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# Robust Automatic Color Image Region Segmentation

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**Abstract:** Color image region segmentation has a significant contribution in analysis of images and retrieval of relevant images. Color image region segmentation helps the end user to sub-divides the user input images into unique homogenous regions of similar pixels based on pixel property. It is the high end image description of objects, scenes and features. The success of image analysis mainly focused on segmentation reliability. Automatic sub-division of the user input images into unique homogenous accurate regions without over-segmentation is a tedious task. Our paper is focused to segment color images automatically into multiple regions accurately based on local maxima of GLCM texture property and pixels are spatially clustered into identical regions. In the proposed method, for the given input image, the number of regions 'R' is identified based on image texture property. Then, the images are clustered into distinct R regions which are based on median centroid. Our proposed approach generated reliable, accurate and non-overlapped multiple regions for the given user input image. Segmented regions can be automatically annotated with distinct labels which in turn help to retrieve relevant images based on image semantics.

**Key words:** Gray level co-occurrence matrix, local maxima, median centroid, region clustering, India

## INTRODUCTION

Images are the vital medium to convey information. Machine learning lies in understanding the images and predicting information for the images. To understand user input images, the images are segmented into distinct multiple regions and identify objects in each region. Color image region segmentation is an efficient process of splitting the input images into distinct uniform and non-overlapping regions. From segmented images meaningful information are extracted which in turn helps in better image understanding. For a given input image I, the segmented image f is divided into unique R regions based on image intensity values or texture criterion. A segmented image f is a subset of several homogeneous regions Ri, i=1,….m , P(Ri) is a predicate of sum of all points in Ri. It must be true for all pixels inside the region and false for pixels in other regions. If the distinct regions Ri and Rj are neighbours, then the union of these regions forms a connected component. Image Segmentation finds a wider application in the research area of high-level image analysis. The color image region segmentation focused on the field of video surveillance, face recognition, object detection, fingerprint recognition, multimedia applications, image retrieval based on image contents and medical imaging.

Color image region segmentation are implied on the intensity property of discontinuity and similarity. Discontinuity property partition the imagesbased on sharp changes in intensity and similarity property divides the imagespurely based on similarity criteria. The color image region segmentation methods are edge based, region based, threshold, features based clustering and model based clustering. In threshold based segmentation technique, a histogram are generated and the image regions are identified on the peaks and valleys of thehistogram. Edge based segmentation discover the multiple object edges from images. In feature space clustering approach, intensity value is found for each pixel and the image pixels are grouped into clusters. Region-based segmentation splits the image into multiple regions after the process of region growing, region-splitting and region merging.

The most important data mining technique is clustering is an unsupervised data mining technique used to group thousands or millions of pixels based on pixel property. It is recommended for high end data analysis where data items are partitioned into different groups based on high cohesion and low coupling property (Peng *et al*., 2011). The clusters formed can be of hard or soft clusters. Hard clustering includes unique data item in every cluster and soft clustering exhibit membership values to be found in multiple clusters. The major issue to be tackled when dealing with color image segmentation based on clustering approach are user input for number of

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clusters and generation of stable and identical clusters. From the issue identified our study is focussed on identifying the number of regions 'R' automatically from the input RGB image based on local maxima of gray level co-occurrence matrix invariant of offset and symmetric property. Based on R regions, RGB image is accurately segmented into R regions based on median centroid clustering.

**Literature review:** Many approaches to color image segmentation have been proposed over the years. Region based segmentation is the widely used method for segmenting color images into distinct regions. The major section of region based segmentation are initial seed selection, region growing and region merging based on single or group of pixel. One of the technique of region based segmentation is clustering approach. The major issue of the clustering based segmentation is that the user has to specify the number of clusters/seeds-K, regions/ cluster formed based on seeds and then region merging can be done if over-segmentation regions are produced. Research study are reviewed on the areas of region segmentation and the researchers work are analyzed.

Peng *et al*. (2011) addressed the automatic image segmentation problem in a region merging style. From the initial over-segmented regions, pixels with homogeneous color are detected and segmented regions are formed by merging the smaller regions based on statistical test. The two major issue of region merging are order of merging and the stopping criteria. The sequential probability ratio test is chosen to reduce the issue of region merging and also cost criteria is set to be minimum.

Huang *et al*. (2010) devised a automatic seed selection and region growing algorithm. The seeds are selected automatically based on non-edge fuzzy membership and smoothness at pixel's neighbor. From the initial seed selection, regions are formed and tiny regions are merged to form segmented regions. The experimental results proved the effectiveness and efficiency of the method.

