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NEIGHBORHOOD-BASED SEGMENTATION OF BIOMEDICAL IMAGES USING BINOMIAL CLASSIFIER TREE

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ABSTRACT

Manual segmentation by individual specialists on medical image dataset is time-consuming, expensive, and suffers from considerable inter and intra rater inconsistency. In addition segmentation is hard for the individual expert to combine the information from numerous portions and various channels when multi spectral data has to be examined. Unsupervised segmentation images as occlusions of textures, designed based on local histogram is well-suited to a broader class of images. The model proved that the local histograms were approximately the convex combinations of the value distributions of its component textures but did not provide with a richer characterization of textures and the pixel wise labeling consumed more time. Texture classification of images with multinomial latent model used a mixture density to obtain spatially smooth class segment. But better segmentation was not achieved for speckle noisy biomedical images and the texture classification of images increased the computational cost. To overcome the poor categorization of texture on medical images, the incorporation of neighborhood-based segmentation and binomial classifier tree-based sorting (NS-BCTS) is applied to demonstrate its utility in detecting the noisy speckle biomedical images in medical imagery. To start with, the neighborhood-based segmentation displays the features of rich set in terms of shape, position, color and neighborhood relations. The features extracted are then given as input to the binomial classifier tree-based sorting, with the data label obtained from the experts to minimize the time consuming process. The binomial classifier tree-based sorting examines each collective feature and labels it across the range to determine the computational cost. The experiment is conducted on biomedical image (i.e.,) lung cancer dataset with the factors such as time consumption, computational cost, running time, accuracy and feature categorization efficiency.

Keywords: *Segmentation, Neighbourhood-based segmentation, Binomial classifier tree-based sorting, Feature Categorization, Local value histograms, Medical imagery.*

1. INTRODUCTION

Image segmentation is one of the fundamental problems which at the same time have been considered as the specific area for larger number of theoretical and practical studies. The purpose of image segmentation is to divide an image into regions and many studies also have focused on different formulations resulting in the most effective algorithms. The purpose of this study [3] is to detect and divide multiregion graph cut image using kernel mapping of the image data. The image data is transformed by applying a kernel function in such a way that the piecewise constant model of the graph cut formulation becomes applicable. In [5] feature selection methods other than boosting was used for efficient object detection using the Greedy Sparse Linear Discriminant Analysis (GSLDA) which has the advantage of both the simplicity and computational efficiency. But the drawback of the model being that efficient classifier was not addressed.

The basic ingredients required for developing any image processing algorithms require the correlations of neighboring pixels with the relationship between the channels. In [7], a novel framework was presented that used an informative reference channel during the processing of another channel. The problem was formulated as the maximum a posteriori estimation problem comprising of a reference channel and probabilistic

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model where the correlations was based on Markov random fields. Though different methods for automatic image registration have been researched in the last few decades, a tradeoff exists in those methods with respect to the quality of images obtained using it or the time taken to perform the image registration.

In [9], a method for automatic image registration through histogram-based image segmentation (HAIRIS) was designed. HAIRIS comprised of combination of different segmentations of the pair of images to be registered, based on the parameters such as the area of the object, ratio between the axis, perimeter and fractal dimension for objects matching. A fast and simple approach for snake self-crossing detection and localization was presented in [12] which can be efficiently adapted to any type of parametric snakes, defined by snaxel coordinates where no sub-pixel accuracy was required.

In [14], kernel versions of maximum autocorrelation factor (MAF) analysis and minimum noise fraction (MNF) analysis was introduced where the kernel orthogonal method handled nonlinearities by transforming data into high dimensional feature space using the kernel function and then performing a linear analysis in that space to detect the maximum noise. The study in [3] investigated the multi-region graph cut image segmentation which consisted of minimizing a functional containing an original data term which referred the image data transformed through a kernel function and achieved optimization. Moreover, the disadvantage of the method was the flexibility with which it can be applied to the images was unaddressed.

