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Exploration and Performance Assessment of Efficient Histopathology Image Pre-Processing and Segmentation Techniques for Breast Cancer Prediction

Vandana Kate Pragya Shukla

Abstract— Evaluation of features after segmentation is a significant process in image processing, especially in the medical field. Medical imaging technologies are widely utilized in clinical diagnosis to guide therapeutic and surgical decisions and to monitor disease advancement, understanding occurrence and re-occurrence of infection and view treatment response. Among all cancer kinds, Breast Cancer (BC) now-a-days has turn out to be a common form of cancer amongst ladies around the world and is the second common cause of most cancers deaths. At present, there aren't any powerful methods to save you and remedy breast cancer, because its cause is not absolutely known. Early detection is the most effective way to enhance breast cancer survivals and might deliver a better hazard of full healing. The main motive of this paper is to implement various efficient image segmentation techniques after preprocessing histopathology BC images of different magnification level and exhaustively compare them to achieve best results. We analyze the outcomes of widely used edge detection based image segmentation methods such as Adaptive K-Means, Multi Class Fuzzy C-Means, Canny, Gabor filter and Homogeneity based PSO and evaluate them via metrics which includes accuracy, precision, recall and F-degree. Various preprocessing strategies like histogram equalization (HE), Adaptive equalization (AE) and Contrast Stretching (CS) are compared and used to enhance the performance of above segmentation methods. Contrast Improvement Index (CII) is chosen as a selection criteria for preprocessed image. Finally one vs. all multiclass SVM classifier is used for BC image classification. Our implementation uses breast cancer dataset having two classes as benign and malignant each in turn having four sub-classes. Images of different magnification levels such as 40x, 100x, 200x and 400x, are considered for BC detection.

Index Terms— Breast Cancer, Classification, Image Segmentation, Multiclass SVM

I. INTRODUCTION

An image is a manner of shifting statistics, and carries masses of beneficial records. Understanding the image and extracting information from the image to perform particular task is a crucial area of application in digital image era. Image segmentation is a method that allows extraction of important objects or regions for further analysis [1]. The use of digital images has been improved at a tremendous speedy pace over the past era.

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* Correspondence Author
Vandana Kate*, Research Scholar, Institute of Engineering and Technology, DAVV Indore, India. Email: vandana.kate@gmail.com
Pragya Shukla, Associate Prof., Instutute of Engineering and Technology, DAVV Indore, India. Email: pragyashukla_iet@yahoo.co.in

Now days either photographs, printed text and other hard copy media are converted into digital form or they are directly attained using sensors and allied electronics gadgets.

Several present day imaging modalities in medicinal drug, including magnetic resonance imaging (MRI), computed tomography (CT) and virtual mammography additionally produce images immediately in digital form [2]. With the development of scientific image processing, the realm of the healthcare place has commenced receiving the advantages of the modern area of diagnostic equipment to perceive the ailments efficiently. Cancer is one of the dreaded ailments, wherein fulfillment price is a considerable problem and is still an unsolved disadvantage. Cancers that are confined to the wall of the organ (usually in stage 1) are often curable with surgery whereas the cancer that has spread outside the organ and to other neighboring parts usually is incurable or very difficult to cure. In such cases the oncologist focuses on extending the life of the patient through chemotherapy, radiation etc Breast cancer is one of the most common sort of cancer, in addition to the primary cause of mortality among ladies. Breast cancers holds second commonplace worldwide after the lung cancer, and is the fifth common reason for loss of life due to cancer 5]. The next section describes the essential terminology of the paper background scenario.

The remaining paper is organized in four sections. Section II describes relative backgrounds details of the work. Section III introduces some prior work in this domain. Section IV provides our proposed work of this paper. Section V illustrates the performance of the developed system. Section VI summarizes the whole work.

II. BACKGROUND

The background study is an important part of any research and provides the context and purpose of the study.

