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Prediction of Colon Cancer Using Region Seed Growing Segmentation and Dnn Classifier

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***Abstract*-To determine the clinical manifestations and optimal management of patients with colorectal cancer (CRC) metastasis advanced malignancy we propose a new predictive modelling by using region seed growing segmentation and classification for predicting the colon cancer disease through continuous monitoring. Here, the region seed growing is used and which is based on transition region extraction for effective image segmentation. Moreover, region seed growing algorithm is used to categorize the transitional region features from the colon cancer image. Inaddition, We used to establish the deep neural network concept for training the image and testing the image with the help of weight estimating classifier.The experiments have been conducted by using the standard images that are collected from database and the current health data which are collected from patient. The results proved that the performance of the proposed prediction model which is able to achieve the better accuracy when it is compared with other existing prediction model.**

Keywords- Colorectal cancer (CRC),

I.INTRODUCTION

Image processing is a widely used methodology in various medical sectors. Image processing involves performing some operations on images to extract some useful information. Image analysis is very helpful in the early detection of various cancers in which time factor is very crucial. Colon cancer is a type of cancer that begins in the large intestine (colon). The colon is the final part of the digestive tract which can be a great threat to human. This model uses the effective transition region extraction method for performing image and Scan images are pre processed in order to remove the Noise.

Here the region growing segmentation algorithm is used in order to segment the portion of defected areas. then we establish the deep neural network concept for training the image and testing the image with the help of WEIGHT ESTIMATING CLASSIFIER. The result image will compared with the dataset images and it will display whether it is benign or malignant.Finally, It is noted that the proposed method outshines the existing methods.In digital image processing and computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as image objects) [7]. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning alabel to every pixel in an image such that pixels with the same label share certain characteristics.The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used for Image Classification [8].

Colon cancer is a type of cancer that begins in the large intestine (colon). The colon is the final part of the digestive tract. Typically affects older adults, though it can happen at any age. It usually begins as small, noncancerous (benign) clumps of cells called polyps that form on the inside of the colon. Over time some of these polyps can become colon cancers.Polyps may be small and produce few, if any, symptoms [9]. For this reason, doctors recommend regular screening tests to help prevent colon cancer by identifying andremoving polyps before they turn into cancer.If colon cancer develops, many treatments are available to help control it, including surgery, radiation therapy and drug treatments, such as chemotherapy, targeted therapy and immunotherapy.Colon cancer is sometimes called colorectal cancer, which is a term that combines colon cancer and rectal cancer, which begins in the rectum.Colorectal cancer mainly affects older adults, but there is a rising incidence in younger people . While incidence rates dropped by 3.6% each year from 2007 to 2016 in adults age 55 and older, they rose by 2% each year in adults under age 55. This year, colorectal

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cancer is estimated to be the fourth most commonly diagnosed cancer in men and women age 30 to 39. When colorectal cancer is found early, it can often be cured. The death rate from this type of cancer in 2017 was 54% less than what it was in 1970.

This is due to improvements in treatment and increased screening, which finds colorectal changes before they turn cancerous and cancer at earlier stages [10]. However, while death rates for adults over age 55 decreased by 2.6% each year from 2008 to 2017, they increased by 1% each year in adults under age 55.There are four stages to determine whether there is a colon cancer or not. The first phase is we get CT scan image data. The second phase, we implement image enhancement to improve quality of image. The third phase is image segmentation which is an important step in the detection of cancer. The fourth stage is Classification that i give us a conclusion whether there is a Colon cancer or not.

II.RELATED WORKS

A technique for image compression using a deep wavelet autoencoder (DWA), which blends the basic feature reduction property of autoencoder along with the image decomposition property of wavelet transform is proposed. The combination of both has a tremendous effect on sinking the size of the feature set for enduring further classification task by using DNN. A brain image dataset was taken and the proposed DWA-DNN image classifier was considered.