Bra *et al*. (2015) conducted an experimental study to cluster the iris and wine data sets by using k-means and watershed segmentation by using HSV and Lab color space. The paper proposed better results showing that HSV color space performs better than L×A×B×color space for noisy images.

Jayasree and Narayanan (2015) proposed an improved Otsu threshold method for color image segmentation by dividing the histogram into class regions based on mean value. Finally, all the class regions are merged which identify the fine structures of the objects even in complex images. The computation cost is reduced due to iterative method.

Kiruthika and Ramya (2014), suggested a method for automatic recognition of follicles in ultrasound images. Theproposed algorithm employed discrete wavelet transform based k-means clustering wavelet transform for follicle detection.

Yedla *et al*. (2010) proposed a technique for initial centroid and provides an efficient way of assigning the data points to suitable clusters which reduces the time complexity. An enhanced K-Means algorithm is proposed with user input of number of clusters.

Bora *et al*. (2014) suggested iterative segmentation process in which the segmentation process stopped when region of interest is separated from the input image. But this region of interest differs from applications and there does not exists a segmentation algorithm to satisfy the global applications. This study also suggested an automatic seeded region growing algorithm for segmentation of color images.

Choong *et al*. (2012) suggested normalized cuts in image segmentation of various sized images is still lacking of analysis of its performance. The researchers try to give an effective image segmentation using graph partitioning method with reduced computation cost. Thus, graph-based image segmentation methods are carried out in multistage approach with computational cost reduced.

Lassalle *et al*. (2015) proposed his work on image segmentation algorithms for large amounts of data. Initially, large images are divided into smaller image tiles which are processed independently to overcome memory issue. A scalable tile-based framework is used for region-merging algorithms to segment large images. Finally, the benefits of this framework are discussed and demonstrated the scalability of this approach by applying it to real large images.

Abdullah *et al*. (2012) suggested that both Otsu and K-means methods failed to produce good quality of segmented regions for complex background and non-uniform illumination images. To overcome this issue, this study proposed an improved inverse threshold based segmentation that was able to partition natural images into several regions accurately. The proposed technique gives better performance than traditional thresholding and clustering techniques.

Sujatha and Pappa (2011) also used k-means clustering for brain segmentation which give better result in identification of tumor in brain images. The proposed algorithm produced better result than fuzzy c-means and adaptive k-means clustering. Both the work depends on user input for number of cluster and unstable clusters are formed.

Tao *et al*. (2007) proposed a technique by incorporating the advantages of mean shift and normalized cut segmentation. The combined method produced effective and robust segmentation of color images with low computational complexity and highly feasible for real-time image segmentation processing.

From the studies surveyed, for segmenting natural images using clustering/region based approach,either the number of clusters/seeds to be specified by the users and criteria for region growing or initial centroid selected randomly. Various techniques have been proposed by a researcher for identifying the number of clusters/seed selection or assignment of initial centroid/criteria for region growing which involves lot of computation and even sometimes produces incorrect segmentation. The techniques are also highly suitable for a specific images or specific application. So, a technique has to be devised to automatically identify the number of regions/seeds-‘ R’ and forming R regions based on centroid to produce accurate segmented regions . The final segmented regions produced should be of high quality obtained with reduced computation and complexity.

## MATERIALS AND METHODS

In the proposed system, automatic color image segmentation is done to produce accurate segmentation of multiple regions. The proposed system accepts an input RGB images , undergone pre-processing stage to remove noise . Optimal seeds ‘R’ are automatically selected based texture features. From the R seed points, distinct R regions are formed. Proposed system block diagram is shown in Fig. 1. The pseudo code of the above process is shown below.

