{11}^2}}{\mu_{20} + \mu_{02} - \sqrt{((\mu_{20} - \mu_{02})^2) + 4\mu_{11}^2}}$$
(14)

Convex Area- It returns the scalar value of number of pixels is present in the input image.

$$Conv(s) = \{\sum_{i=1}^{|S|} \alpha_i x_i \mid (\forall: \alpha_i \ge 0) \Lambda \sum_{i=1}^{|S|} \alpha_i = 1\}$$
(15)

Equiv Diameter- It returns the scalar value of diameter of the circle in the original image<sup>28</sup>.

$$EquiDiameter = sqrt(4 * \frac{Area}{p_i}) \quad (16)$$

Extent- It returns the scalar value of pixels present in the region in the total bounding box.

$$Extent = \frac{A_S}{A_B}$$
(17)

Where,  $A_s = Area \ of \ shape$ ,  $A_B = Area \ of \ bounding \ rectangle$ 

Major Axis Length- It returns scalar value of pixels length of the major axis of the ellipse. It has the same normalized second central moments of the region.

$$r_a = 2\left(\frac{\beta_1}{|R|}\right)^{1/2} = \left(\frac{2\alpha_1}{|R|}\right)^{1/2}$$
 (18)

Minor Axis Length- It returns the scalar value of pixels length of the minor axis of the ellipse that has same normalized second central moments of the region<sup>29</sup>.

$$r_b = 2\left(\frac{\beta_2}{|R|}\right)^{1/2} = \left(\frac{2\alpha_2}{|R|}\right)^{1/2}$$
 (19)

Orientation- It returns the scalar value of angle between x-axis and the major axis of the ellipse and it has the same second –moments as the region.

$$x = \bar{x} + \beta x_d = \begin{pmatrix} \bar{x} \\ \bar{y} \end{pmatrix} + \beta \begin{pmatrix} \cos(\theta_R) \\ \sin(\theta_R) \end{pmatrix} (20)$$

$$x_{d} = \cos(\theta_{R})$$

$$= \begin{cases} 0 \text{ for } A = B = 0 \\ \left[\frac{1}{2}\left(1 + \frac{B}{\sqrt{A^{2} + B^{2}}}\right)\right]^{1/2} \text{ otherwise} \end{cases}$$

$$y_{d} = \sin(\theta_{R}) = \begin{cases} 0 & \text{for } A = B = 0 \\ \left[\frac{1}{2}\left(1 - \frac{B}{\sqrt{A^{2} + B^{2}}}\right)\right]^{1/2} \text{for } A \ge 0 \\ -\left[\frac{1}{2}\left(1 - \frac{b}{\sqrt{A^{2} + B^{2}}}\right)\right]^{1/2} \text{for } A < 0 \end{cases}$$

Where, 
$$A = 2\mu_{11}(R)$$
,  $B = \mu_{20}(R) - \mu_{02}(R)$ .

Solidity- It returns the scalar values of the proportion of the pixels are present in the region.

Solidity = 
$$\frac{\text{Area}}{\text{Convex Area}}$$
 (21)

Perimeter- It returns the scalar value of the distance around the boundary of the region<sup>30-31</sup>. To calculate the distance between each adjoining pair of pixels around the border of the region is giving the output is called perimeter.

$$P(R) = \sum_{i=0}^{M-1} length(C'_i) \qquad (22)$$

 $C'_i =$ 

Where  $[C'_0, C'_1, C'_2 \dots C'_{M-1}]$  with length

$$(C) = \begin{cases} 1 \ for \ c = 0, 2, 4, \dots \\ \sqrt{2} \ for \ c = 1, 3, 5, \dots \end{cases}$$

### 3.4. Color-Intensity Based Using FCM

Fuzzy C-means (FCM) is a clustering technique which allows one piece of data to belong to two or more clusters (Fig.8). It gives information of colors are present in each pixels of the image<sup>32-33</sup>. This algorithm implements by assigning membership to each data point corresponding to each cluster center on the basis of distance between the cluster center and the data point. It allows each data point to belong to multiple clusters with varying degrees of membership<sup>34-35</sup>.

