COMPARATIVE STUDY OF CERTAIN SEGMENTATION TECHNIQUES FOR CLASSIFICATION OF FOOD OBJECTS' IMAGES

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Abstract: *This paper presents a comparative study of certainon segmentation techniquees for classification of food objects from multiple food objects' images. We have used color and texture features for identification and the algorithms, namely, thresholding, region growing, k-means clustering and Chan-Vase are being adopted for segmentation. An active contour method based on Chan-Vase model has given good segmentation results for multiple food objects. A back propagation neural network (BPNN) is used as the classifier. Different types of south Indian food objects like Idli, Vada, Puri, Cutlet, and Samosa, are considered for the study. The classification accuracy for combined features is found to be 82%. The work finds application in automatic serving by robots in pharamaceutical industry, food industry, hotels, motels, Cafeteria, shaping malls, etc.*

IndexTerms: Image Segmentation, Color Features, Textural Features, Back Propagation Neural Network

1. INTRODUCTION

Now a days, computer vision system employing image processing techniques has been developed rapidly, which can be quantitatively used to characterize size, shape, color and texture properties of foods. Image processing systems play a major role in the food quality evaluation by maintaining accuracy and consistency while eliminating the subjectivity of manual inspections. These systems offer flexibility in application and can be reasonable substitutes for the human visual decision-making process. The recognition and classification of images containing multiple food objects is a challenging task, since it requires segmenting the individual food objects and further classify them individually. The computer vision systems have been used for recognition and classification of various singleton and bulk agriculture produces such as fruits, vegetables and flowers and food objects in the Indian context such as Idli, Vada etc,. We have carried out literature survey to find out the connected works being carried in the area of computer vision applications in food processing.

(Domingo Mery and Franco Pedreschi, 2005) have proposed an algorithm for segmentation of color food images which consists of three steps. Firstly, computation of a high contrast grey value image from an optimal linear combination of the RGB color. Secondly, estimation of a global threshold using a statistical approach and morphological operations in order to fill the possible holes presented in the segmented binary image. The suggested threshold is limited to separate only the food image from the background.

(Da-Wen Sun and Cheng-Jin Du, 2004) have proposed segmentation method for complex food images by stick growing and merging algorithm, which includes approaches like: system initialization, stick merging, sub region merging and boundary modification. It is started from an initial decomposition of the image into small sticks and non sticks. The small sticks are merged to obtain the initial sub regions on the basis of homogeneity criteria. Finally, non-sticks and separate small sticks are merged and the degree of boundary roughness is reduced by boundary modifications.

(Chan and Vise, 2001) have proposed a new model for active contours to detect objects in a given image, based on techniques namely curve evolution, Mumford–Shah functional for segmentation and level sets. The developed model detects objects whose boundaries are not necessarily defined by gradients. (Anami B.S. et al., 2005) have proposed a method for identification and classification of singleton food objects using a neural network classifier. Different types of color and texture features are used to develop a neural network model. (Anami B S et al., 2009) have proposed a method for identification and classification of Bulk Sugary food objects using a neural network classifer. Different types of texture features are used to develop neural network model. (Gui Jiang - sheng, et.al, 2009) have proposed a novel approach for fruit shape detection in RGB space, which is based on fast level set and Chan-Vese model named as Modified Chan-Vese model (MCV). This algorithm is fast and suitable for fruit sorting because it does not need re-initializing. The proposed method has been applied to fruit shape detection with promising results.

(D.M. Hobson, et al., 2007) have proposed segmentation algorithm by choosing rice grains as food objects so as to identify different varieties of rice grains through digital image analysis. It has applied threshold, canny edge detector and gradient methods to find the edge segmentation. The texture methods are used for rice grain identification. (Antonio Carlos Loureiro et al., 2008) have developed a method for classification of Lemons and Tomatoes using image processing. The method allows calculation of volume, area, averages, border detection, averages, border detection, image improvement and morphological operations in a variety of image archive formats. (Liyanage C De Silva and Anton Pereira, 2003) have proposed an algorithm for color image segmentation of food objects using a modified watershed segmentation algorithm. The color images of food samples are broken down into groups of similar characteristics and to identify rapid changes in pixel colors within the food sample and isolate such anomalies into segments. Prior to this segmentation, a Gaussian low pass filter is applied for image enhancemt the image. It is also used threshold edge detection techniques in finding the boundaries of the different food samples and to separate the food objects from the background.