The performance criterion for the DWA- DNN classifier was compared with other existing classifiers such as autoencoder-DNN or DNN, and it was noted that the proposed method outshines the existing methods.Innovative And Special Approaches Of Segmentation Algorithms [2]. They propose that from the various applications suggested by several researchers the performance of k-Means algorithm is well suited for this type of medical dataset analysis. Most of the researchers are using the k-Means algorithm; also it is more suitable than other algorithms in the medical data set explored and analyzed the problem of partitioning medical data. They enhanced the existing traditional algorithms (k-Means, Density-Based Spatial Clustering Of Applications with Noise (DBSCAN) and FCM) and proposed k-Means, DBSCAN and FCM Clustering Algorithm performance evaluation.

[3] Segmentation using an improved thresholding-based technique. Traditional methods were unable to produce good quality segmented areas due to the complex background and non-uniform illumination of images captured under natural environment. Therefore, this paper proposed an improved thresholding-based segmentation integrated with an inverse technique (TsTN) that was able to partition natural images correctly. The three segmentation techniques were implemented on fruit images and their performance was evaluated based on the ground truth. The segmentation techniques performance was compared quantitatively using evaluation method, Rand Index (RI).

The analysis results showed that TsTN has the ability to produce good quality segmented images. Furthermore, this segmentation technique was proven to be more accurate than the traditional thresholding and clustering techniques. [4] In classification stage, k-nearest neighbors, support vector machines, naive bayes, artificial neural networks, and logistic regression methods are used.It has been given comparatively in the detection of lung cancer accuracy rates, F-1 measure, precision, sensitivity, specificity among classifiers. Classification accuracy; support vector machines, neural networks, k-nearest neighbor, logistic regression, naive bayes algorithms gave the best result depending on the data, respectively.

[5] Predicting Lung Cancer Using Fuzzy Cluster Based Segmentation and Classification. Fuzzy C-Means Clustering algorithm is used to categorize the transitional region features from the feature of lung cancer image. In this work, Otsu thresholding method is used for extracting the transition region from lung cancer image. Moreover, the right edge image and the morphological thinning operation are used.

Deep learning for lung Cancer detection and classification [6]. To detect the location of the cancerous lung nodules, this work uses novel Deep learning methods. This work uses best feature extraction techniques such as Histogram of oriented Gradients (HoG), wavelet transform-based features, Local Binary Pattern (LBP), Scale Invariant Feature Transform (SIFT) and Zernike Moment. After extracting texture, geometric, volumetric and intensity features, Fuzzy Particle Swarm Optimization (FPSO) algorithm is applied for selecting the best feature. Finally, these features are classified using Deep learning.

III. DESIGN METHDOLOGY

The existing model has augmented the input image with fuzzy clustering method, involves assigning data points to clusters such that items in the same cluster are as similar, while items belonging to different clusters are as dissimilar. The classification module is consists of two sub components namely Association Rule Mining and the Decision Tree Classifier for making decision over the preprocessed colon images whether the given pre-processed image is normal or disease affected image.

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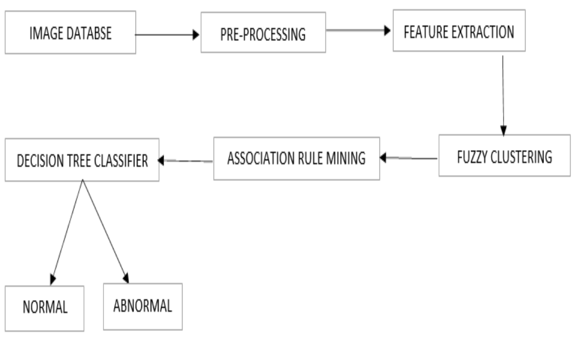

Figure 1. Existing System

The existing FCM is used for finding an image partition that has 'p' with fuzzy clusters for a group of features fj ∈R, j = 1, 2, …, C minimizing the cost function.