A. Medical Imaging

Medical imaging is a valuable tool in medicine. Important medical imaging techniques are:

- *MRI* – to produce two-dimensional images of the body and brain.
- *Elastography* - to map the elastic properties of tender tissue inside the frame..
- *Ultrasonography* - to provide pix of a foetus, abdominal organs, coronary heart, breast, muscular tissues, tendons, arteries and veins for diagnostic purposes.

- *Radiography* - to become aware of bone fractures, pathological modifications in lungs and to diagnose positive styles of colon cancer, and many
- *Histopathology*- is the microscopic examination of extracted biological tissues, conscientiously prepared into histological sections and stained utilizing histology stains (such as Immuno-Histochemical (IHC), Hematoxylin-Eosin (H & E)) to observe the appearance of diseased cells and tissues in very fine detail.

Segmentation is often a first processing level to extract areas of importance which includes visualization, measurement, registration, motion evaluation etc. It is often described as partitioning an image into a finite number of semantically non-overlapping regions as shown in figure 1. In medical applications, it is a fundamental process and supports medical diagnosis, surgical planning and treatments. The success of image analysis depends on how accurate partitioning of an image has been done, where each partition resemble different objects or parts of objects. A better segmentation is naturally one in which:

- Pixels in the same partition have same grey scale or multivariate values
- Neighboring pixels in different categories have unrelated values

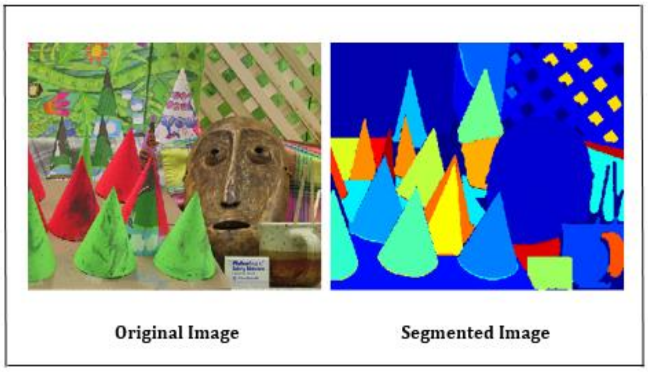


Figure 1: Image Segmentation

B. Image Segmentation Techniques

A great variety of segmentation methods has been proposed in the past decades. There are in general three approaches to segmentation, classified as shown in figure 2.

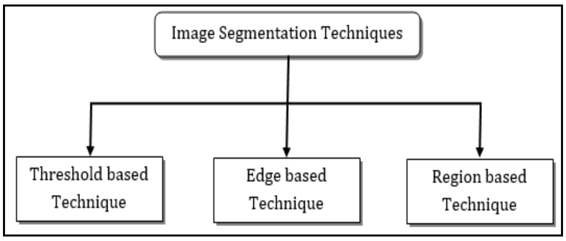


Figure 2: Classification of Image Segmentation

Threshold based segmentation is the most effective method of image segmentation which directly divides the image based totally on intensity levels of different objectives. Threshold segmentation may be divided into local threshold and Universal threshold technique. The Universal threshold technique divides the image into two separations as target and the background with the aid of the use of a single threshold value [17]. The local threshold divides the image into a couple of target areas and backgrounds via the usage of multiple thresholds.

In this method image is segmented by comparing pixel values with the predefined threshold limit L . Let I(u,v) be an input Image and O(u,v) be an output image then following equation describes the threshold method –

$$O(u,v) = \begin{cases} 0, & I(u,v) < L \\ 1 & I(u,v) \geq L \end{cases}$$

where, I(u,v) is the pixel Intensity at the position (u,v). The method is called adaptive thresholding when a different threshold is used for different regions in the image.

The gain of the threshold method is that the calculation is easy and the operation velocity is faster. In particular, whilst the target and the background have excessive contrast, true segmentation effect may be obtained.