(Munkevik Per et.al, 2004) have proposed a new method for automatic grading of ready meals using machine vision. The different components of a meal are segmented and features are extracted. A self-organizing feature map (SOFM) is then trained using examples of meals graded as "approved" by sensory experts. The trained SOFM is then used to discriminate invalid meals from valid ones, by considering the similarity between the test samples and the acquired sensory models as a measure of food quality. (Beveridge, J. et al., 1989), have presented a working system for segmenting images of complex scenes. The system integrates techniques that have evolved out of many years of research in low-level image segmentation at the University of Massachusetts and elsewhere. The system first produces segmentations based upon an analysis of spatially localized feature histograms. These initial segmentations are then simplified using a region merging algorithm. Parameter selection for the local histogram segmentation algorithm is facilitated by mapping the multidimensional parameter space to a one-dimensional parameter which regulates.

(Cheng-Jin Du, Da-Wen Sun, 2006) have reviewed recent advances in learning techniques for food quality evaluation using computer vision, which includes artificial neural network, statistical learning, fuzzy logic, genetic algorithm, and decision tree. Artificial neural network (ANN) and statistical learning (SL) remain the primary learning methods in the field of computer vision for food quality evaluation.

(Hongxu Ni and Sundaram Guansekaran, 2004) have proposed an algorithm called the *X–Y* sweep method for image segmentation. In the proposed method, a visual scene is swept in *X*-direction and *Y*-direction and two sets of run-length codes are generated. According to the width conditions and spatial relations with the neighbor run-length codes, the run-length codes are grouped as segments. A joint is formed by collecting the pixels that cannot be swept through in *X*-direction or *Y*-direction. The topological sorting method is used to find the best match. The *X–Y* sweep method can work correctly to all the shred-shaped objects. An accuracy of 99% was obtained for pre-cut touching and overlapping straight copper wires. The test with "in situ" cheese shreds was about 95% accurate in estimating the shred lengths.

From the literature survey, it is revealed that computers are applied for segmentation and classification of food objects and food products including grains, poultry carcass fruits like apple, mangoes. This study has shown that machine-based inspection of food products can be implemented effectively, reducing or even eliminating the need for both intensive human intervention and to assure quality. But no appreciable work is carried out connected with recognition segmentation and classification of South Indian food objects, which we find in fast food stalls, cafeteria and restaurants. Hence, we have considered Segmentation and classification of food object images of south Indian based on color and texture features. The work is useful in automatic serving of food by robots in restaurants, inspection of food quality in food industry, automatic food preparation and monitoring etc.

The paper is organized into seven different sections. Section 2 contains the proposed methodology. Section 3 and section 4 present a different segmentation techniques and feature extraction techniques respectively. Section 5 gives description of artificial neural network model. The results and discussion are given in section 6. The paper is concluded with section 7.

2. PROPOSED METHODOLOGY

The proposed methodology consists of five stages, namely, image acquisition, segmentation, feature extraction, development of artificial neural network and classification. The schematic block diagram encompassing all the stages of the proposed methodology is shown in Figure 1.

2.1 Image Acquisition

The images of food objects are collected from different restaurants. A color camera, (Dxc-3000a, Sony make), is used for image acquisition. Photos are taken under natural day light. The orthogonal images are taken for the purpose of training the classifier. The distance between the camera and the food object is kept almost constant as variation in distance changes the color and textural features. The images acquired from the camera are of size 1920 X 1080 pixels. These acquired image samples are reduced to 300*300 pixels for the reason of reduction in complexity of storage and computation time during feature extraction stage. The image samples used in this work include combination of more than one type of food objects.