p C   m
J Uð ;MÞ ¼ ∑ ∑ Ui;j di;j   ð2Þ
i¼1 j¼1

Where U = [Ui, j] is a fuzzy partition matrix, Ui, j ∈ [1, ∞] is the membershipcoefficient ofjth imageobject inthe ith cluster. Here, the term M = [m1, …. mp] is a cluster centre matrix. Moreover, the term m ∈ [1, ∞] is also point out as a fuzzification parameter that uses the standard distance metric called Euclidean distance which is calculated between the regions xj and mi. The steps of the proposed fuzzy cluster based transition feature variance based segmentation algorithm works are as follows. The extraction of image objects from the previous step called morphological region filling for extracting the object regions where 1 denotes the image object masks whereas 0 indicates the background portion of the input image. The 1 values have been replaced with the original grey image values for extracting the segmented image object. Moreover, the value 0 can be replaced with the intensity value 255 for making the background of the segmented image result as white.

IV.PROPOSED SYSTEM

The proposed incremental classification algorithm selects any one rule of the image data which is able to split its set of samples into subsets as number of sets effectively in one class or the other class in this work. The information gain value is calculated for the process decision making by using all the input image features such as transition regions, range, morphological region, pixels as items sets. These all features with the highest normalized information gain value have been selected for making decision In the traditional classification approach has been used like Association Rule Mining or Decision Tree Classifier whereas in this proposed method called temporal association rule and decision tree combined features have been used for the medical image classification. In this method takes decision over the medical images by using the segmented input images and thetransition features. Finally, it provides the result with the classification of the cancer images as normal image and disease affected image. In the proposed system an enhanced interactive model is designed. An interactive sequence of images is fetched from the scanner database. Those images are pre processed and further segmented for the required feature. The segmented data is further classified through a region growing segmentations in which the image sequence if validated frame by frame for the set of duration. Here the threshold required for segmenting adjusts itself according to the segmented area and position. The result image will compared with the dataset images and it will display whether it is benign or malignant.

1. Preprocessing- If the input images are color images means we are convert to gray scale from that color images. In the complement of a binary image, zeros become ones and ones become zeros; black and white are reversed. In the output image, dark areas become lighter and light areas become darker. Images may have different types of noise. In image enhancement, the goal is to accentuate certain image features for subsequent analysis or for image display. Examples include contrast and edge enhancement, pseudo-coloring, noise filtering, sharpening, and magnifying. Image enhancement is useful in feature extraction, image analysis and an image display. The median filter is used in order to remove the noise from the image. Median filtering is a nonlinear operation often used in image processing to reduce salt and pepper noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges

2. Segmentation- The image features like color, weight, and depth and pixel information to apply before the classifier. Here we used the region growing segmentation algorithm is used in order to segment the portion of defected areas. Image segmentation is typically used to locate objects and boundaries in images. More precisely image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image.

Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. As image segmentation methods, there are two kinds of active contour models according to the force evolving the contours: edge- and region-based. Edge based active contours apply an edge detector, typically based on the image gradient, to locate the boundaries of sub-regions and to draw the contours to the detected boundaries. Edge-based approaches are closely connected to the edge-based segmentation. Region based activecontours apply the statistical information of image intensity inside each subset instead of searching geometrical boundaries. Region-based approaches are also closely connected to the region-based segmentation.

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images. More precisely image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture.

There are two major approaches in image segmentation: edge- and region- based. Edge based segmentation partitions an image based on discontinuities with sub-regions, while region-based segmentation does the similar function based on the uniformity of a desired property within a sub-region.

3. Types Of Segmentation- We can say that image segmentation can be approached from three perspectives: Region approach, Edge approach and Data clustering. The region approach falls under similarity detection and edge detection and boundary detection falls under discontinuity detection. Clustering techniques are also under similarity detection.