Edge based segmentation is a common approach of detecting boundaries and discontinuities in an photo. An edge is a fixed of associated pixels, with adjacent pixels having identical depth degree. Any pixels can be distinguished by estimating the depth gradient [3], i.e. variance in evaluation. An edge is a well known concept and does no longer always need to shape a closed path. In edge-based segmentation, an edge filter is implemented to the image, categorizing pixels as facet or non-edge relying on the clear out output.

Region-based segmentation functions iteratively via grouping neighbouring pixels having feature comparable values, and as a consequence splitting group of pixels which might be unrelated in value. Region based segmentation strategies are noise resistant and splits an image into numerous areas based mostly on pre-described standards, i.e. color, depth or unique object. Region based segmentation strategies are labeled into 3 essential classes, i.e. region growing, region splitting, and location merging [18]. Contrary to edge based method which locate the object boundaries and then proceeds to discover the object itself by filling them in, a region based technique starts offevolved inside the middle of an item after which grows apparently till it detects object limitations [14].

III. LITERATURE SURVEY

For cancer analysis, many segmentation methods have been proposed for different medical image modalities to address various types of cancer such as cervical [11-13], prostate [15] and breast cancer [6-9] such as Active contour Model, Hough Transform, Adaptive Thresholding, H-Maxima Transform, Graph Cuts, Clustering etc. The major challenge faced is that structures of the cells are very specific to particular cancer type and may vary significantly. Therefore, the above mentioned methods cannot be straightforwardly utilized for segmentation of all types' images.

In histology image analysis, majority of work rely on thresholding techniques and clustering techniques for nuclei segmentation. Thresholding technique is the simplest way to differentiate nuclei from background by analyzing every image pixel intensity. But their downside is that they are sensitive to noises, background variation and depth heterogeneity [16,17,19].

Clustering techniques group pixels having similar features without labeling the objects [20, 21, 22]. Other popular nuclei segmentation techniques are Graph cut methods [7], Active Contour [23, 24] and watershed method [29].

Maqlin Paramanandam et al. [25] developed enhance segmentation set of rules for detecting separable nuclei from Hematoxylin and Eosin (H&E) marked breast histopathology snap shots. This detection strategies evaluates nuclei saliency map with the use of tensor voting observed by aspect extraction of the nuclei at the saliency map using Loopy Back Propagation (LBP) on a Markov Random Field (MRF). The method turned into examined on entire-slide pix and frames of breast most cancers histopathology pics. Investigational effects exhibit unique segmentation performance with powerful precision and dice-coefficient costs, upon testing on valued-grade breast most cancers snap shots comprising of many thousand nuclei. **S. Sasikala** et al. [26] equated various to be had segmentation techniques for segmentation of mammogram pix. **Samir M. Badawy et al**. [27] have implemented improved double thresholding-based approach for Mammograms' image segmentation. Furthermore, authors added the borders to the segmented picture as an define supporting medical doctors to without difficulty find the breast cancers into various Mammograms. Simplification for this look at is probable no longer simplest on x-ray but for all biomedical pics, as a sophisticated segmentation manner for better visualization, detection, and characteristic extraction and so improved prognosis. Likewise, this guide thresholding technique has the benefit of decreased processing time and additionally processing storage range.

Abdul Qayyum et al. [28] proposed a simple approach for breast most cancers detection in virtual mammograms. Proposed method consists of 3 fundamental phases, i.e. segmentation of breast location, elimination of pectoral muscle and classification of breast muscle into not unusual and uncommon tissues. Breast muscle segmentation changed into accomplished via using the use of Otsu's segmentation method, in the end removal of pectoral muscle is finished via canny area detection and straight line estimate method. In subsequent step, Gray Level Co-occurrence Matrices (GLCM) changed into used for feature extraction. At the cease, SVM classifier was educated to classify breast vicinity into commonplace and unusual tissues.

However, a preprocessing step for stain normalization or improving evaluation isn't always considered in these strategies, as a result lowering the accuracy of the detection system. In addition, there is a loss of quantitative assessment of the preprocessing techniques. To deal with these shortcomings, we have applied a few recognized segmentation techniques on well preprocessed images.