**Algorithm A; Pseudo code**

```
voidautoregseg(I, ?, â )
{
//Input- I : RGB Image
// Input- ?, â- gray levels
// Output – Segmented Regions
% Optimal Seed Formation
  G= 0.2989 * R + 0.5870 * G + 0.1140 * B
simg=medfilt2(G)

% Seeds Formation based on texture
forgl= 8 : â
  {
GLCM(gl)=graycomatrix(simg,gl)

D(gl)=diagonal.GLCM(gl)
LM(gl)=findpeaks(D(gl))
  }
  R=histogram(max(LM))

% Image Transformation
lab =rgb2lab(I)
vecab=ab(:) –min(ab)+1

 % Region Clustering
for i = 1:R
medcent=i*median(ab)/R+1
while (true)
 {
oldcent=medcent;
dist= cityblock(distab);
for i=1:k
updmedcent=ceil(vecab);
if (oldcent == updmedcent)
break;
  }
}
```

**Image Pre-processing:** An input RGB image is processed to identify number of seeds in the image automatically. For determining the number of regions, the input RGB is converted into gray scale image. The grayscale image is retrieved from the RGB image by mixing 30% of RED, 60% of GREEN and 11% of BLUE. The grayscale image conversion is done to specify image brightness information. The resulting image will be two dimensional, the value 0 for black and the value 255 for white. The gray scale values are in the range of 0 to 255. Gray Scale image is obtained by using Eq. 1:

$$G = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B \tag{1}$$

Gray scale image are passed into pre-processing stage. Smoothing techniques are applied to remove noise

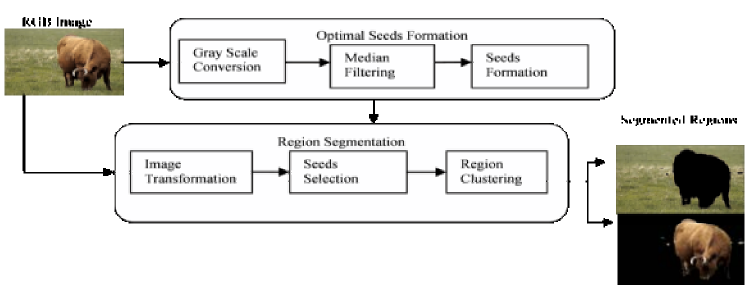


Fig. 1: Proposed system block diagram

in the images but in turn adversely affect edges. But, it is important to preserve the edge which shows the physical appearance of images. So, median filtering is used toremove outliers without reducing the image sharpness. Median filtering is a effective nonlinear method used to remove noise from images by also preserving edges. The median filter is carried out by moving through pixel by pixel of image, replacing each value with themedian value of neighboring pixels. The neighbors are called the "window" which slides, pixel by pixel over the entire image. The window can be of size 3×3 or 4×4 of square matrix and the window pixel value is calculated. Image smoothening is done applying median filtering to the input image by using Eq. 2:

$$\text{simg} = \text{medfilt2}(G) \tag{2}$$

**Optimal seeds formation:** Statistical methods are used to find the spatial distribution of gray values by calculating local features at each point which defines the qualities of texture. Statistical methods may be further classified into first-order, second-order, third and higher order texture which consider the relationships among pixels or groups of pixels. A simple one-dimensional histogram is not useful in characterizing texture features to reveal spatial property. Hence, the two-dimensional GLCM matrix is used in texture analysis to estimate image properties related to second-order statistics.

The GLCM is a square matrix specify the spatial distribution of the gray-levels in the texture image. It was defined by Haralick in 1973 shows that often a reference pixel with intensity value i occurs in a specific relationship to its neighboring pixel j. So, each element in GLCM matrix is the number of occurrences of the pair of pixel with value i and j which are at the distance relative to each other. The spatial relationship between two neighboring pixels can be specified in many ways with different offsets and angles and the default tone is between pixel and its immediate neighbor to its right.

The generation of symmetrical co-occurrence matrices for a 4×4 image of neighboring pixel (d = 1), along four possible directions as [0 1] for 0 degree, [-1 1] for 45 degree, [-1 0] for 90 degree and [-1 1] for 135 degree. In the below GLCM matrix, element (1,1) contains the value 1 due to that two horizontal adjacent pixels have the values 1 and 1. Element (1,2) in the input contains 2 instances of horizontal pixel value 1 and 2. The process continued and the sample GLCM is shown below in Fig. 2-3.

In our proposed system, GLCM matrixes are generated invariant of offset direction and symmetric property for a range of gray level between α and β. By trial and error process, the value of ∞ = 9 and β = 13 are obtained for our test images to generate regions of two, three or more. The diagonal elements of GLCM matrix are obtained by using Eq. 3:

$$D = M_{ij}\ \text{if}\ I = j i, j\ \ \{1,2 .. l\} \tag{3}$$

where l represent grey levels taken for GLCM matrix. To compute local maxima, peaks are identified by comparing diagonal elements of GLCM with its neighboring values..If the element is larger than its neighbors, then the element is identified as local peak or local maxima. For a given image, the total number of peaks identified is equal to the total number of regions. Peaks are identified for varying gray levels and the frequency table are updated. For the given input image, the number of distinct regions is equal to the maximum length of local maximum. The identified number of regions is equal to the number of seeds for region segmentation (Fig. 3).