Objective function

$$J_m = \sum_{i=1}^{D} \sum_{j=1}^{N} \mu_{ij}^m \|x_i - C_j\|^2$$
(23)

|--|

Where D=No. of data points, N= N number of clusters, m=Fuzzy partition matrix exponent for controlling the degree of fuzzy overlap with m > 1.

 $x_i = ith data point$ 

 $C_i$  = centre of the jth cluster

 $\mu_{ij}$ 

= degree of membership of  $x_i$  in the jth cluster

### 3.4.1. Steps for Fuzzy C-means clustering technique

Step 1: Load the input image.

Step 2: Randomly initialize the cluster membership values  $\mu_{ij}$ .

Step 3: Calculate the cluster centers.

$$C_{j} = \frac{\sum_{i=1}^{D} \mu_{ij}^{m} x_{i}}{\sum_{i=1}^{D} \mu_{ij}^{m}}$$
(24)

Step 4: Update.

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N} \left(\frac{\|\mathbf{x}_i - \mathbf{c}_i\|}{\|\mathbf{x}_i - \mathbf{c}_k\|}\right)^{\frac{2}{m-1}}}$$
(25)

After segment the image using with FCM, the segmented image is converted into histogram<sup>36</sup>. The histogram is used to extract the features of color-intensity. There are 5 features are extracted from the histogram data for color-intensity values. The features are mean, median, co-variance, standard deviation and range<sup>37</sup>.

Mean- It gives the mean value of the color segmented image using with histogram of FCM.

$$\mu = \frac{1}{N} \sum_{i=1}^{N} A_i \tag{26}$$

Median- It gives measurement of properties for the data set. To find the middle number of a dataset of n ordered numbers<sup>38</sup>.

$$Med(A) = Median(A[1], A[n/2], A[n])$$
(27)

Co-variance- It gives the variance between two random variables of the color segmented image.

$$Cov(A,B) = \frac{1}{N-1} \sum_{i=1}^{N} (A_i - \mu_A) (B_i - \mu_B) \quad (28)$$

Standard deviation- It gives the square root of the variance<sup>39</sup>.

Step 5: Calculate the objective function, j<sub>m</sub>.

Step 6: Repeat steps 2-4 until  $j_m$ , improves by less than a specified minimum threshold or until after a specified maximum number of iterations.



Figure 8: Output of FCM color segmentation

$$S = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} |A_i - \mu|^2}$$
(29)

Where  $\mu$  is the mean of A

$$\mu = \frac{1}{N} \sum_{i=1}^{N} A_i$$

Where  $\mu_A = mean \ of \ A$ ,  $\mu_B = mean \ of \ B$ , For matrix: C(i, j) = cov(A(:, i), A(:, j))

Range- It returns the difference between the maximum and minimum values of input data<sup>40-41</sup>. Range = Max-Min (30)

#### 4. EXPERIMENTAL RESULTS

The proposed feature extraction techniques were stimulated using MATLAB R2015a. There are 228 Pap smear slide images are used to extract 22 features of 7 different classes. The seven different classes are indicates the stages are affected by cancer. Table.2 shows the implementation details of proposed method. The input images were observed with using of proposed technique and it can be successfully implemented on several Pap smear slides in finding distinct information from the image and to provide several feature information related to texture, region and colorintensity features. Table.3 (see Appendix) gives the

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extracted information of cancerous and noncancerous Pap smear slide images.

Table 2: Implementation details of proposed method

Software	MATLAB R2015a
Data sets	Pap Smear Slide images
Feature Extraction Techniques	Edge detection: Fuzzy logic Region detection: Threshold Color-intensity detection: Fuzzy C- means Clustering
Operating System	Windows 7
Data set File Format	Image (jpeg format)
Purpose	Feature Extraction

This paper proposes feature extraction methods that can overcome the manual diagnosis system. The manual screening process suffers from high falsepositive rate and low false-negative rate due to human error and it is very cost effective for diagnosing by experts. The automated system produces better results of extracted features of Pap smear images and implementation for further work.