With the occlusions involved in an image, localization and identification of an object in a specified image is considered to be the challenging task. Therefore, to increase the accuracy level of recognition of object, many models have been designed. Here in [4], a new framework for localization of object using the multiple class phenomenon is introduced that incorporates different levels of contextual interactions. The framework studies the contextual interactions at the pixel, region and object level using three different sources namely, semantic, boundary support, and contextual neighborhoods and finally applies a conditional random field to incorporate object level interactions.

The objective behind image classification is to assign specific class value for each corresponding pixel image with respect to a feature space. Then these features form the basic properties for the images as intensity or amplitude. In addition some other features can also be used as advance abstract image descriptors. In [1], a non-Gaussian MRF based model was used for the representation of texture values. In this model, the work flows on the assumptions that the regression error is an independent factor and identically distributed with the help of t-distribution. But the drawback was the increase in computational cost with the increase in larger number of classes.

Even with the methods mention, segmentation is not trivial. But, the existing method only makes certain level of assumptions about the images it has to segment. Whenever these assumptions are met, the process works, and if they do not meet, it fails. As a result a new mathematical and algorithmic framework was designed in [2] for unsupervised image segmentation. The images were modeled as occlusions of random images which showed that local histograms were useful tool for segmenting. But the drawback was richer categorization of features was not possible using local histogram.

To overcome the poor categorization of texture on medical images and to minimize the computational cost, neighborhood-based segmentation and binomial classifier tree-based sorting (NS-BCTS) is introduced to demonstrate its utility in detecting the noisy speckle biomedical images in medical imagery.

The remainder of this paper is organized as follows. In Section 2, demonstrates the state-of-art involved in the segmentation and classification approaches used for medical database. In Section 3, the incorporation of neighborhood-based segmentation and binomial classifier tree-based sorting applied on medical images are presented. Section 4 explains about the Lung Cancer Data Set from UCI repository described 3 sort of pathological lung cancers. Section 5 performs result analyzed using table and graph values and finally concluded the work in Section 6.

2. STATE-OF-ART

With the increasing growth of images acquired through the digital cameras, quality evaluating algorithms become highly necessary to select images for the final application by avoiding the images that possess minimum quality level. In [6], the solution to the problem of no-reference quality assessment is addressed with the help of digital pictures corrupted with blur. But the tradeoff using

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this method was that the performance level achieved was not up to the mark. A new algorithm for solving the problem of optimization of regularized image restoration and improve the performance level was built in [8].

A hybrid approach called conditional random model [10] was designed to robustly detect and localize texts present in the natural scene images. To filter out the non-text components, a conditional random field (CRF) model considering both the unary and binary component with supervised parameter learning was presented. In [11], a novel face representation and recognition method was presented by detecting the information jointly in image space, scale and orientation domains. In [13], a direct primal-dual approach towards a global minimization was presented using the continuous Potts model for multiclass labeling problems applied for multi-phase image segmentation.

Image segmentation refers to the process of detecting the boundaries between distinct regions in any image and partitioning the pixels. Some of the applications of image segmentation include, sensing of remote objects, video processing. At the same time, there exist different classic approaches including graph cuts, active contours, Gabor filtering, clustering, watersheds, region growing and so on.

Based on the aforementioned methods, a model that effectively segments the biomedical images using binomial classifier tree is designed that display rich set of features terms of shape, position, color and neighborhood relations. Followed by it the features obtained are fed as input to the binomial classifier tree-based sorting for faster evolution and minimizing the time consumption to detect the noisy speckle images with lung cancer image given as input. To illustrate these advantages, we also ran the tests with various classes of real images including Lung Cancer dataset from UCI repository that described 3 sort of pathological lung cancers.

3. THE REFLECTIVE PROCESS AN INCORPORATED FORM OF SEGMENTATION AND SORTING ON BIOMEDICAL IMAGES

An incorporated form of segmentation and sorting of biomedical images using neighborhood-based segmentation and binomial classifier tree-based sorting approach is applied on biomedical images to detect the noisy speckle images. The framework of NS-BCTS approach is shown in Figure 1.