IV. PROPOSED WORK

This section demonstrates the functional and theoretical aspects of the working model. Figure 3, as shown below contains the different components of the proposed functional model for performance comparison:

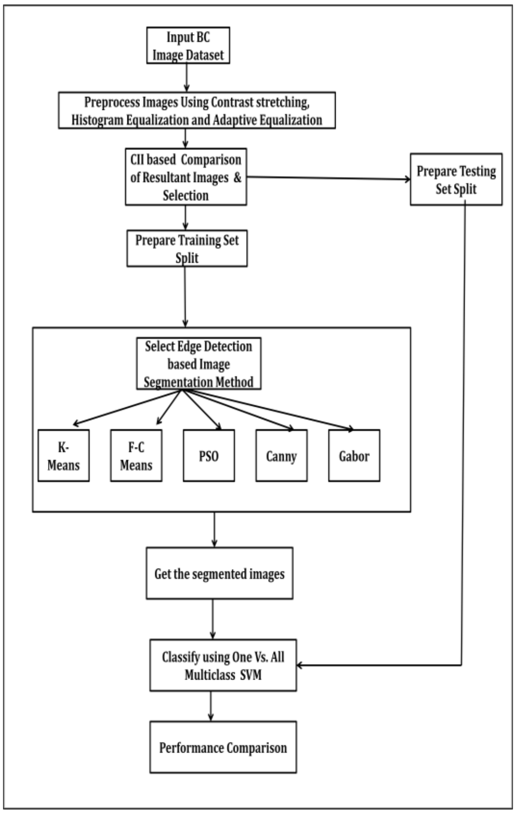


Figure 3: Proposed System Architecture

The work in this paper is intended to provide comparative data model for medical image dataset of breast cancer tissues. The medical image dataset used contains two classes i.e. benign and malignant. Each class further contains four sub classes each with images of zoom level 40x, 100x, 200x and 400x of various patients. The process works in different phases such as-

A. Pre-Processing: The preprocessing level is an crucial step in improving the quality of the image.. To enhance the histopathology image contrast, three enhancement methods, namely, histogram equalization (HE), Adaptive equalization (AE) and Contrast Stretching (CS) are applied [31-33]. The contrast improvement index (CII) is evaluated for every resultant image for assessing the performance of the implemented image enhancement techniques in phrases of the luminance, evaluation, and structure.The better the CII cost, the better is the photo.

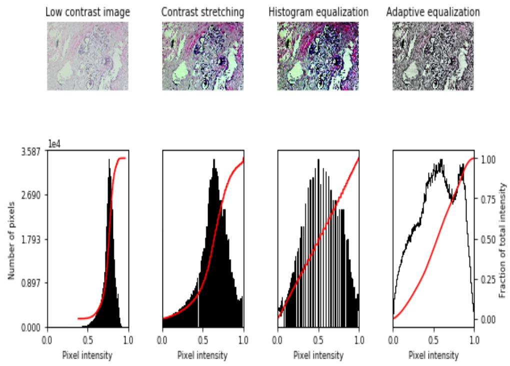


Figure 4: Image Enhancement Method comparison

B. Segmentation Process: In this phase, we apply edge based segmentation methods on processed image obtained from above step. The process takes BC images as input for chosen algorithm namely Adaptive k-means, fuzzy c-mean, gabor filter, canny edge filter and PSO learning which processes each sample images one by one to produce enhanced featured dataset. The output of each algorithm is the segmented images and respective feature dataset. The various segmentation methods are illustrated below:

1. Edge Segmentation with adaptive K-Means

Adaptive k-means is an automatic and rapid way to generate accurate segmentation results of any input Color image (3 channel(0-255)) or gray image (single channel(0-255)) and avoids the interactive input of initial cluster number value to start iteration. It uses the principle of k Means which takes Euclidean distance as the similarity metric to find the most advantageous segmentation effects. Most importantly it generates consistent output for same image.