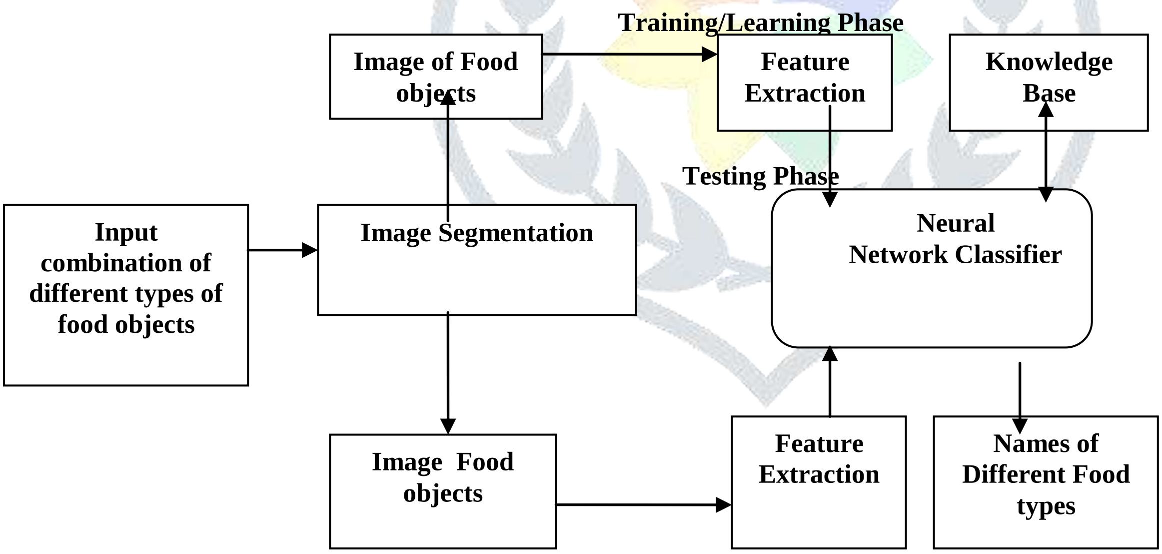


Figure 1: Block diagram of Methodology

We have used the combination of south Indian food objects, namely, Idli, Vada, Cutlet, Burfi and Samosa for acquiring it images of food samples. These types of food are used as snacks by people in common in south India. Figure 2 gives the images of these food types. The number of Idlies and Vadas are varied in the image samples like one Idli one Vada, two Idlies and two Vadas and the like. Even images of one Idli and multiple Vadas and vice versa are considered for the image samples. The same process is repeated for other types of food objects. For image acquisition the food objects are organized neatly. We have considered distinguishable and non distinguishable images of the food objects for the study. Distinguishable food objects means heare is easily differentiable from one object to another object with color aswell as texture. Figure 3 shows the image samples having more then one food type considered in the work. The images of individual food objects from images containing more then one type need to be extracted through suitable segmentation process.

Figure 2: Images of Food Objects

Figure 3: Images of multiple Food Objects

3. IMAGE SEGMENTATION

In this work we have attempted certain segmentation techniques namely thresholding, region growing, K-Means and Chan-Vase based model for their suitability in the work.

3.1. Segmentation using Thresholding

Thresholding-based segmentation is a particularly effective technique for scenes containing solid objects resting upon a contrasting background. It distinguishes the object from the remaining part of an image with an optimal value. Algorithm1 gives the steps involved in segmentation of image based on thresholding. Figure4 gives a sample input image and the corresponding output image using thresholding.

Algorithm 1: Thresholding

Input: Input image, Intial threshold value T0=

Output: Segmented image

Start

Step1 Select an initial threshold value (T0) and group pixels in to two groups G1 and G2.

Step2Compute the average gray level values mean1 and mean2 for the pixels in regions G1 and G2.

for i= 1 and 2

Step3 Compute a new threshold value

T= (1/2) (mean1 +mean2)

Step4 Repeat steps 2 through 3 until difference in T in successive iterations is smaller than a predefined parameter T0.

End

Input Image

Segmented Image

(a)

Input Image

Segmented Image

(b)

Figure 4: (a) Two Food objects Segmentation (b) Multiple Food object Segmentation using Thresholding

3.2 Segmentation using Region growing

In this method we start with a seed pixel, examining local pixels around it, determine the most similar one, which are included in the region if similaarity is met. This process is continued until no more pixels are added. Algorithm 2 gives the steps involved in segmentation of image using region growing. Figure 5 gives a sample input image and the corresponding output image using region growing.

Algorithm 2: Region Growing

Input: Input image

Output: Segmented image

Start

Step 1: Select the seed pixel within the image.

Step 2: For each seed pixel grow a region.

Step 3: Set the region prototype to be the seed pixel.