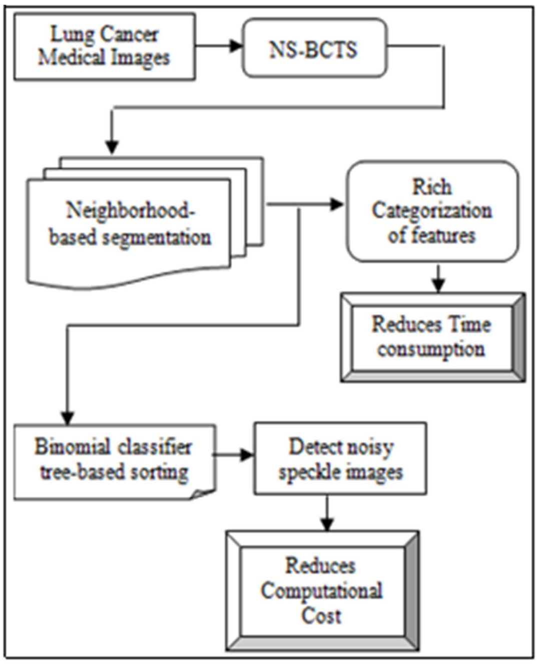

Figure 1: Framework of NS-BCTS approach

Figure 1 describes the framework of neighbourhood-based segmentation and binomial classifier tree-based sorting approach which combines the segmentation and sorting to detect structure without noise. From the figure, the lung cancer medical images are given as input to the NS-BCTS approach. The NS-BCTS approach is divided into two sections. The first section concentrates on the segmentation of the lung cancer medical images using the neighbourhood-based segmentation (NS). The obtained output from NS has rich categorization of features in terms of terms of shape, position, color and neighborhood relations. The second section focuses on the binomial classifier tree-based sorting (BCTS) to detect the noisy speckle images.

To the best of knowledge, the NS-BCTS approach is developed to segment the medical images and to categorize the rich set of features. The bank of features characterizes each aggregate in terms of color strength, texture, shape, and position. These features were selected in consultation with expert radiologists. All the features are computed as part of the segmentation process, and they are used in turn to further classify using the binomial classifier. The binomial classifier tree-based sorting step examines each aggregate and a pixel wise label is performed. The

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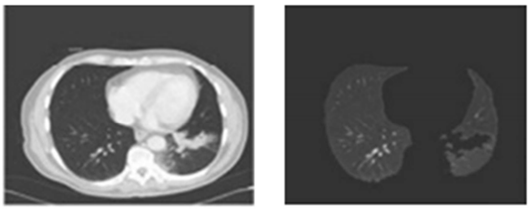
binomial classifier tree-based sorting is incorporated across range to determine the wound on lung cancer images.

By combining segmentation and sorting which are able to make use of integrative, regional properties that provide statistics of segments, distinguish their overall shapes, and localize their borders. At the same time, the rich hierarchical decomposition produced by the NS-BCTS algorithm permit us to have a great extent on segmentation process. Even when a wound is not segmented properly, namely when it is not fully covered by one aggregate, generally expect to find some aggregate in the hierarchy that adequately overlaps it to allow sorting in NS-BCTS approach.

3.1 Neighborhood-based Segmentation structure

In this section, the neighborhood-based segmentation for detecting abnormal lung images from lung cancer dataset is presented. In the initial stage, the NS approach obtains as input several scans along with a delineation of the wounds in these scans. The system uses NS segmentation to offer an entire hierarchical decomposition of the data into regions analogous to both significant anatomical structures and wounds. Each aggregate is equipped with a collection of features ranging from shape, position, color to neighborhood relations. Finally, a sorting is applied to distinguish between the aggregates that correspond to wounds from those that correspond to non wounded area.