### **5. CONCLUSION**

This work we have achieved to extract the features of Pap smear images with various techniques. We have seen fuzzy logic method used for extracting texture features. We used threshold method for extracting region information. Fuzzy Cmeans clustering technique used for extracts colorintensity information. Further work is pursuing for classifying the cancerous and non-cancerous cells are present in the Pap smear slide using with these feature information.

### REFERENCES

- [1] World Health Organization, *Comprehensive Cervical Cancer Control: A Guide to Essential Practice*, WHO Press, 2006.
- [2] Anil Jain, *Fundamentals of Digital Image Processing*, Prentice Hall.1989.
- [3] Rafael. C. Gonzalez, Richard. E. Woods, *Digital Image Processing*, Addison Wesley, Massachusetts, 1999.

- [4] E. Saber, A.M. Tekalp, "Integration of color, edge and texture features for automatic regionbased image annotation and retrieval," *Electronic Imaging*, 7, pp. 684–700, 1998.
- [5] Izhar Haq, Shahzad Anwar,et.al., "Fuzzy logic based edge detection in smooth and noisy clinical images, PLUSONE, 10(9).
- [6] B.K.Panigrahi et.al, A Fuzzy entroy based multi-level image thresholding using differential evolution, springer publishing, pp. 386-395, 2015.
- [7] C.Lopez-Molina, H.Bustine, et.al, "Generation of fuzzy edge images using trapezoidal membership functions", Atlantic press, EUSFLAT-LA 2011.
- [8] Neha Agarwal, Rishabh Agarwal, Sushil kumar, "Fuzzy edge filter-edge detection and feature extraction technique for any JPEG image", IJCSC, vol.1, No.2, July-Dec 2010, pp.387-390.
- [9] Srikant Patnaik, K.Parvathi, S.K.Mandal, "Development of simple edge detection technique using FIS", Journal of advanced research in Dynamical and Control systems, vol.9, sp-12/2017.
- [10] Biswajit Pathak, Ankita Bhuyan, et.al, "Graylevel co-occurrence matrix implementation based on edge-detection information forsurface texture analysis", Association of computer electronics and electrical engineers, 2014.5.360.
- [11] Mohamed A.El-sayed, Sayed F.Bahgat, et.al, "Novel Approach of edges detection for digital images based on hybrid types of entropy", Appl.Math.Inf.Sci.7, No.5, 1809-1817(2013).
- [12] M.Rakesh, T.Ravi,"Image segmentation and detection tumor objects in MR brain images using Fuzzy C-means(FCM) algorithm, IJERA, vol.2, Issue 3, May-Jun 2012, pp.2088-2094.
- [13] Tara Saikumar, P.Yugandar, et.al, "Colour based image segmentation using fuzzy Cmeans clustering", IACSIT press, vol.14(2011).
- [14] G.Ravindran, T.Joby Titus et.al, "Analysis of image segmentation techniques for texture feature extraction, IJESRT, 6(6), June, 2017.
- [15] Abdallah A. Alshennawy, and Ayman A. Aly Edge Detection in Digital Images using Fuzzy Logic Tecniques, *IEEE Tran*.
- [16] L.I. Kuncheva, F. Steimann, "Fuzzy diagnosis," Artificial Intelligence in Medicine, vol. 16, pp. 121-128, 1999.