**Image transformation:** A color space is a three co-ordinate system which is used to specify, create and visualize color. The parameters describe the position of the color within the color space being used. RGB color space model is based on red, green and blue of tri-chromatic colors. RGB color model is easy to implement

| | | | | |
|---|---|---|---|---|
| 1 | 1 | 5 | 6 | 8 |
| 2 | 3 | 5 | 7 | 1 |
| 4 | 5 | 7 | 1 | 2 |
| 8 | 5 | 1 | 2 | 5 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | 2 | 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 1 | 2 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |

Fig. 2: Gray level co-occurrence

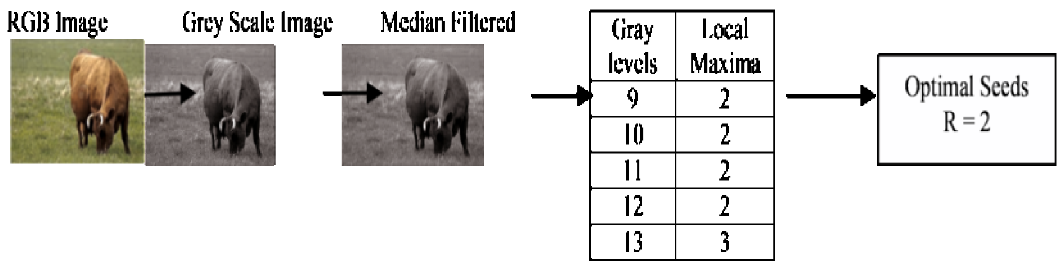


Fig. 3: Optimal seeds-'R' formationb

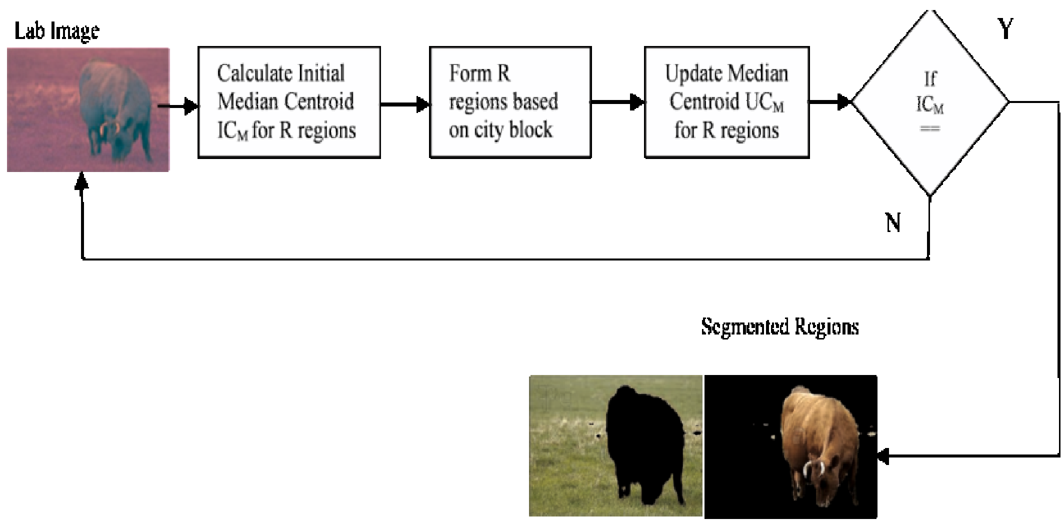


Fig. 4: Region clustering

but non-linear with visual perception and is widely used in computer system and television. It is device dependent and specification of colors is semi-intuitive.