(a) (b)

Figure 2: Original Lung Medical Image (b) Wounded part Segmented Image using DR

Figure 2 (a) illustrates the original lung cancer spreader image and 2(b) denotes the wounded part segmented image using neighborhood-based segmentation and binomial classifier tree-based sorting approach. The segmentation model is extended to handle rich categorization of features on medical images using neighborhood-based segmentation. The lung cancer medical images are obtained and it is represented using the grid $G = (P, L)$. Each grid G of pixel $'i'$ is represented where the $P = (1, 2, 3, \dots, n)$ and $'n'$ is total number of pixels attained. A neighborhood-based segmentation associates each pair of neighboring pixel i and j. The $NS_{i,j}$ reproduce the disparity between the two neighboring pixels i and j.

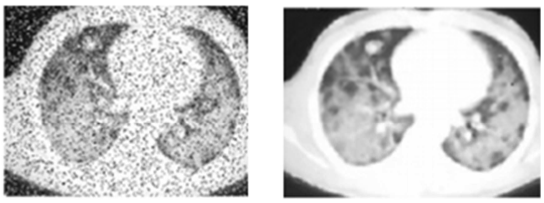
$$\mathrm{NS_{i,j}} = \gamma\,|\mathrm{cs_i} - \mathrm{cs_j}| \quad (1)$$

Where, $\mathrm{cs_i}$ and $\mathrm{cs_j}$ denote the color strength of the two neighboring pixel, and γ is a positive predefined constant that is determined with experience. The noisy speckle images are detected in larger portion in NS approach using the condition vector. Every segment in NS approach S ∈ P is associated with a condition vector $\mathrm{CV} = (c_1, c_2, \dots, c_n)$ representing the assignments of pixel to a segment 'S'

$$\mathrm{NSm_{i,j}} = \mathrm{NS_{i,k}} \left| \sum_{k} k\,! = i \right| \quad (2)$$

$$\mathrm{NSm_{i,j}} = \mathrm{NS_{i,k}} \quad (3)$$

The matrix with two neighboring pixels $\mathrm{NS_{i,j}}$ and $\mathrm{NSm_{i,j}}$ is the Laplacian matrix of G whose elements are i, j, k. Fig 3 (a) illustrates the noise speckle lung cancer image and 3(b) NS-BCTS based preprocessed lung image.



(a) (b)

Figure 3: (a) Noise Speckle Lung Image (b) NS-BCTS based Preprocessed Lung Image

The NS approach measure sums the neighborhood pixels along the boundaries of medical image where $'S'$ is the normalized image. Segments that yield negligible values of $\tau(S)$ are considered. The NS approach permit random real assignments to $'c'$ for preprocessing, the minimum for τ is obtained by the minimal generalized eigen vector $'c'$ of

$$\mathrm{NSmc} = \lambda \mathrm{NSc_{i,k}} \quad (4)$$

The condition is that the $\lambda >$ represents the lung cancer medical image which detect the noise speckle very easily and the objective is to find those partitions characterized by small values of τ .

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3.2 Richer Categorization of Features

The incorporation of neighborhood-based segmentation in the proposed performs affine transformation in order to align the different sequences provided for each images. The alignment acquires the neighborhood pixels and uses the same positioning parameters to reduce the computational cost. Hence, given the NS aligned scans, each pixel includes a vector of color strength. The preliminary step for feature categorization is expressed as,

$$Feature\ NS_{i,j} = \sum_{c=1}^{d} \gamma_c \left(cs_i^c - cs_j^c \right)^2 \quad (5)$$

The color strength feature determines the initial pixel utilization information from all $'d'$ ranges. The color strength $'c_s'$ from pixel $'i'$ to $'j'$ are analyzed with constantγ_c. All the parameters used in the lung cancer medical image experiments are based on two arbitrarily chosen calibration scans for each type of data.