4. Classification Of Image Segmentation Techniques- There are several existing techniques which are used for image segmentation. These all techniques have their own importance. These all techniques can be approached from two basic approaches of segmentation i.e. region based or edge based approaches. Every technique can be applied on different images to perform required segmentation. These all techniques also can be classified into three categories.

4.1 Structural Segmentation Techniques - The structural techniques are those techniques of image segmentation that relies upon the information of the structure of required portion of the image i.e. the required region which is to be segmented.

4.2 Stochastic Segmentation Techniques- The stochastic techniques are those techniques of the image segmentation that works on the discrete pixel values of the image instead of the structural information of region.

4.3 Hybrid Techniques- The hybrid techniques are those techniques of the image segmentation that uses the concepts of both above techniques i.e. these uses discrete pixel and structural information together. In further parts of this paper the various techniques of segmentation are discussed and compared. Mathematical description is avoided for simplicity therefore all the techniques are described theoretically. The popular techniques used for image segmentation are: thresholding method, edge detection based techniques, region based techniques, clusteringbased techniques, watershed based techniques, partial differential equation based and artificial neural network based techniques etc. These all techniques are different from each other with respect to the method used by these for segmentation.

V.TECHNIQUES OF IMAGE SEGMENTATION

Thresholding methods are the simplest methods for image segmentation. These methods divide the image pixels with respect to their intensity level. These methods are used over images having lighter objects than background. The selection of these methods can be manual or automatic i.e. can be based on prior knowledge or information of image features. There are basically three types of thresholding

1) Global Thresholding: This is done by using any appropriate threshold value/T. This value of T will be constant for whole image. On the basis of T the output image q(x,y) can be obtained from original image p(x ,y) as:q(x,y)={1,$if p(x, y) > T$ 0, $if p(x, y) < T$ }

Variable Thresholding: In this type of thresholding, the value of T can vary over the image. This can further be of two types:

- Local Threshold: In this the value of T depends upon the neighborhood of x and y.
- Adaptive Threshold: The value of T is a function of x and y.

The values of thresholds can be computed with the help of the peaks of the image histograms. Simple algorithms can also be generated to compute these. Edge Based Segmentation Method: The edge detection techniques are well developed techniques of image processing on their own. The edge based segmentation methods are based on the rapid change of intensity value in an image because a single intensity value does not provide good information about edges. Edge detection techniques locate the edges where either the first derivative of intensity is greater than a particular threshold or the second derivative has zero crossings.

In edge based segmentation methods, first of all the edges are detected and then are connected together to form the object boundaries to segment the required regions. The basic two edge based segmentation methods are: Gray histograms and Gradient based methods. To detect the edges one of the basic edge detection techniques like sobel operator, canny operator and Robert‟s operator etc can be used. Result of these methods is basically a binary image. These are the structural techniques based on discontinuity detection .Region Based Segmentation Method- The region based segmentation methods are the methods that

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segments the image into various regions having similar characteristics. There are two basic techniques based on this method .

Region splitting and merging methods:The region splitting and merging based segmentation methods uses two basic techniquesi.e. splitting and merging for segmenting an image into various regions. Splitting stands for iteratively dividing an image into regions having similar characteristics and merging contributes to combining the adjacent similar regions. Following diagram shows the division based on quad tree.Clustering Based Segmentation Method:The clustering based techniques are the techniques, which segment the image into clusters having pixels with similar characteristics. Data clustering is the method that divides the data elements into clusters such that elements in same cluster are more similar to each other than others. There are two basic categories of clustering methods: Hierarchical method and Partition based method. The hierarchical methods are based on the concept of trees. In this the root of the tree represents the whole database and the internal nodes represent the clusters. On the other side the partition based methods use optimization methods iteratively to minimize an objective function. In between these two methods there are various algorithms to find clusters. There are basic two types of clustering.