E-ISSN: 1817-3195

ISSN: 1992-8645	www.jatit.org	]

- [17] I. Virant-Klun, J. Virant, "Fuzzy logic alternative for analysis in the biomedical sciences," Computers and Biomedical Research, vol. 32, pp. 305-321, 1999.
- [18] P. Vidya, S. Veni and K.A. Narayanankutty, "Performance Analysis of Edge Detection Methods on Hexagonal Sampling Grid", International Journal of Electronic Engineering Research, Volume 1 Number 4 (2009) pp. 313– 328.
- [19] R.W. Conners and C.A. Harlow, "A theoretical comparison of texture algorithms", IEEE Trans. on Pattern Analysis and Machine Intell., Vol. PAMI-2, pp. 204-222, 1980.
- [20] Raman Maini and Dr. Himanshu Aggarwal, "Study and Comparison of various Image Edge
- Detection Techniques", International Journal of Image Processing (IJIP), Vol. 3: Issue(1).
- [21] J.M.H. du Buf, M. Kardan and M. Spann, "Texture Feature Performance of Image Segmentation", Pattern Recognition, Vol. 23, pp. 291-309, 1990.
- [22] Abdallah A. Alshennawy and Ayman A. Aly,"Edge Detection in Digital Images Using Fuzzy Logic Technique",World Academy of Science, Engineering and Technology (51), 2009.
- [23] Shemil Shajan & Mohamed Fazulur Rahuman.M, "Image Edge Detection using Fuzzy Logic", International Conference on Computing and Control Engineering(ICCCE 2012), 12 & 13 April, 2012.
- [24] Jaideep Kaur and Poonam Sethi, "Evaluation of Fuzzy Inference System in Image Processing", International Journal of Computer Applications (0975-8887), Volume 68-No.22, April 2013.
- [25] C. Kang, and W. Wang, "A novel edge detection method based on the maximizing objective function.", Patt. Recog., 40, 609-618 (2007).
- [26] B. Mitra, "Gaussian Based Edge Detection Methods- A Survey ". IEEE Trans. on Systems, Manand Cybernetics, 32, 252-260 (2002).
- [27] B. Singh and A. P. Singh, "Edge Detection in Gray Level Images Based on the Shannon Entropy", J. Comput. Sci., 4, 186-191 (2008).
- [28] Gonzalez, R.C., Woods, R.E., Eddins, S.L., 2003. Digital Image Processing Using MATLAB. Prentice-Hall, New Jersey, pp. 536–593.
- [29] Brajpal Singh Jadon and Neelesh Gupta, "Fuzzy logic technique in digital images using

edge Detection", Int'l Conf.on Cloud, Big Data and Trust, RGPV, Nov 13-15, 2013.

- [30] B. Pathak and D. Barooah, "Texture analysis based on the Gray-Level Co-occurrence Matrix considering possible orientations", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 2, No. 9, pp. 4206-4212, 2013.
- [31] ShervanFekriErshad, "Texture Classification Approach Based on Combination of Edge & Co-occurrence and Local Binary Pattern", Int'l Conf. IP, Comp. Vision, and Pattern Recognition, 626-629, 2011.
- [32] A. Baraldi, F. Parmiggiani. "An Investigation Of The Textural Characteristics Associated With GLCM Matrix Statistical Parameters", *IEEE Trans. on Geoscience and Remote Sensing*, vol. 33, no. 2, pp. 293-304, March 1995.
- [33] H. Tian, S.K. Lam, T. Srikanthan, "Implementing Otsu's Thresholding Process Using Area-Time Efficient Logarithmic Approximation Unit", Proc. of the International Symposium on Circuits and Systems, vol. 4, pp. IV/21-IV/24, 25-28 May 2003.
- [34] P. Mohanaiah,P. Sathyanarayana,L. GuruKumar,"Image Texture Feature Extraction Using GLCM Approach,"International Journal of Scientific and Research Publications, Volume 3, Issue 5, 2 ISSN 2250-3153,1-3,2013.
- [35] Minakshi Banerjee and Malay K. Kundu: "Edge based features for content based image retrieval.PatternRecognition, "Vol. 36, p. 2649-2661,2003.
- [36] M.Swain and D.Ballard, "Color Indexing", Int. Journal of Computer Vision, vol.7, no. 1, pp. 11-32, 1991.
- [37] S.Sural, G.Qian and S.Pramanik, "A Histogram with Perceptually Smooth Color Transition for Image Retrieval", Proc. Fourth Int. Conf. on CVPRIP, Durham, 2002.
- [38] Jie Yu, Peihuang Guo, Pinxiang Chen, Zhongshan Zhang and Wenbin Ruan, "Remote sensing image classification based on improved fuzzy c -means", Ceo-Spatial Information Science, vol.11, no.2, pp:90-94, 2008.
- [39] J. C. Bezdek. Pattern Recognition with Fuzzy Objective Function Algorithms. Plenum Press, New York, 1981.