2. Edge Detection using Gabor filters

Gabor filters are linear band pass filters i.e they allow only specific band of frequencies and reject the others [4]. A 2D Gabor function may be articulated as :

$$G(x,y,\lambda,\Psi,\sigma,\Upsilon) = \exp(-(x'^2+\Upsilon^2 y'^2)/(2\sigma^2))\exp(i(2\pi x'/\lambda + \Psi))$$

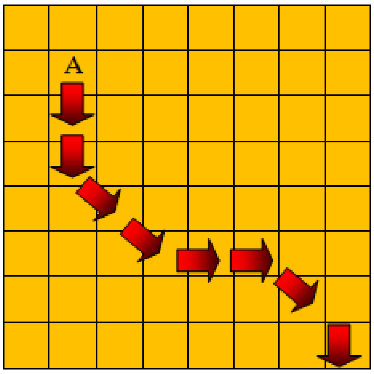
Where $x' = x * cos(theta) + y * sin(theta)$ and $y' = y * cos(theta) - x * sin(theta)$

x and y are the coordinates of given BC image, λ is the wavelength of the sinusoidal wave, ϕ is the orientation of the Gabor function, controlling type of features the filter responds to. ψ is the phase shift of the Gabor function, γ is the spatial factor ratio, controlling ellipticity variant of Gaussian function, σ is the standard deviation(SD) of the Gaussian function used in Gabor filter and controls the spread of Gaussian function .

Gabor filters with four wavelengths, $\lambda = 2, 4, 6$ and 8, and orientations in the range $[0, 2\pi]$ was convolved with BC image. The values of the other parameters are as follows: phase offset in range $[0\ pi/2]$, aspect ratio 0.5, and bandwidth 1.

3. Homogeneity based edge Segmentation using Particle Swarm Optimization

PSO is a function optimizer which works on the principle of mutual cooperation among unintelligent particles to find the optimal solution to a given problem. In this method every particle represents a potential solution to a problem and tries to update itself based on its own and neighboring particle experience. Here for the particular problem of BC image classification, addressed in this paper, each particle is assumed to represent a edge curve and overall objective is to find optimal fitting curve on an object's edges. Each particle is encoded as N dimensional particle lying in the range [0,8] representing direction of the movement of curve [34] as shown in figure 4. The particle for representing the edge curve defined in cube will be-



5	5	4	4	3	3	4	5	0	0	….

Figure 4: N dimensional particle lying in the range [0,8]

As quantity of pixels on curve is less than dimension of particle different cells will be set to 0. As pixels on an edge curve of an image have uniform intensity and larger homogeneity than the pixels not on the curve PSO maximization objective function fc of a curve C is stated below which is based on the uniformity (Uc) and homogeneity (Hc) factors-

$$fc = \begin{cases} -\infty & H_c < \text{Threshold} \\ (H_c - U_c) * L_c & H_c \geq \text{Threshold} \end{cases}$$

Where –

$$H_c = \frac{1}{L_c}\sum_{i \in c} H_{p_i},$$

$$H_{p_i} = \begin{cases} \max\left(\left\{\left|I_{p_i} - I_{N_j}\right| j = 1 \ldots 8\right\}\right) & \text{if} > \text{Threshold} \\ 0 & \text{Otherwise} \end{cases}$$

$$\& \quad L_c = \frac{1}{L_c}\sum_{i=1}^{L_{c-1}} \left|I_{p_{i+1}} - I_{p_i}\right|$$

Here p_i is the i^{th} pixel on curve C , L_c is the length of curve, N_j is the neighbor of any pixel P_i , I_p is intensity of pixel P_i and threshold value lies between 0 to 255.