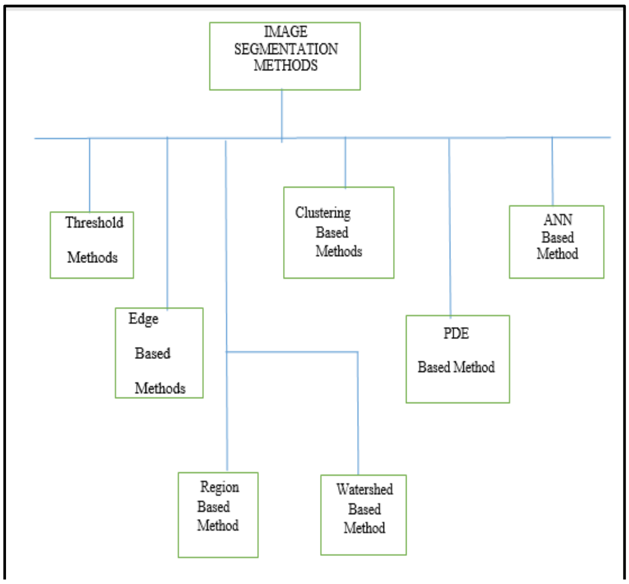

Figure 2.Image Segmentationmethods

Hard clustering: Hard clustering is a simple clustering technique that divides the image into set of clusters such that one pixel can only belong to only one cluster. In other words it can be said that each pixel can belong to exactly one cluster. These methods use membership functions having values either 1 or 0 i.e. one either certain pixel can belong to particular cluster or not. An example of a hard clustering based technique is one k-means clustering based technique known as HCM. In this technique, first of all the centers are computed then each pixel is assigned to nearest center. It emphasizes on maximizing the intra cluster similarity and also minimizing the inter cluster equality. Soft clustering: The soft clustering is more natural type of clustering because in real life exact division is not possible due to the presence of noise. Thus soft clustering techniques are most useful for image segmentation in which division is not strict. The example of such type of technique is fuzzy c-means clustering. In this technique pixels are partitioned into clusters based on partial membership i.e. one pixel can belong to more than one clusters and this degree of belonging is described by membership values. This technique is more flexible than other techniques. Watershed Based Methods: The watershed based methods uses the concept of topological interpretation. In this the intensity represents the basins having hole in its minima from where the water spills. When water reaches the border of basin the adjacent basins are merged together. To maintain separation between basins dams are required and are the borders of region of segmentation.

Table 1. Comparison Table

Segment ation Techniq ue	Descri ption	Advanta ges	Disad vanta ges
Threshol ding Method	based on the histogram peaksofthei magetofind particularthr eshold values	no need of previous information, simplest method	highly dependent on peaks, spatial details are notconsidered
Edge Based Method	based on discontinuity detection	good for imageshaving better contrast between objects	not suitable for wrong detected or too many edges
Clusteri ng Method	based on division into homogeneou s clusters	fuzzy uses partial membership therefore more useful for real problems	determining
Watersh ed Method	based on	results are more stable, detected boundaries are continuous	complex c alculation of gradients
PDE Based Method	based on the working of differential equations	fastest method, best for time critical applications	More computational complexity

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ANN Based Method	based on the simulation of learning process for decision making	no need to write complex programs	more wastage of time in training

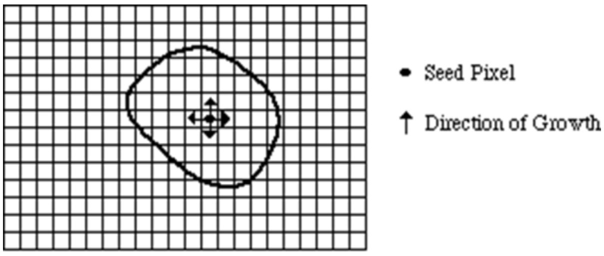

Figure 2. Start of Growing a Region

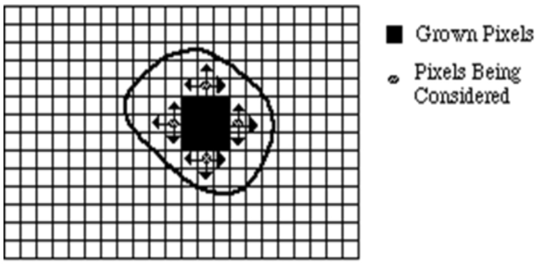

Figure 3. Growing process afterfew Iteration.