Step 4: Calculate the similarity between the region prototype and the candidate Pixel.
Step 5: Calculate the similarity between the candidate and its nearest neighbor in the region.
Step 6: Include the candidate pixel if both similarity measures are higher than
Experimentally -set thresholds.
Step 7: Update the region prototype by calculating the new principal component.
Step 8: Go to the next pixel to be examined.

End

Input Image

Segmented Image

(a)

Input Image

Segmented Image

(b)

Figure 5: (a) Two Food objects Segmentation (b) Multiple Food object Segmentation using region growing with distance 4

3.3 Segmentation using K-means clustering.

In this method K is the number of clusters used in order to segment the image here k=2 because two types of food objects are there in the image. The clustering has been done based on the colors present in the image and converted from RGB color space to L*a*b* color space. The algorithm 3 gives the steps of k-means segmentation method. Figure 6 gives a sample input image and the corresponding output image using k-means clustering.

Algorithm 3: k-means segmentation
Input: Input image
Output: Segmented image

Start
Step1: Select K value representing by the objects that are being clustered.
These points represent initial group centroids.
Step2: Assign each object to the group that has the closest centroid.
Step3: When all objects have been assigned, recalculate the positions of the K centroids.
Step4: Repeat Steps 2 and 3 until the convergence is attained (e.g. no pixels change clusters).

End

Input Image

Segmented Image

(a)

Input Image

Segmented Image

(b)

Figure 6: (a) Two Food objects Segmentation (b) Multiple Food object Segmentation using K-Means

3.4 Segmentation using Chan-Vase model.

The Chan-Vase method is a region-based segmentation model which is based on the active contour model, the Mumford-Shah functional and the Osher-Sethian level set method. Given a grayscale image I: $\Omega c R^P \rightarrow R_+$ (p=2, 3), the Chan-Vase method finds a curve C that represents a partition of (Ω) into two regions Ω_{in} and $\Omega_{out.}$ So that they give an optimal piecewise constant approximation of the image. The contour C minimizes the energy, as given by the equation (1)

$$E(C, c1, c2) = \lambda 1 \int_{\Omega in} (I(x) - c1) \uparrow 2) + \mu \text{length}(C) \qquad \text{... (1)}$$

where c1 and c2 are the average intensities in Ω_{in} and Ω_{out} image domains respectively and λi, μ are parameters. The algorithm 4 shows the steps of Chan-Vase method based segmentation process. Figure 7 gives a sample input images and their corresponding segmented images.

Algorithm 4: Chan-Vase Method
Input: Input image
Output: Segmented image
Start
Step 1: Initialize n=0
Step 2: Increment n=n+1
Step 3: Compute intensities c1 and c2 inside and outside the active contour
Step 4: Evolving level-set function.
Step 5: Repeat until the solution is stationary or $n>n_{max}$ Go to the next pixel to be examined.
End


Input Image


Segmented Image

(a)


Input Image


Segmented Image

(b)

Figure7: (a) Two Food objects Segmentation (b) Multiple Food object Segmentation using Chan-Vase Model

4. FEATURE EXTRACTION

The south Indian food objects are easily identified by color and hence color is chosen as one feature in this work. In case of certain food objects, we get overlap in the color feature. We have used texture features based on gray level co-occurance matrix. In total 18 color features and 24 texture features are extracted from the images of food objects.

4.1 Color Feature Extraction

The RGB (Red, Green, Blue) components are obtained from the original images of the food objects. The Hue (H), Saturation(S) and Intensity (I) components are extracted from these RGB components. The equations (2), (3) and (4) give Hue, Saturation and Intensity respectively for an image sample.

$$H = cos^{-1}\left\{ \frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}} \right\} \qquad \text{... (2)}$$

$$S = 1 - \frac{3}{(R+G+B)}\left[min(R,G,B)\right] \qquad \text{... (3)}$$

$$I = \frac{1}{3}(R+G+B) \qquad \text{... (4)}$$

The equations (5), (6) and (7) are used to evaluate mean, variance and range of the image samples. The steps involved in color feature extraction are given in Algorithm 5. A sample graph is shown in Figure 8, which gives the color features of Idli food Object.