A lab color space model with dimension L for lightness, a and b for color opponent. The L×a×b× color space includes all perceivable colors, whose gamut exceeds those of the RGB and CMYK color models. The important attributes of the L×a×b×model isdevice independence that is the colors are independent of their nature of creation or the device they are displayed on. The conversion of RGB image into Lab image is done by Eq. 4:

$$\text{lab} = \text{rgb2lab(I)} \tag{4}$$

In the proposed algorithm first check whether, the given data set contain the negative value attributes. If the data set contains the negative value attributes then transform the data set into the positive space by subtracting data value minimum attribute value of the data set. The transformation is calculated by calculating the distance from origin to each data point in the data set of negative values. If data set contains positive value then the transformation is not required. The transformed value of converted Lab image is given by Eq. 5:

$$\text{vecab} = \text{ab}(:) - \text{min(ab)}+1 \tag{5}$$

**Region clustering:** Clustering approach is highly suitable for image segmentation task. The major issue of clustering algorithm is that the user has to specify the number of clusters and stable clusters are not produced due to random centroid selection. In our proposed system, number of regions-R automatically generated and passed into region clustering process. After Image transformation, the initial median centroid is chosen as a seed point for R regions. For every region, city block distance is calculated for each data points and the data points are clustered into corresponding regions. Again update the median centroid as per the region formation of the data points. If the initial and updated centroid are same, stops the process anddisplay the segmented regions. If not, repeat the process until all the data points are segmented into corresponding regions (Fig. 4). A sample graphical user interface for the proposed system is shown in Fig. 5.