However starting with a particular seed pixel and letting this region grow completely before trying other seeds biases the segmentation in favour of the regions which are segmented first.This can have several undesirable effects:Current region dominates the growth process ambiguities around edges of adjacent regions may not be resolved correctly. Different choices of seeds may give different segmentation results. Problems can occur if the (arbitrarily chosen) seed point lies on an edge.To counter the above problems, simultaneous region growing techniques have been developed :Control of these methods may be quite complicated but efficient methods have been developed . Similarities of neighbouring regions are taken into account in the growing process. No single region is allowed to completely dominate the proceedings. A number of regions are allowed to grow at the same time. Easy and efficient to implement on parallel computers.

V. ADVANTAGES OF REGION GROWING

- Region growing methods can correctly separate the regions that the same properties we define.
- Region growing methods can provide the original images which have clear edges with good segmentation results.
- Region growing starts from a set of seed points.

- An alternative is to start with the whole image as a single region and subdivide the regions that do not satisfy a condition of homogeneity.

Basic concept of seed points:The first step in region growing is to select a set of seed points. Seed point selection is based on some user criterion (for example, pixels in a certain grayscale range, pixels evenly spaced on a grid, etc.). The initial region begins as the exact location of these seeds.The regions are then grown from these seed points to adjacent points depending on a region membership criterion. The criterion could be, for example, pixel intensity, grayscale texture, or color.Since the regions are grown on the basis of the criterion, the image information itself is important. For example, if the criterion were a pixel intensity threshold value, knowledge of the histogram of the image would be of use, as one could use it to determine a suitable threshold value for the region membership criterion.

There is a very simple example followed below. Here we use 4-connected neighborhood to grow from the seed points. We can also choose 8-connected neighborhood for our pixels adjacent relationship. And the criteria we make here is the same pixel value. That is, we keep examining the adjacent pixels of seed points. If they have the same intensity value with the seed points, we classify them into the seed points. It is an iterated process until there are no change in two successive iterative stages. Of course, we can make other criteria, but the main goal is to classify the similarity of the image into regions.

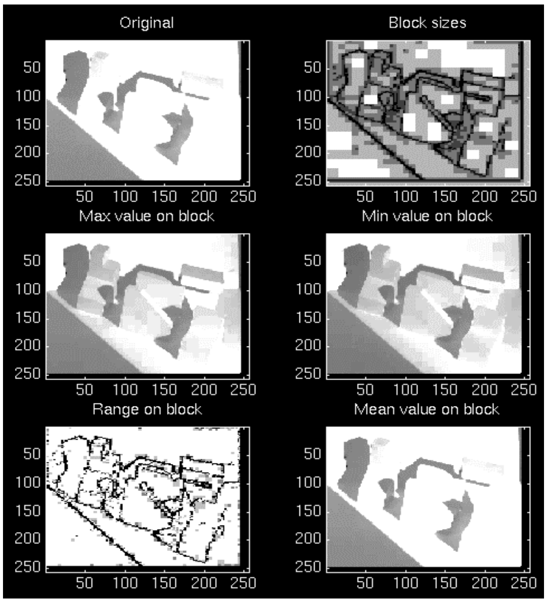

Figure 3. Results.