$$Mean \quad \mu = \sum_{x} x \sum_{y} P(x,y) \qquad \ldots\ldots (5)$$

$$Variance = \sum_{x,y} (x-\mu)^2 P(x,y) \qquad \ldots\ldots (6)$$

$$Range = Max\ (p(x,y)) - min\ (p(x,y)) \qquad \ldots\ldots (7)$$

Algorithm 5: Color Feature Extraction
Input: Original 24-bit color image.
Output: 18 color features
Start
Step 1: Separate the RGB components from the original 24-bit input color image.
Step 2: Obtain the HSI components from RGB components using the above equations (2), (3) and (4).
Step 3: Find the mean, variance, and range for each RGB and HSI components.
Stop

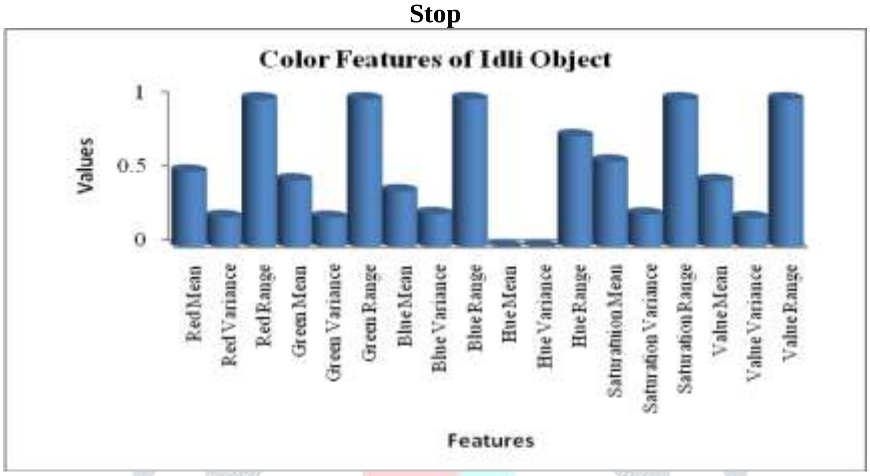


Figure 7: Color Features of Idli Food Object Image

4.2 Texture Feature Extraction

We have used certain texture features that are extracted using Gray Level Co-occurance matrix (GLCM). The steps involved in texture feature extraction using GLCM are given in Algorithm6. This algorithm is used to extract a total of 24 GLCM features. The following equation (8) is used to compute the co-occurrence matrix.

$$C = \frac{1}{4}(P_{00} + P_{450} + P_{900} + P_{1350}) \qquad \ldots (8)$$

The eight GLCM features used are mean, variance, range, energy, maximum-probability, contrast, inverse difference moment and correlation. The equations (9) through (16) are being used. The graph shown in Figure 8 gives texture features of Idli food object.

$$Mean\ \mu = \sum_{x,y} xP(x,y) \qquad \ldots (9)$$

$$Variance\ \ \sigma = \sum_{x,y} (x-\mu)^2 P(x,y) \qquad \ldots (10)$$

$$Maximum\ probability = max(P(x,y)) \qquad \ldots (11)$$

$$Energy = \sum_{x,y} P^2(x,y) \qquad \ldots (12)$$

$$Entropy = -\sum_{x,y} P(x,y) \log_2(P(x,y)) \qquad \ldots (13)$$

$$Contrast = \sum_{x,y} |x-y|^k P^{\lambda}(x,y) \qquad \ldots (14)$$

$$Inverse\ difference\ moment = \sum_{x,y;x \neq y} \frac{P^{\lambda}(x,y)}{|x-y|^k} \qquad \ldots (15)$$

$$Correlation = \frac{\sum_{x,y}[(xy)P(x,y)]) - \mu_x \mu_y}{\sigma_x \sigma_y} \qquad \ldots (16)$$

Where μ_x, μ_y σ_x, σ_y are standard deviations defined by,

$$\mu_x = \sum_{x} x \sum_{y} P(x,y)$$

$$\mu_y = \sum_{y} y \sum_{x} P(x,y)$$

$$\sigma_x = \sum_{x} (x - \mu_x)^2 \sum_{y} P(x,y)$$

$$\sigma_y = \sum_y (y-\mu_x)^2 \sum_x P(x,y)$$

Algorithm 6: GLCM feature extraction
Input: RGB components of original image
Output: Texture features
Description : $P_{\varphi,d}(x,y)$ means GLCM matrices in the direction φ = 0^0, 45^0,90^0 *and* 135^0 and d=1

Start
Step 1: For all the separated RGB components, derive the Co-occurrence Matrices
$P_{\varphi,d}(x,y)$ in four direction ($\varphi = 0^0$, 45^0,90^0 *and* 135^0) and $d=1$
Step 2: Calculate Co-occurrence features namely, mean, variance, range are using Equation (2) thru equation (4).
Step 3: **C**alculate other Co-occurrence features like Energy, Maximum Probability, Contrast, Inverse Difference Moment and Correlation using Equation (6) thru (13).
Stop.