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- [40] A.Patil and Y.S..Lalitha, "Classification of crops using FCM segmentation and texture, color feature",International Journal of Advanced Research in Computer and Communication Engineering, Vol. 1, Issue6, pp 371-377, August 2012.
- [41] P. S. Hiremath and J. Pujari, "Content Based Image retrieval based on Color, Texture and Shape features using Image and Its Complement", International Journal of Computer Science and Security, vol. 1, no. 4,2010, pp. 25-35.

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### Table.3 Feature Information of 7 Different Classes

Table.3 (Description): Class1-Normal Superficial, Class2-Normal Intermediate, Class3-Normal Columnar, Class4-Light Dysplastic, Class5-Moderate Dysplastic, Class6-Severe Dysplastic, Class7- Carcinoma-In-Situ

Features/ClassesClass1Class2Class3Class4Class5Class6Class7Contrast1.59650.40400.81860.40511.15761.62280.7746Correlation0.16720.27960.25220.20630.25420.14550.3176Energy0.78540.93690.88350.94130.82660.77250.8819Homogeneity0.91910.97900.95900.97970.94190.91660.9611Entropy0.54360.54360.39550.39550.49800.54360.4980Skewness7.73677.80707.79207.80687.77157.73397.7935Kurtosis61.226461.971961.814961.970261.599061.196261.8309Area83690419373077497768488064Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidit		1	1	1	1	1	1	
Correlation0.16720.27960.25220.20630.25420.14550.3176Energy0.78540.93690.88350.94130.82660.77250.8819Homogeneity0.91910.97900.95900.97970.94190.91660.9611Entropy0.54360.54360.39550.39550.49800.54360.4980Skewness7.73677.80707.79207.80687.77157.73397.7935Kurtosis61.226461.971961.814961.970261.599061.196261.8309Area83690419373077497768488064Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter <td< td=""><td>Features/Classes</td><td>Class1</td><td>Class2</td><td>Class3</td><td>Class4</td><td>Class5</td><td>Class6</td><td>Class7</td></td<>	Features/Classes	Class1	Class2	Class3	Class4	Class5	Class6	Class7
Energy0.78540.93690.88350.94130.82660.77250.8819Homogeneity0.91910.97900.95900.97970.94190.91660.9611Entropy0.54360.54360.39550.39550.49800.54360.4980Skewness7.73677.80707.79207.80687.77157.73397.7935Kurtosis61.226461.971961.814961.970261.599061.196261.8309Area83690419373077497768488064Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540 <td>Contrast</td> <td>1.5965</td> <td>0.4040</td> <td>0.8186</td> <td>0.4051</td> <td>1.1576</td> <td>1.6228</td> <td>0.7746</td>	Contrast	1.5965	0.4040	0.8186	0.4051	1.1576	1.6228	0.7746
University0.91910.97900.95900.97970.94190.91660.9611Entropy0.54360.54360.39550.39550.49800.54360.4980Skewness7.73677.80707.79207.80687.77157.73397.7935Kurtosis61.226461.971961.814961.970261.599061.196261.8309Area83690419373077497768488064Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Correlation	0.1672	0.2796	0.2522	0.2063	0.2542	0.1455	0.3176
Entropy0.54360.54360.39550.39550.49800.54360.4980Skewness7.73677.80707.79207.80687.77157.73397.7935Kurtosis61.226461.971961.814961.970261.599061.196261.8309Area83690419373077497768488064Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Energy	0.7854	0.9369	0.8835	0.9413	0.8266	0.7725	0.8819