Then we can conclude several important issues about region growing :

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1. The suitable selection of seed points is important:The selection of seed points is depending on the users. For example, in a grayscale lightning image, we may want to segment the lightning from the background. Then probably, we can examine the histogram and choose the seed points from the highest range of it.
2. More information of the image is better.: Obviously, the connectivity or pixel adjacent information is helpful for us to determine the threshold and seed points.
3. The value, “minimum area threshold”: No region in region growing method result will be smaller than this threshold in the segmented image.
4. The value, “Similarity threshold value“: If the difference of pixel-value or the difference value of average grayscale of a set of pixels less than “Similarity threshold value”, the regions will be considered as a same region.

The criteria of similarities or so called homogeneity we choose are also important. It usually depends on the original image or variance), color, and texture or shape and the segmentation result we want. Some criteria often used are grayscale (average intensity).Region-based segmentation:The main goal of segmentation is to partition an image into regions. Some segmentation methods such as thresholding achieve this goal by looking for the boundaries between regions based on discontinuities in grayscale or color properties. Region-basedsegmentation is a technique for Region-based segmentation determining the region directly. The basic formulation is a logical predicate defined over the points in set and is the null set

- The segmentation must be complete; that is, every pixel must be in a region.
- Requires that points in a region must be connected in some predefined sense.
- Indicates that the regions must be disjoint.
- Deals with the properties that must be satisfied by the pixels in a segmented region. For example, if all pixels in have the same grayscale.
- Indicates that region and are different in the sense of predicate .

This module is used to establish the back propagation neural network concept for training the image and testing the image with the help of weight estimating classifier. The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units. This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents. The result image will compared with the dataset images and it will display whether it is normal or abnormal.Image classification analyzes the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing: training and testing. In the initial training phase, characteristic properties oftypical image features are isolated and, based on these, a unique description of each classification category, i.e. training class, is created. In the subsequent testing phase, these feature-space partitions are used to classify image features.

The description of training classes is an extremely important component of the classification process. In supervised classification, statistical processes (i.e. based on an a priori knowledge of probability distribution functions) or distribution-free processes can be used to extract class descriptors. Unsupervised classification relies on clustering algorithms to automatically segment the training data into prototype classes. In either case, the motivating criteria for constructing training classes is that they are:Independent, i.e. a change in the description of one training class should not change the value of another,Discriminatory, i.e. different image features should have significantly different descriptions, andReliable, all image features within a training group should share the common definitive descriptions of that group.

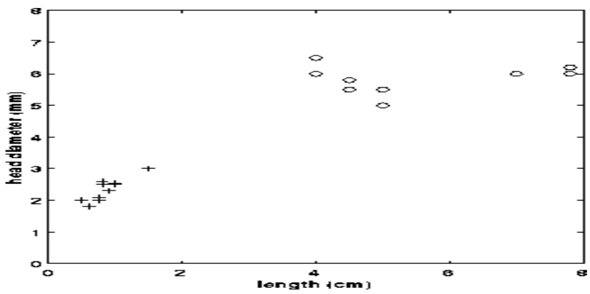

Figure 4 Feature space: + sewing needles, o bolts.

A convenient way of building a parametric description of this sort is via a feature vector, where n is the number of attributes which describe each image feature and training class. This representation allows us to consider each image feature as occupying a point, and each training class as occupying a sub-space (i.e. a representative point surrounded by some spread, or deviation), within the n-dimensional classification space. Viewed as such, the classification problem is that of determining to which sub-space class each feature vector belongs. For example, consider an application where we must distinguish two different types of objects (e.g. bolts and sewing needles) based upon a set of two attribute classes (e.g. length along the major axis and head diameter). If we assume that

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we have a vision system capable of extracting these features from a set of training images, we can plot the result in the 2-D feature space, shown in Figure 4.