Wounds often are characterized by properties of collections that emerge at intermediate scales, and difficult to extract unique range procedure. Such properties include, intensity homogeneity, principal direction of the wound, and color strength contrast. Pixel by pixel analysis is limited in its ability to utilize such range dependent properties. The neighborhood-based segmentation in NS approach provides a recursive mechanism for calculating properties all along with the segmentation process. First, the NS approach uses collection properties to construct the segmentation and secondly, the features obtained using the NS approach are fed as input to the binomial classifier tree-based sorting (BCTS) approach to perform sorting as described below in section 3.3. The actual effect of each of these features is determined by high dimensional feature vector.

3.3 Binomial Classifier Tree-based Sorting (BCTS)

Once the input lung cancer medical images are segmented using the neighborhood-based segmentation approach, rich categorization of features are obtained which are fed as input to perform the binomial classifier using tree-based sorting to minimize the computational cost by detecting noisy speckle images. The NS-BCTS incorporating segmentation and classification in which each collective feature are characterized by high-dimensional feature vector and the sorting stage proceeds. On the basis of the classification rule, the given set is classified into two groups ('wounds' or 'unwounded') and tree-based sorting is performed using the collective features. Then, given an unlabeled scan the sorting is used to detect the wounds.

To construct the binomial classifier tree-based sorting, a learning process is applied with collection of $'N'$ candidate segments. Each candidate is described by a high-dimensional feature condition vector $'v'$ and the portion indicating a shadow mask is marked as wound. The NS-BCTS approach contain a mixed collection of wound and unwounded pixel and sort the segmented image across the range to determine the noisy speckle images to minimize the computational cost.

Figure 4 constructs the binomial classifier tree-based sorting (BCTS) in NS-BCTS approach. As illustrated in the figure, a subset of the NS approach (image1, image 2, …, image n) are selected and used to construct a binomial classifier tree-based sorting from the root downwards. At the root (i.e.,) the tree-based sorting consists of all the labeled medical image segments constantly split into two subsets. The Binomial Classifier Tree-based Sorting detects the noisy speckle images and sorts based on the tree-based model for reducing the computational cost.

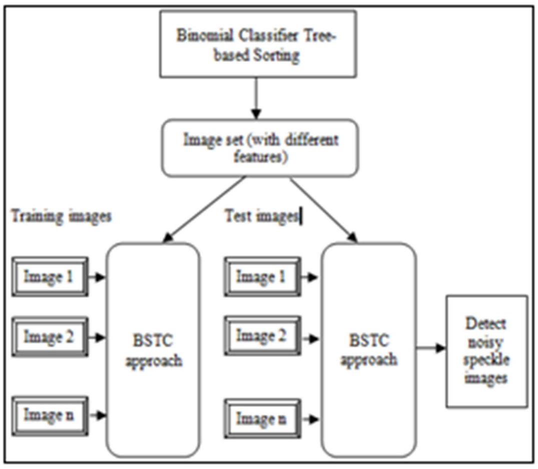

Figure 4: Binomial Classifier Tree-based Sorting

The algorithmic representation of neighborhood-based segmentation and binomial classifier tree-based sorting approach is given below:

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Begin
Input: Lung Cancer Medical Images
Output: Segmented Image without noise speckle
1 Preprocess medical image with noise speckle
2 Repeat recursively for segment image till last pixel 'i', 'j'
3 Compute the neighborhood-based segment
4 Define Laplace matrix 'NSm' of grid 'G' form
5 Segmented image perform richer feature categorization
6 Sorting based on binomial classifier tree-based sorting approach
7 Incorporate segment and sorting for minimal computational cost and time
End

The output of the NS approach includes the set of rich categorization of features in the form of graphs in all scales with the neighborhood pixels between them. The binomial classifier tree-based sorting process is applied to three sets of segmentation scales, small, intermediate, and large segments corresponding. Once the images are trained, proceed to apply NS approach to an unlabeled test data. At this stage the system obtains as input of a single lung image. A medical image segments and extracts features using the NS approach. Finally, each collection of features is sorted using binomial classifier tree-based sorting as wounded and non-wounded area, to effectively categorize the rich features.