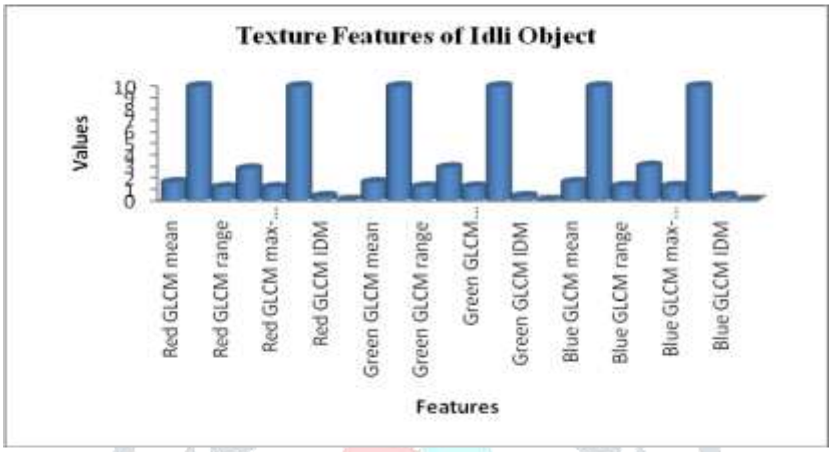


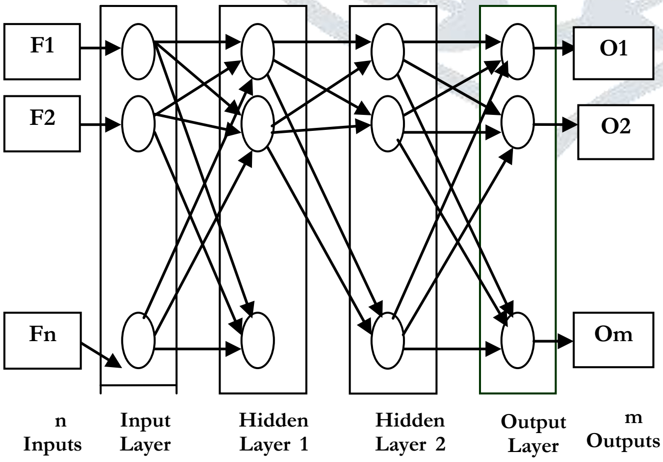
Figure 8: Texture Features of Idli Food Object Image.

5.0 Neural Network Based Classifier

A multilayer feed forward neural network with back propagation learning is used as a classifiear and is shown in Figure 9. The number of layers in the input layer equals to 42 of input features namely Read Mean, Red Variance Red CM mean etc. The number of layers in the output layer equals the 5 food objects to be classified, as Idli, Vada, Puri etc. The number of nodes in the hidden layer is calculated using the equation 17 and is equal to 38.

$$n = \frac{I+O}{2} + y^{0.5} \qquad \ldots (17)$$

Where n=number of nodes in hidden layer, I=number of input features, O=number of outputs, and y=number of input patterns in the training set.



where F1, F2…FN are input features and O1, O2…Om are outputs of food object type.
Figure 9: Artificial Neural Network Classifier

5.1 Training and Testing

Training and testing of neural networks based classifier are performed using sample images of food objects. We have considered 1000 image samples (200 samples of each type). The classifier is trained with 500 samples (100 each of type) and tested with remaning 500 samples. The images are divided into three sets as training, testing, and validating sets.

6. RESULTS AND DISCUSSION

This section gives the results of experimentation on the developed methodology. The training and testing are carried out with color and texture features. A comparative analysis of the segmentation techniques on the classification accuracy of food objects is carried out. The images are categorized in to distinguishable and non distinguishable food objects. The effect of mixing of the food objects with 100%, 75%, 50%, 0% distinguishable objects on classification accuracy are given. We have used the formula (16) to estimate the classification accuracy.

$$Accuracy = \frac{Correctly\ recognized\ samples}{Total\ No\ of\ Test\ samples} \times 100 \quad \text{.........} \ (18)$$

6.1 Classification Accuracy of Distinguishable and Non Distinguishable Food Objects

The graphs shown in Figure 10 and Figure 12 show the classification of accuracy of neatly organized distinguishable and non distinguishable food objects. It is evident from the graphs that Chan-Vase based segmentation technique has performed better then other methods. For distinguishable food objects even K- Mean's method has given 72% of classification accuracy.

