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Improved Lung Cancer Segmentation Using K-Means and Cuckoo Search

Paramjit Singh, Pankaj Nanglia, Aparna N Mahajan

***Abstract:** Lung Cancer is among the deadliest disease that tolls mass every year. Information technology is playing an indispensable part in availing the most successful diagnosis and top treatment strategies to fight the condition when detected at an earliest stage. The work encompasses the improvement in the quality of image segmentation of Computer Tomography (CT) medical images of lung cancer. The paper evaluates the performance of two algorithms as a post segmentation process, namely, Artificial Bee Colony (ABC) and Cuckoo Search (CS). Support Vector Machine(SVM) is also used as a cross validator over the post segmentation algorithms ABC and CS. The experimental evaluation includes Accuracy, Precision, Error, Segmentation Time, Recall and F-measure to determine the success of the proposed hybrid model. The proposed results exhibit an improved Accuracy, Precision, Recall and F-measure by 5%, 6%, 3%, 4% and 10%, 11%., 12%, 11% for k-ABC and k-CS respectively.*

***Keywords:** Lung Cancer, image segmentation, k-mean clustering, k-ABC, k-CS.*

I. INTRODUCTION

Among the various types of cancers, Lung Cancer exhibits the most challenging fatal malignancy around the world. [1, 2]. It becomes mandatory to diagnose it before it becomes untreatable and virulent. Lung cancer can be categorised as Small Cell Lung Carcinoma (SCLC) and Non-Small Cell Carcinoma (NSCLC) [3]. Tobacco smoking over the period directly contributes to 85% of the total lung cancer cases still it is interesting to know that there are 10–15% lung cancer cases with the people who have never smoked [4]. In such cases, air pollution, second hand smoking, asbestos, and radon gas are the culprits. An early diagnosis of cancer offers more effective treatment medical imaging Computer Tomography (CT) and radiography forms the conventional methods to detect the presence of lung cancer.

II. RELATED WORK

Gomathi in 2012 had devised a SVM based method to distinguish benign cancer from malignant lung cancer nodules.

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The CT images were used as raw images for the study. The results had shown a high accuracy when SVM is used with RBF kernel for classification [7]. Praveen et al. in 2014 proposed an automatic computer aided detection system for diagnosis of cancer nodules in lung cancer CT images. In the design SVM classifier was used to distinguish normal, malignant and benign CT images. The experimental evaluation showed that RBF kernel outperformed in the automatic detection system [8]. In 2014, Moftah et al. presented an image segmentation approach based on adaptive k-means. The authors proposed the work so as to enhance the efficiency of the image segmentation. The experimental evaluation had shown improved results for mean, median, entropy, solidity, circularity and standard deviation [9]. In 2017, Dhal and Das presented a new modified cuckoo search with histogram equalization along with a different local and global search approach. The experimental evaluation showed that the proposed modified search approaches were outstanding to the existing cuckoo search modifications [10]. Dhanachandra et al. in 2015 proposed a method for the enhancement of image quality with the application of partial stretching enhancement prior to k-means. The purposed technique obtained better results for Peak to Signal Noise Ratio as well for Root Mean Square Error in comparison to k-means [11]. Rendon-Gonzalez and Ponomaryov in 2016 proposed a methodology to eradicate the background image noise using masks, threshold and morphological techniques. The authors had shown that their proposed methodology had achieved an accuracy, specificity and sensibility of 78.08%, 80.92% and 84.93%, respectively [12]. Sarker et al. in 2017, proposed a method that employed the strengths of k-means clustering along with the morphological image processing techniques for three-dimensional lung cancer segmentation with the ability to calculate size of tumor with diameter more than 7mm and also identified the stage that the cancer had reached. The proposed method demonstrated an experimental accuracy and specificity of 95.68% and 98%, respectively [13]. Moriya et al. in 2018 employed the application of k-means clustering algorithm. The results had shown that multi-threshold Otsu and k-means exhibited the instrumental Normalized Mutual Information (NMI) score of 0.626 [14]. In 2018, Perumal et al proposed the identification of cancer in CT images with the help of Enhanced Artificial Bee Colony Optimization (EABC). The results showed better results for segmentation using wavelet transform with haar family [15]. Tripathi et al. in 2019 were also involved in the comparative analysis of image segmentation approaches such as Watershed, Threshlding, Partial Differential Equation (PDE), Edge detection.