Skewness7.73677.80707.79207.80687.77157.73397.7935Kurtosis61.226461.971961.814961.970261.599061.196261.8309Area83690419373077497768488064Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Homogeneity	0.9191	0.9790	0.9590	0.9797	0.9419	0.9166	0.9611
Kurtosis61.226461.971961.814961.970261.599061.196261.8309Area83690419373077497768488064Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Entropy	0.5436	0.5436	0.3955	0.3955	0.4980	0.5436	0.4980
Area83690419373077497768488064Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Skewness	7.7367	7.8070	7.7920	7.8068	7.7715	7.7339	7.7935
Major axis length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Kurtosis	61.2264	61.9719	61.8149	61.9702	61.5990	61.1962	61.8309
length33.961743.334953.403668.490287.0157111.4797112.2926Minor axis length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Area	836	904	1937	3077	4977	6848	8064
length31.435726.787346.366857.790873.231878.989292.0183Eccentricity0.37850.78610.49620.53670.54010.70570.5731Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540		33.9617	43.3349	53.4036	68.4902	87.0157	111.4797	112.2926
Orientation-26.729839.20366.5674-37.853345.5611-12.2252-53.9403Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540		31.4357	26.7873	46.3668	57.7908	73.2318	78.9892	92.0183
Convex area85692419713173507970378313Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Eccentricity	0.3785	0.7861	0.4962	0.5367	0.5401	0.7057	0.5731
Equiv diameter32.625633.926549.661562.592079.604793.3764101.3282Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Orientation	-26.7298	39.2036	6.5674	-37.8533	45.5611	-12.2252	-53.9403
Solidity0.97660.97840.98270.96970.97990.97310.9700Extent0.79170.69970.82780.76310.79750.78280.8071Perimeter101.3760109.4650156.4550203.4790256.5070306.0130333.2540	Convex area	856	924	1971	3173	5079	7037	8313
Extent         0.7917         0.6997         0.8278         0.7631         0.7975         0.7828         0.8071           Perimeter         101.3760         109.4650         156.4550         203.4790         256.5070         306.0130         333.2540	Equiv diameter	32.6256	33.9265	49.6615	62.5920	79.6047	93.3764	101.3282
Perimeter         101.3760         109.4650         156.4550         203.4790         256.5070         306.0130         333.2540	Solidity	0.9766	0.9784	0.9827	0.9697	0.9799	0.9731	0.9700
	Extent	0.7917	0.6997	0.8278	0.7631	0.7975	0.7828	0.8071
Maar 1.8744 2.2555 2.0028 2.0260 2.4652 2.4200 2.1000	Perimeter	101.3760	109.4650	156.4550	203.4790	256.5070	306.0130	333.2540
Mean 1.8/44 2.3333 2.9028 2.9209 2.4033 2.4200 2.1009	Mean	1.8744	2.3555	2.9028	2.9269	2.4653	2.4200	2.1009
Median         2.0000         2.0000         3.0000         3.0000         2.0000         2.0000         2.0000	Median	2.0000	2.0000	3.0000	3.0000	2.0000	2.0000	2.0000
Standard deviation         0.8860         0.7756         1.1034         1.0544         1.0421         1.0808         0.9788		0.8860	0.7756	1.1034	1.0544	1.0421	1.0808	0.9788
Covariance         0.7850         0.6016         1.2176         1.1118         1.0859         1.1681         0.9580	Covariance	0.7850	0.6016	1.2176	1.1118	1.0859	1.1681	0.9580
Range         3.0000         3.0000         3.0000         3.0000         3.0000         3.0000         3.0000	Range	3.0000	3.0000	3.0000	3.0000	3.0000	3.0000	3.0000