images

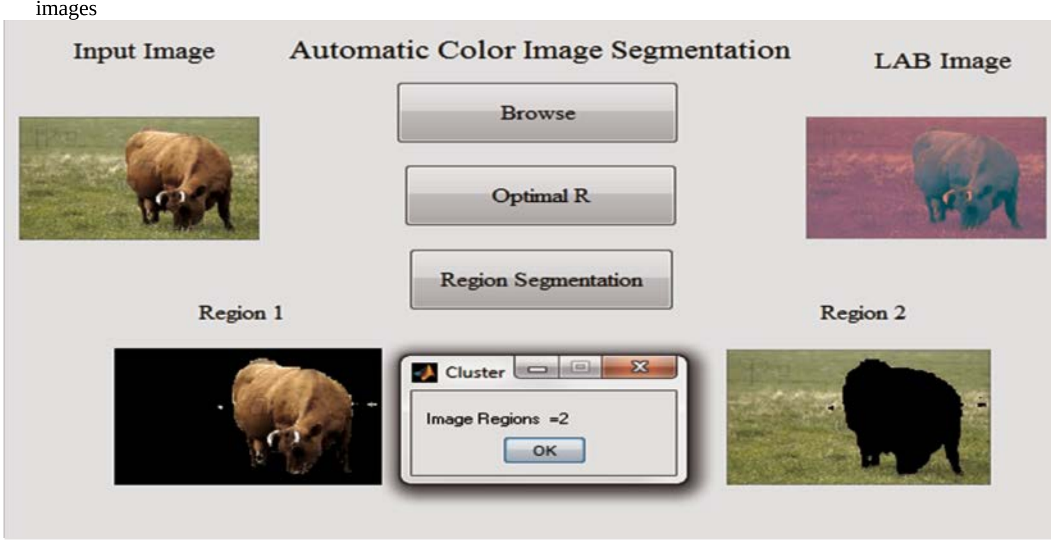


Fig. 5: Automatic color image segmentation

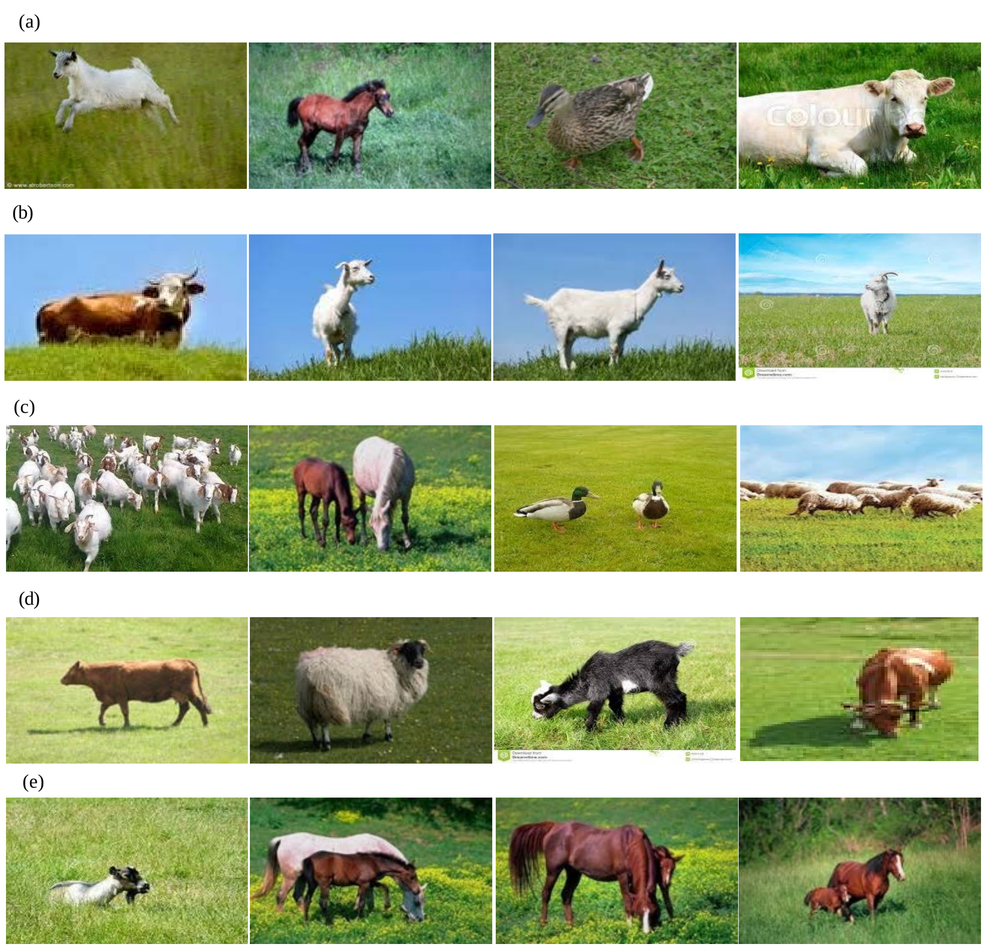


Fig. 6: Sample image: a) Two regions image; b) Three regions image; c) Group object images; d) Shadow object images; e) Occlued object images

Fig. 7: Region segmentation: a) Three regions image; b) Group object image; c) Two regions image; d) Shadow object image; e) Oceluded object image

## RESULTS AND DISCUSSION

The data sets used for automatic color image segmentation are taken from collection of internet, mscroid and corel images. A sample of 51 images of multiple test case are chosen such as images of two regions, three regions , group objects , shadow objects and occluded objects to form images of two or three regions. Sample images of multiple test cases are shown in Fig. 6 and the segmented images of multiple test cases are shown in Fig. 7.

A confusion matrix holds information about actual and predicted classifications done by a classification system. The entries in the confusion matrix are true positive, true negative, false positive and false negative. The True Positive (TP) is the number of correct prediction, True Negative (TN) is the number of in-correct prediction, False Positive (FP) is the number of incorrect predictions and False Negative (FN) is the number of incorrect predictions that a pixel does not belong to a cluster . The confusion matrix for the existing and proposed system of optimal seed selection – 'R' are shown in Table 1.

The performance metrics evaluated from the confusion matrix are Rate of Correctly Classified Instance (RCCI), Rate of Incorrectly Classified Instance (RICCI), accuracy, precision, recall, f-score, specificity, fall and miss. Accuracy is the most basic and ubiquitous metric. The accuracy is the proportion of the total correct number of predictions. Accuracy is determined using the Eq. 6:

Table 1: Confusion matrix for optimal seed selection – 'R'

| Test Images | Existing system[10] 'K' – No. of clusters | | Proposed system 'R' – No. of Regions | |
|---|---|---|---|---|
| Two Regions | 34 | 11 | 40 | 5 |
| Three Regions | 1 | 5 | 4 | 2 |

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \tag{6}$$

Precision is a measure specify the ratio of the positive predictions to the sum of the number of true positive pixels and false positive pixels shown in Eq. 7:

$$\text{Precision} = TP / (TP+FP) \tag{7}$$

The recall or sensitivity specify the true positive rate of the class that were correctly identified. Recall is calculated using the below equation and there's a trade-off between precision and recall shown Eq. 8:

$$\text{Recall / Sensitivity} = TP/ (TP+FP) \tag{8}$$

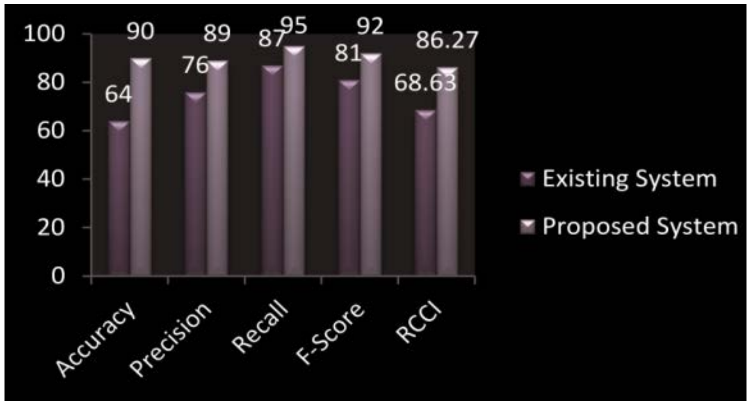


Fig. 8: Comparative performance metrics chart 1

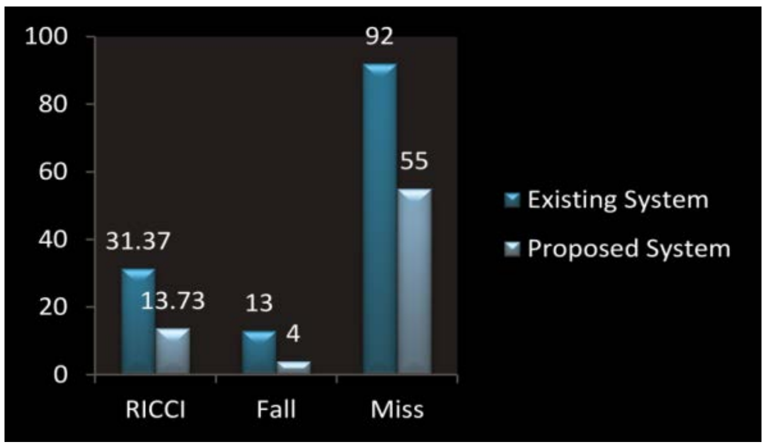


Fig. 9: Comparative performance metrics chart 2

Table 2: Comparative performance evaluation for optimal seed selection 'R'

| Metrics | Existing system | Proposed system |
|---|---|---|
| Accuracy | 0.64 | 0.9 |
| Precision | 0.76 | 0.89 |
| Recall | 0.87 | 0.95 |
| F-Score | 0.81 | 0.92 |
| RCCI | 68.63 | 86.27 |
| RICCI | 31.37 | 13.73 |
| Fall | 0.13 | 0.04 |
| Miss | 0.92 | 0.55 |

The F-score represent the true positive rate of the class. It is calculated based on Eq. 9:

$$\text{F-Score} = 2TP/(2TP+FP+FN) \quad (9)$$

The rate of correctly classified instance (RCCI) is given by the Eq. 10:

$$RCCI=(TP+TN))/(TP+TN+FP+FN) \quad (10)$$

The rate of in-correctly classified instance (RICCI) is given by the Eq. 11:

$$RICCI=(FP+FN)/(TP+TN+FP+FN) \quad (11)$$

Fall and Miss of the system can be computed as using the Eq. 12,13:

$$Fall = FP / (TN+FP) \quad (12)$$

$$Miss = FN / (TP+FN) \quad (13)$$

Performance metrics of the proposed system are evaluated for the above metrics and shown in Table 2 for identification of 'R' and accurate segmentation. The performance charts of the proposed algorithm in comparisons with the existing system are shown in Fig. 8. Accuracy of the proposed algorithm improved by 26% , precision by 13%, recall by 8%, f-score by 11%. The rate at which identification of number of regions - 'R' for the sample images correctly – RCCI increased by 17.6%

The performance chart in terms of RICCI, Fall and Miss are shown in Fig. 9. The rate at which incorrectly classified instance are reduced by 18% , fall rate reduced by 11% and miss rate reduced by 37 % in comparisons