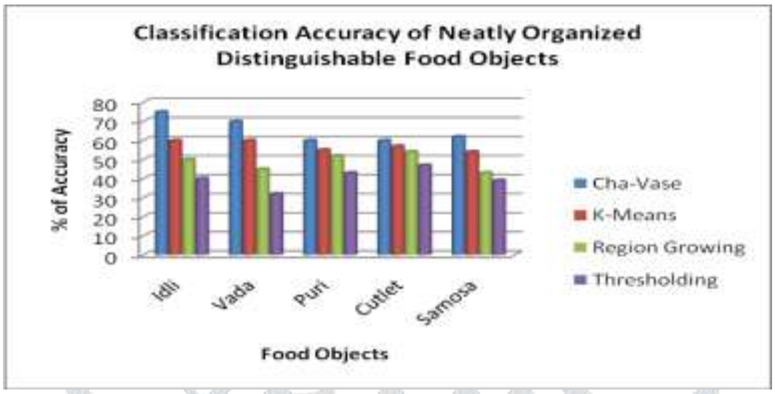


Figure 10: Classification Accuracy of Neatly Organized Distinguishable Food Objects

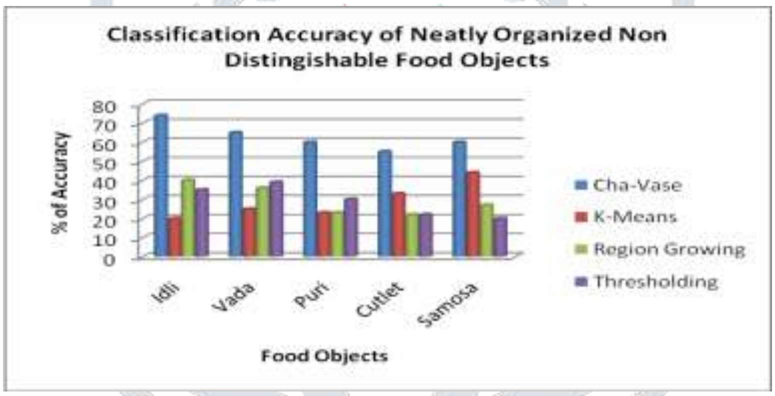


Figure 11: Classification Accuracy of Neatly Organized Non Distinguishable Food Objects

6.2 Effect of mixing the food objects on classification accuracy

The graphs shown in Figure 12 to Figure 15 give the classification accuracies for segmented images of food objects. Each image sample comprises of 100%, 75%, 50%, and 0% distinguishable food objects. The highest and lowest classification accuracies are around 82% and 80% respectively for almost all food objects on mixing with 100% distinguishable food objects using combined color and texture features. The classification accuracy decreases when we increase the mixing with non distinguishable food objects. From the results it is evident that the Chan-Vase based method using combined color and texture features has given better results and suitable for the work.