4. A EXPERIMENT ON LUNG CANCER DATASET USING NS-BCTS

Performance experiments of NS-BCTS approach are conducted with various conditions using MATLAB coding. Lung Cancer dataset from UCI repository is taken for the experimental work to categorize the rich features. Lung Cancer Data Set from UCI repository described 3 sort of pathological lung cancers. Lung Cancer Data Set contains 58 features and 3 classes with 32 instances. Attribute 1 is the class label and all predictive attributes are insignificant, taking on integer values from zero to three.

The NS-BCTS approach is compared against the existing unsupervised segmentation Images as Occlusions of Textures (US-OT) and Texture classification of SAR images with Multinomial Latent (ML) model. The performance factors such as time consumption, computational cost, running time, accuracy and feature categorization efficiency are taken for experimental evaluation.

Time consumption using NS-BCTS is the time consumed to perform the process using the neighborhood-based segmentation. Running time measures the time taken to perform both the segmentation and sorting process for the given lung cancer dataset. Computational cost refers to the cost involved to identify the neighborhood pixel in order to categorize the rich set of features. Accuracy evaluates the ratio of all instances of the lung cancer images that are separated correctly which represents the ratio of number of correct classifications to the number of incorrect classifications given as below

$$\mathrm{Acc} = \frac{\text{No of correct classifications}}{\text{No of incorrect classifications}}$$

Feature categorization efficiency measures the color strength feature which determines the initial pixel utilization information from all 'd' ranges as illustrated in (5).

5. DISCUSSIONS ON NS-BCTS APPROACH

We developed an incorporated approach that combines neighborhood-based segmentation and binomial classifier tree-based sorting for detecting noisy speckle images in order to classify the wounded and non-wounded area from lung cancer dataset. Our study focuses on analyzing Lung Cancer Data Set from UCI repository which described 3 sort of pathological lung cancers. The utility of our method was demonstrated in various experiments using different types of lung cancer images. Comparison of our results to other existing unsupervised segmentation Images as Occlusions of Textures (US-OT) and Texture classification of SAR images with Multinomial Latent (ML) model yields better results in terms of time consumption, computational cost, running time, accuracy and feature categorization. Table 1 given below shows the measure of time consumption with our model NS-BCTS approach and comparison is made with two other models namely, US-OT model and ML model respectively.

Table 1: Tabulation for time consumption

No. of features	Time Consumption (sec)		
	NS-BCTS approach	US-OT model	ML model
2	22	27	30
4	25	32	35
6	28	35	42
8	32	40	48
10	34	45	53
12	37	52	57
14	40	55	60

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Figure 5 illustrates the time consumption with respect to the number of features. From the figure it is illustrative that the time consumed is comparatively lesser using the neighborhood-based segmentation and binomial classifier tree-based sorting approach than when compared with the existing, US-OT model [2] and ML model [1] respectively. This is because with the application of neighborhood-based segmentation, rich categorization of features are obtained which in turn reduces the time consumption using NS-BCTS approach than the US-OT model and ML model. Comparatively, using NS-BCTS approach, the time consumption is reduced from 22-40% when compared to the US-OT model and 36-55% when compared to the ML model.

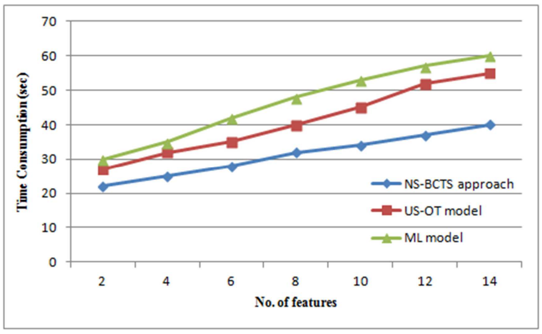

Figure 5: No. of features Vs time consumption

Table 2 and Figure 6 depict the computational cost with respect to the number of features. An elaborative comparison is made with two models, US-OT [2] and ML [1] model respectively. The rate at which the computational cost is performed is lesser using the proposed NS-BCTS approach than the other two models. The minimum computational cost obtained using the NS-BCTS approach because the rich set of features are given as input to the binomial classifier tree-based sorting which in turn reduces the computational cost. Comparisons of the proposed NS-BCTS approach with two other models US-OT [2] and ML [1] model reveal that NS-BCTS approach performed 8-13% efficient than the US-OT and 13-20% better than the ML model respectively.