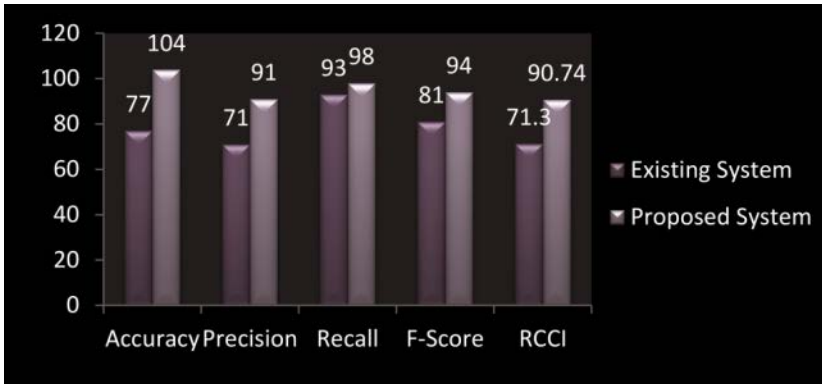


Fig. 10: Comparative performance metrics shart 3

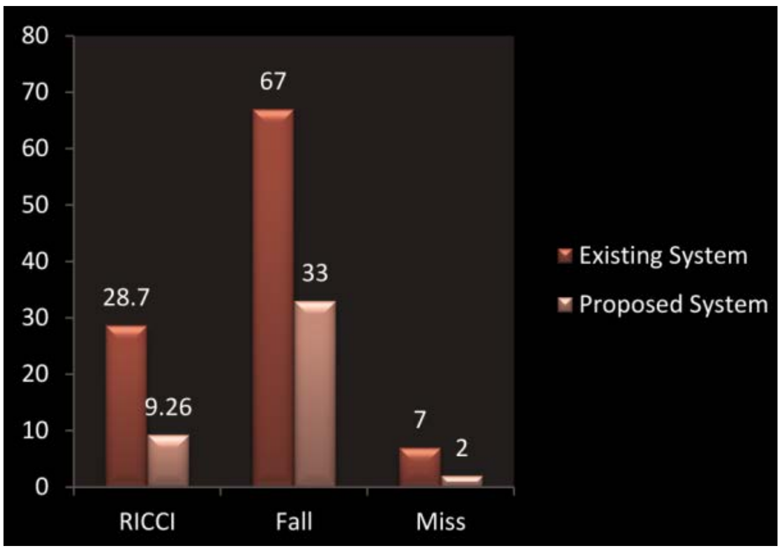


Fig. 11: Comparative performance metrics shart 3

Table 3: Confusion matrix for automatic region segmentation

| Test Images | Confusion matrix | | | |
|---|---|---|---|---|
| | Existing System[10] | | Proposed System | |
| Two Regions | 64 | 26 | 82 | 8 |
| Three Regions | 5 | 13 | 2 | 16 |

Table 4: Comparative performance evaluation for automatic region segmentation

| Metrics | Existing system [10] | Proposed system |
|---|---|---|
| Accuracy | 0.77 | 1.04 |
| Precision | 0.71 | 0.91 |
| Recall | 0.93 | 0.98 |
| F-Score | 0.81 | 0.94 |
| RCCI | 71.30 | 90.74 |
| RICCI | 28.70 | 9.26 |
| Fall | 0.67 | 0.33 |
| Miss | 0.07 | 0.02 |

with the existing system. Proposed algorithm produced drastic improvements in all the metrics and also worked for efficiently for multiple test cases.

After obtaining 'R' number of regions automatically, the input images are segmented accurately into R regions based on clustering approach. The confusion matrix and performance metrics for the fast k-means and proposed algorithm are shown in Table 3 and performance metrics comparisons are listed in Table 4.

From the performance chart shown in Fig. 10, accuracy of the proposed algorithm improved by 27% , precision by 20%, recall by 5%, f-score by 13%. The rate at which segmentation of ideal regions which are correctly produced RCCI increased by 19.44%.

The performance metrics of RICCI, Fall and Miss shows a drastic improvements which are shown in Fig. 11. The rate at which incorrectly classified instance are reduced by 19.44% , fall rate reduced by 34% and miss rate reduced by 5 % in comparisons with the existing system. Proposed algorithm produced drastic improvements in all the metrics and produced accurate segmentation efficiently for multiple test cases.

Thus, our automatic colour image segmentation is better when compared with previous method by identifying 'R' accurately based on statistical measure and producing accurate segmentation for variety of test images. Proposed algorithm shows better performance in terms of several evaluation metrics when compared with the existing algorithm

## CONCLUSION

In this study, an approach for automatic color image segmentation is introduced by identifying number of regions in the images and accurately segmenting the images into 'R' regions. The proposed system input is the RGB image which identify 'R'-number of regions based on local maxima. Then, the image is segmented into R regions based on median centroid to produce accurate segmentation. The proposed method is compared with existing methods and our approach produced accurate segmentation by considering color and texture features. Extensive experiments are conducted on MSCROID data sets and shows that our framework produced better efficiency and accuracy. The future scope of the work is to annotate the regions and can retrieve relevant images based on image semantics.

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