ALGORITHM

{

For each pixel P not marked as an edge on an image do

Initialize PSO population randomly for pixel P
Repeat
{
For every particle do
{
Decode the particle as curve C
Evaluate f_c
If f_c > optimal fitness value then
{Set current value as the newly found best Particle
}
End if
}

For every particle do
{

The particle velocity

$v_i(t) = (v_{i1}(t), \; v_{i2}(t), \ldots\ldots\ldots v_{ij}(t) \ldots\ldots\ldots v_{iN}(t))$, of particle i at the time t is updated utilizing the following formula-

$$v_{ij}(t+1) = w * v_{ij}(t) + c_1 r_{1j}\left(y_{ij}(t) - x_{ij}(t)\right) +$$
c2r2jzjt− xijt

where w is called the inertia factor ranging usually between $[0.4, 0.9]$, c_1 and c_2 are learning or acceleration factors ranging between$[2, 2.05]$, r_{1j} and r_{2j} are random variables between $[0, 1]$, and velocity v_{ij} ranges between $[-10, 10]$. Update particle position according to eq. - $x_i(t+1) = x_i(t) + v_i(t+1)$
}

Until maximum iterations is surpassed or minimum error criteria is attained.
}

4. Edge Segmentation using Canny Edge Detection

Canny Edge Detection evolved by using John F. Canny in 1986 is a multistep set of rules stated as below:-

1. Noise Reduction using 5X5 Gaussian filters to avoid any deviation using edge detection.
2. Finding Edge Gradient (G) and Angle ϴ (as horizontal, vertical or two diagonal types) for each pixel of a given image using Sobel Kernel filtering as $G = \sqrt{G_x^2 + G_y^2}$ and $\Theta = \tan^{-1}(\frac{G_Y}{G_X})$ where G_x is first derivative in x direction and G_y is first derivative in y direction.
3. Non-maximal suppression considers a pixel point as an edge point if its gradient intensity is greater than the two pixels along the positive and negative gradient direction or else it is suppressed and put to zero.
4. Double threshold detection decides which are all edges are really edges are not using two threshold values, minVal and maxVal. If the edge pixel gradient is bigger than the maxVal, it's far taken into consideration to be a strong aspect factor. If the brink gradient is smaller than the maxVal and larger than the minVal, it is marked as a susceptible area point, and points underneath the minVal are suppressed.

5. Edge Detection using Multi Class Fuzzy C-Means (FCM)

FCM uses the concept of fuzzy logic useful for modeling complex systems which imitates human behavior of dealing with non-linear, imprecise and noisy data [30]. It is a method based on minimization of the cost characteristic and lets in any information point to belong to at least one or greater clusters.

1. Let $IM = x_i$, $i = 1,2,\ldots,N$ $x_{i,} \in R$ where $x_i = (x_i, y_i, z_i)$ denote a HE stained coloured BC image with total N pixels to be partitioned into C Classes/ Clusters using Fuzzy Membership function
2. Convert IM to Gray Scale
3. Reshape the image size of IM
4. Initialize number of Clusters (C), Minimum Improvement(MI) , Fuzzy Partition Matrix (Ui) and Fuzzy Membership Weighting Exponent (M>1)
5. Create a vector of initial cluster centers as $C^K = [c_j]$ and calculate degree of Membership of each pixel x_i in j^{th} cluster computed using following equation as-

$$U_{ij} = \frac{1}{\sum_{k=1}^{C} \left\|x_i - c_j\right\|^2 / \left\|x_i - c_k\right\|^{2^{1/M-1}}}$$

6. Update cluster centers as-

$$\text{new } c_j = \left(\sum_{i=1}^{N} U_{ij}^{M} * x_i\right) \Big/ \left(\sum_{i=1}^{N} U_{ij}^{M}\right)$$

7. Calculate minimization cost function which represents the distance from cluster centre to any pixel point weighted with the membership grades of that pixel point's as-

$$J_m = \sum_{k=1}^{C} \sum_{i=1}^{N} U_{ki}^{M} \left\|x_i - c_j\right\|^2$$

8. Iterate till the minimum permissible error is achieved or maximum number of iteration are completed
9. Get the FCM partitioned clusters and select the desired cluster using morphological methods for feature extraction

C. Training and Testing set: Here greater featured dataset is transformed in sub-units specifically training set and test set. The partition of records is achieved on the idea of 70-30% ratio with the aid of random selection of sample images. The 70% of statistics is used for training of the computational statistics version and the closing 30% of records is used for checking out or validation of studying algorithm.