At this point, we must decide how to numerically partition the feature space so that if we are given the feature vector of a test object, we can determine, quantitatively, to which of the two classes it belongs. One of the most simple (although not the most computationally efficient) techniques is to employ a supervised, distribution-free approach known as the minimum (mean) distance classifier. This technique is described below.Minimum (Mean) Distance Classifier. Suppose that each training class is represented by a prototype (or mean) vector:

$$m_j = 1/N_j \sum_{x\in\omega_j} x \text{ for } j = 1, 2, ..., M$$

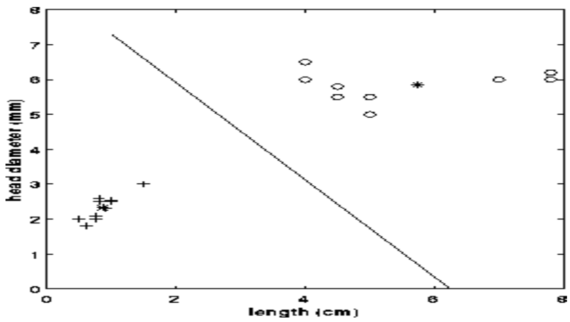

Figure 5 Feature space: + sewing needles, o bolts, * class mean.

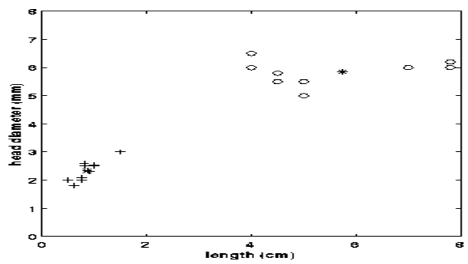

Figure 6 Feature space: + sewing needles, o bolts, * class mean, line = decision surface.

In practice, the minimum (mean) distance classifier works well when the distance between means is large compared to the spread (or randomness) of each class with respect to its mean. It is simple to implement and is guaranteed to give an error rate within a factor of two of the ideal error rate, obtainable with the statistical, supervised Bayes' classifier. The Bayes' classifier is a more informed algorithm as the frequencies of occurrence of the features of interest are used to aid the classification process. Without this information the minimum (mean) distance classifier can yield biased classifications. This can be best combatted by applying training patterns at the natural rates at which they arise in the raw training set.The intent of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or "themes".

This categorized data may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization (Lillesand and Kiefer, 1994). The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground.Image classification is perhaps the most important part of digital image analysis. It is very nice to have a "pretty picture" or an image, showing a magnitude of colors illustrating various features of the underlying terrain, but it is quite useless unless to know what the colors mean. (PCI, 1997). Two main classification methods are Supervised Classification and Unsupervised Classification.

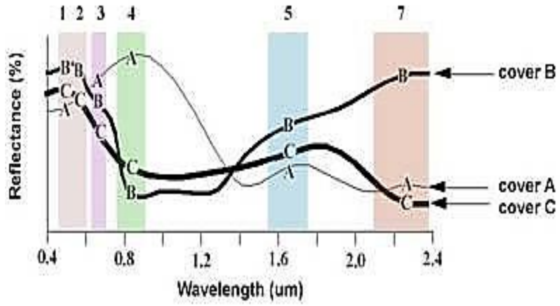

Figure 7. Spectral Reflectance curve of 3 land covers

V.CONCLUSION AND FUTURE SCOPE

In this paper, we study a general inference framework for extracting colon cancer from medical image sequences. This model uses the effective transition region extraction method for performing image segmentation .A collaborative formulation of tumor segmentation is discussed by jointly integrating region and boundary information. Here we used the region growing segmentation algorithm is used in order to segment the portion of defected areas. We used to establish the deep neural network concept for training the image and testing the image with the help of weight estimating classifier. The proposed segmentation process is used for improving the classification accuracy.The result image will compared with the dataset images and it will display whether it is benign or malignant. . The experimental results proved that the efficiency of the proposed model in terms of prediction accuracy when it is compared with the existing models. The proposed model has been achieved 90% as prediction accuracy and it is more than 5% than the prediction accuracy of other existing models.

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Future Works- If we prefer more dataset to train the classifier, we can still improve the performances matrices. Since we do not have that much samples, atleast the future work should be done with more dataset.

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