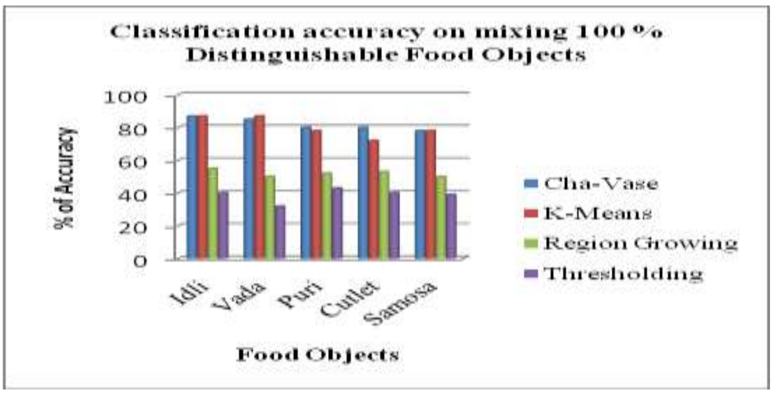


Figure 12: Classification Accuracy on Mixing 100% Distinguishable Food Objects

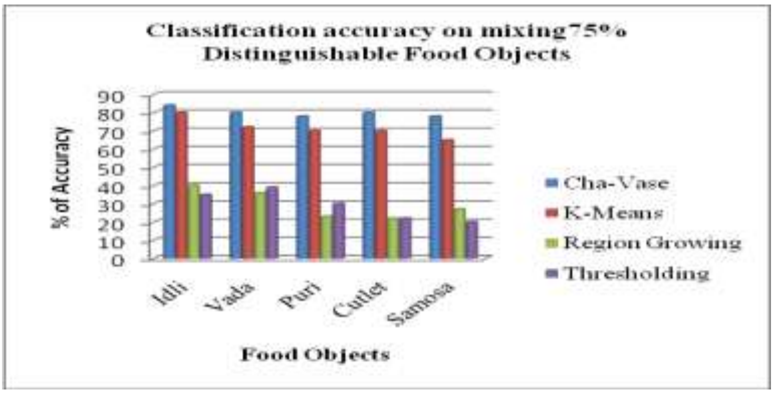


Figure 13: Classification Accuracy on Mixing 75% Distinguishable Food Objects

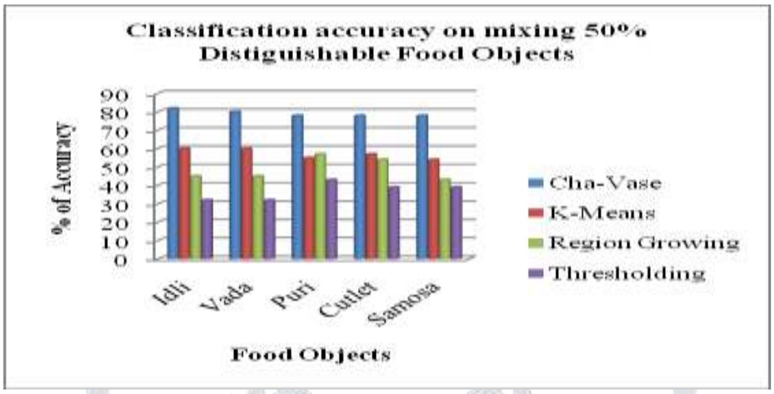


Figure 14: Classification Accuracy on Mixing 50% Distinguishable Food Objects

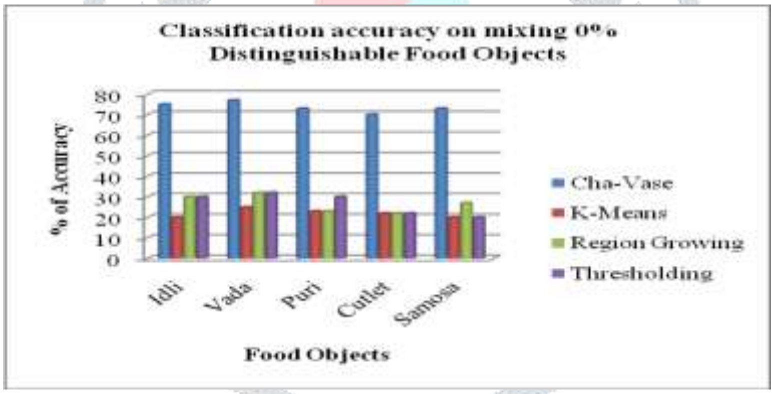


Figure 15: Classification Accuracy on Mixing 0% Distinguishable Food Objects

7. CONCLUSION

In this paper, we have proposed a methodology for identification and classification of images of multiple food objects placed in a plate using color and texture features. Different types of segmentation techniques like Thresholding, Region Growing, K-Means and Chan-Vase based model are used to test their suitability in the process of classification. The image segmentation using Chan-Vase method has given better accuracy of recognition compared to other techniques. The maximum classification accuracy of 80% is observed with the images of Idli and minimum classification accuracy of 76% is observed with the images of Puri when the objects are organized. The work finds application in automatic food serving by robots in restaurants, hotels, malls, food industry, pharmacentical industry etc. The scope exists for increasing the classification accuracy through perfect segmentation as we normally have either over segmentation or under segmentation of the food objects in the image.

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