Table 2: Tabulation for Computational cost

No. of features	Computational cost (sec)		
	NS-BCTS approach	US-OT model	ML model
2	15	17	18
4	18	20	22
6	20	22	24
8	22	24	26
10	25	27	29
12	30	32	34
14	35	38	42

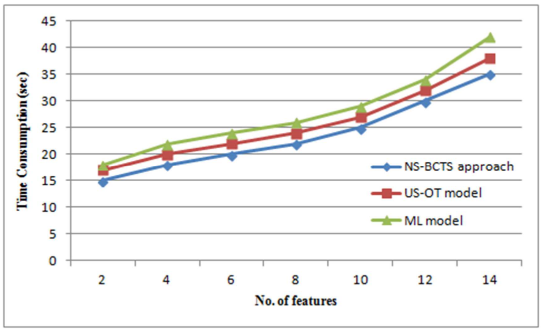

Figure 6: No. of features Vs Computational cost

Table 3 and Figure 7 illustrate the running time required to overcome the poor categorization of features with respect to the lung cancer images ranging from 5 to 35. The proposed approach is implemented using the incorporation of both the segmentation and sorting using neighborhood-based segmentation and binomial classifier tree-based sorting. From the figure it is evident that the running time using the proposed NS-BCTS approach is lesser than the other two models. This is because using the neighborhood segmentation approach using the color strength of the two neighboring pixel and detect the noisy speckle images efficiently. The BCTS approach using the tree-based sorting splits the labeled medical image segments into two subsets by minimizing the running time. Comparatively, the NS-BCTS approach is 4-12% better than the US-OT [2] model and 20-30% better than the ML [1] model.

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Table 3: Tabulation for Running time

No. of lung cancer images	Running time (sec)		
	NS-BCTS approach	US-OT model	ML model
5	10	11	13
10	12	13	15
15	14	15	17
20	14	15	17
25	17	18	22
30	22	23	28
35	25	28	30

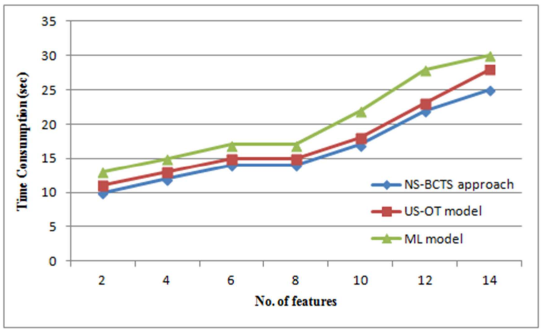

Figure 7: No. of lung cancer images Vs Running time

In Table 4 shows the parameters for calculating the accuracy at which the neighborhood-based segmentation is achieved by considering the number of features. The Neighborhood-based Segmentation accuracy is determined based on the number of features extracted from the given lung cancer input image. The value of the proposed NS-BCTS approach is compared with the existing US-OT and ML model respectively.

Table 4: Tabulation for Accuracy

No. of features	Neighborhood-based Segmentation Accuracy (%)		
	NS-BCTS approach	US-OT model	ML model
2	65	60	58
4	72	67	62
6	75	70	66
8	80	73	68
10	82	74	72
12	84	77	74
14	85	80	75

Figure 8 describes the neighborhood-based segmentation accuracy determined based on the number of features extracted from the given lung cancer input image. Compared to the existing US-OT model [2] and ML model [1], the proposed NS-BCTS approach provides higher rate of accuracy. Since the proposed NS-BCTS approach used neighborhood-based segmentation and tree-based sorting for detecting the noisy speckle images, the sorting is performed in an easy manner using binomial classifier. The accurate information is obtained by applying the affine transform that categorizes the image data into wounded and unwounded. Higher the classification accuracy, more accurate the detection of speckle images are. Compared to the US-OT [2] model, the proposed NS-BCTS approach achieved 5-9% better accuracy rate and 10-15% better than the ML [1] model.