D. One Vs. All Multi-Class SVM Classifier: This phase performs the classification of the segmented images. For this, we classify segmented images using one vs all support vector machine (M_C SVM) for multiclass classification. One vs all will educate/train one classifier in step class thus in total we have 8 classifiers (as there are total 8 sub-classes). For any class *i* it will expect *i*-labels as positive and the rest as negative. As it is much less sensitive to imbalanced datasets the algorithm works favorably well.

E. Performance Comparison: Here we perform computational analysis to demonstrate the performance of all the above five segmentation algorithms used. The metrics used for performance comparison of individual segmentation algorithm are precision, recall and f-measure.

Precision: Precision degree is the ratio of the range of correct positive outcomes and range of all positive outcomes. It measures the exactness of any classifier. The better the precision method much less are the false positives (FP), at the same time as the decrease precision technique reflects greater wide variety of fake positives. The formula goes as:

$$Precision\ Rate(P) = \frac{TP}{TP + FP}$$

-TP is the number of true positives.

-FP is the number of false positives.
Higher value of precision indicates a very good performance by means of the segmentation technique. Below figure 5 depicts comparable performances of Adaptive K-Means, Gabor and FCM with respect to precision as a measure. Here X-axis represents the algorithm applied and the Y axis shows the performance in terms of precision charge percentage.

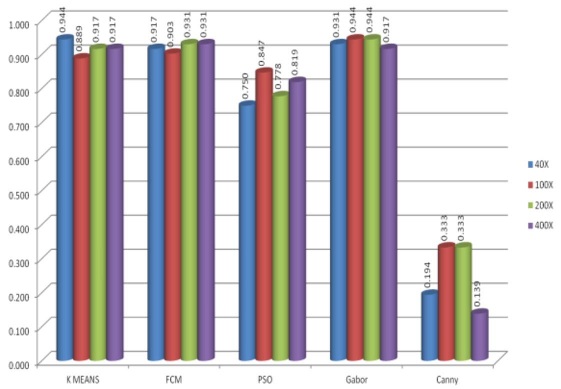


Figure 5: Precision Rate comparison

Recall: Recall is the proportion of the wide variety of correct positive outcomes and number of positive results that should have been returned. It measures the completeness or the sensitivity of the implemented classifier. Higher the recall smaller are the false negatives (FN), while decreased recall rate reflects extra false negatives. Recall rate is defined as:

$$Recall\ Rate(R) = \frac{TP}{TP + FN}$$

-FN is the number of false negatives
Recall gives data about the correctly identified edge pixels in an image. The figure 6 depicts the comparative recall rate of selective five segmentation algorithm. In order to show the performance of all algorithms, the X-axis contains the algorithm applied and the Y axis shows the performance in terms of recall rate percentage. As demonstrated Multiclass SVM classified images gives better result with respect to Adaptive K-Means, Gabor and FCM. The high recall means that an function returned most of the pertinent results.

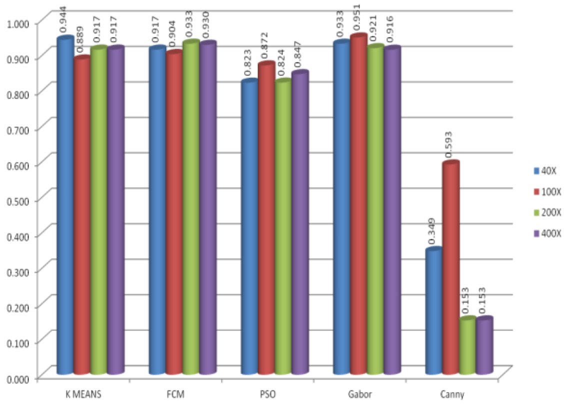


Figure 6: Precision Rate comparison

F-Measure
F-degree is used to measure efficiency and success of segmentation based totally on the values of precision (P) and recall (R). In order to have uni-modal degree with higher effectiveness, F-measure is calculated by combining precision and recall. It is a weighted average of precision and recall, in which F1 rating reaches its exceptional value at 1 or towards 1 and worst value at 0 or closer to 0. It may be described as:

$$FMeasure = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Figure 7 shows the F-Measure information for different segmentation algorithm and different input medical image dataset. According to this graph Adaptive K-Means, FCM and Gabor are giving much better performance for F-Measure parameter as compared to others. Overall the performance is summarized in table below. The table 1 summarizes performance by averaging the particular values of precision, recall and f-measure for 40x, 100x, 200x and 400x magnified BC images.

Table 1: Average Performance

Average performance			
Algorithm Used	Precision	Recall	Fmeasure
K MEANS	0.917	0.917	0.917
FCM	**0.920**	**0.921**	**0.921**
PSO	0.799	0.842	0.819
Gabor	**0.934**	**0.930**	**0.929**
Canny	0.250	0.312	0.259

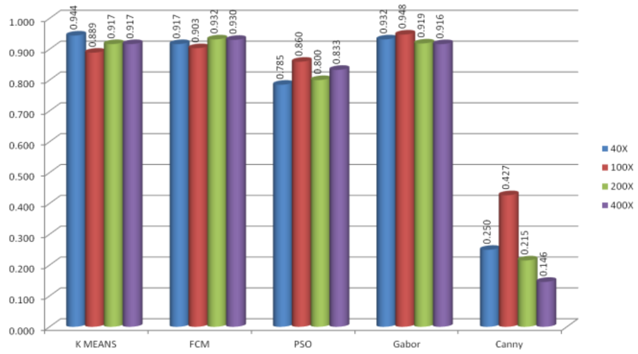


Figure 7: F Measure comparison

V. CONCLUSION

Image segmentation plays a dynamic role in various medical-imaging applications, by automating the extraction of functional structures and other regions of interest. In a conventional feel, image segmentation is the division of an image into areas, wherein parts within vicinity are similar according to a few uniformity predicate, and distinctive between neighboring areas. Due to its importance, segmentation algorithms have been studied and compared on this paper. We have compared five different image segmentation methods namely Adaptive k-means, fuzzy c-mean, gabor filter, canny edge filter and PSO for analyzing their efficiency in breast cancer classification and each method includes histopathological image pre-processing step for improving the results. These algorithms have implemented in MATLAB environment using key performance factor that is precision, recall and F-measure.

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AUTHORS PROFILE

Prof. Vandana Kate received the BE degree in Computer Engineering from Jabalpur Engineering College in 2002 , ME degree in Computer Engineering from Institute of Engineering & Technology affiliated to DAVV University , Indore in 2010 and Currently pursuing PhD in Computer Engineering from the same university . She is working as Associate Professor in Acropolis Institute of Technology and Research and has a vast experience in teaching of more than 15 years . Her research interests include pattern recognition, machine learning, and medical image analysis and computer vision. She has many publications in leading international journals and peer-reviewed conferences, in various fields of Computer Science.

Dr. Prof. Pragya Shukla received ME, PhD degree in Computer Engineering from Institute of Engineering and Technology affiliated to DAVV University, Indore. She has guided many BE , ME student projects and managing many PhD research scholars working in the field of Artificial Intelligence, Image Processing and AI. She is at present holding position of Professor in IET, DAVV, with huge teaching experience and research understanding. She has more than 25 publications in prestigious scientific international journals and peer-reviewed conferences covering various fields of Computer Science. She is also the PhD guide of Prof. Vandana Kate who is working in the field Breast Cancer cell processing using soft computing techniques.