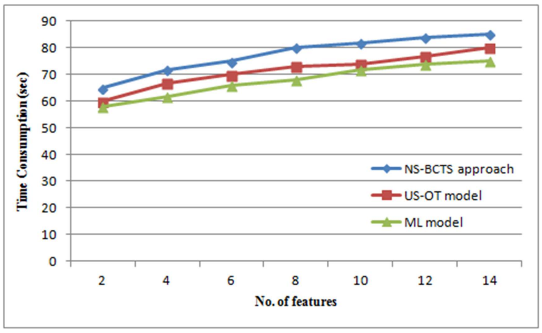

Figure 8: No. of features Vs Neighborhood-based Segmentation accuracy

Table 5 and Figure 9 illustrate the feature categorization efficiency with respect to the number of input, lung cancer images ranging from 5 to 35. With the increase in the number of input images, though the feature categorization efficiency decreases, but comparatively higher than the two existing models, US-OT model [2] and ML model [1] respectively. This is because the neighbor-hood-based segmentation using hierarchical decomposition displays the rich set of features in terms of shape, position, color and neighborhood relations which is again given as the input to the binomial classifier tree-based sorting and detects the noisy speckle biomedical images in medical imagery in an efficient manner. This maximizes the feature categorization efficiency. Comparatively, the NS-BCTS approach is 2-7% better than the US-OT model [2] and 6-11% better than the ML model [1].

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Table 5: Tabulation for Feature Categorization efficiency

No. of input images	Feature Categorization efficiency (%)		
	NS-BCTS approach	US-OT model	ML model
5	72	70	67
10	68	64	62
15	65	61	59
20	62	60	55
25	58	56	52
30	55	53	50
35	52	48	48

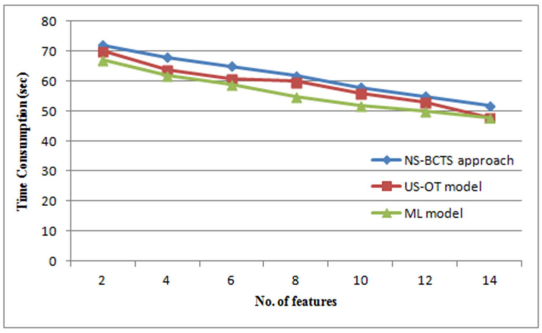

Figure 9: No. of input images Vs Feature Categorization efficiency

6. CONCLUSION

An efficient and new implementation of incorporation of neighborhood-based segmentation and binomial classifier tree-based sorting is presented and applied to the lung cancer images. This representation provides an overall control in detecting the noisy speckle biomedical images in medical imagery to reduce the time and computational cost. The proposed approach largely alleviate the problem of texture classification on medical images with rich set of features obtained using the application of neighborhood-based segmentation. The noisy speckle images were detected efficiently using the tree-based sorting. Finally, each collection of features is sorted with the help of binomial classifier tree-based sorting into wounded and non-wounded area, to effectively categorize the rich features. Simulations conducted using the Matlab proved the effectiveness of the method in terms of time consumption, computational cost, feature categorization efficiency, running time. It is found that on average, NS-BCTS approach required 30 sec and need 17% of the running time compared to the other two models. While the experimental results show that the proposed method segment the lung cancer images of different scales and levels of quality by improving accuracy and efficiency, it is worth conducting a more comprehensive analysis on the effect of quality of image and the number of effective features being segmented on the proposed method as future work.

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