The author had also involved the SVM classifier and the presented study showed the appropriateness of CT images to reach accurate results [16]. Prabhukumar et al. in 2019 proposed an improved lung cancer diagnosis system for high volume CT images of Fog environment. Cuckoo search is employed for the identification of optimal features for lung cancer classification into benign or malignant. The training and classification step involved the engagement of SVM machine learning [17]. The technique is evaluated against Early Lung Cancer Action Program (ELCAP) public database. The resultant system achieved mean accuracy of 98.51%, sensitivity of 98.13% and specificity of 98.79% [18]. Sa et al. in 2019 worked for the comparative study involving segmentation methods involved in lung parenchyma tissues. The results showed that Watershed approach showed demonstrated results with 96.57% accuracy when it was tested with 400,000 lung parenchyma images [19-20].

III. MATERIALS AND METHODS

A. Database

The proposed work uses ELCAP a Public Access Research Database of Lung Image Datasets designed and developed by Cornell University. The database comprises of 500 low-dose CT Scan Images (documented) with 1.25 mm slice thickness. The dataset is available at the URL http://www.via.cornell.edu/lungdb.html.

B. Proposed Method

The segmentation process categorizes the entire image in two segments namely BBG and WBG as discussed earlier. As shown in Figure 1(a), Lung nodule has both the parts BBG and WBG out of which the feature extraction mechanism only requires WBG as shown in Figure 1(b).

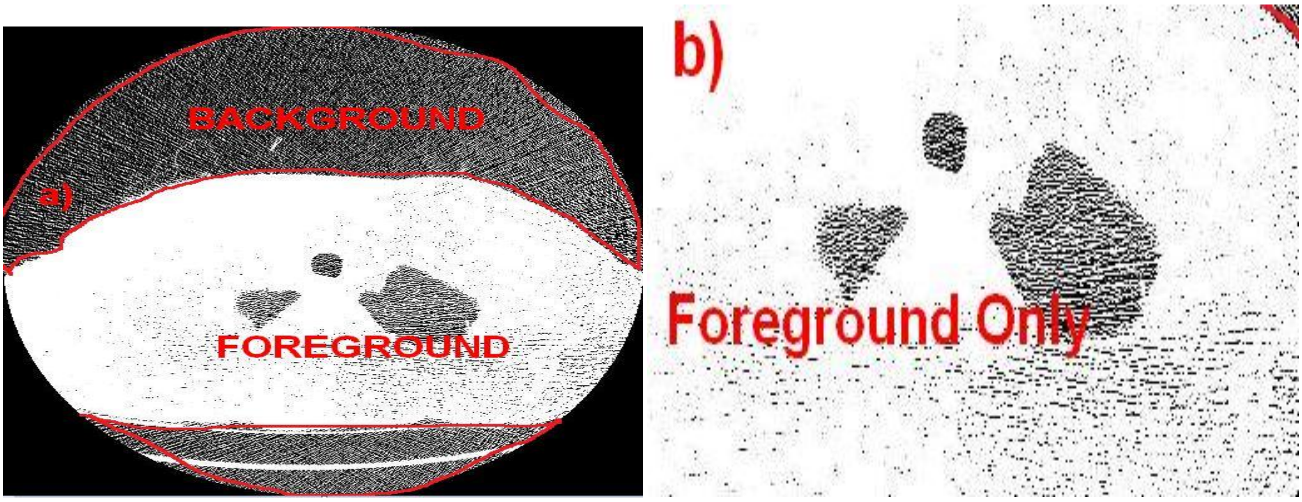

Fig.1 Background and Foreground

The process of segmentation is also referred to as ROI selection. Though the segmentation process can be best done manually but it becomes a very tiring job when the image count is high. If the classification of cancer types is to be done by Software Aided Designs (SAD), the image count in the training section is always high in order to make the SAD more precise and accurate. The proposed work methodology uses k-means algorithm for the primary segmentation process which is followed by the optimization algorithm. The proposed methodology uses two Swarm Intelligence based optimization techniques namely Artificial Bee Colony (ABC) and Cuckoo Search (CS). The work flow is represented by Fig.2.

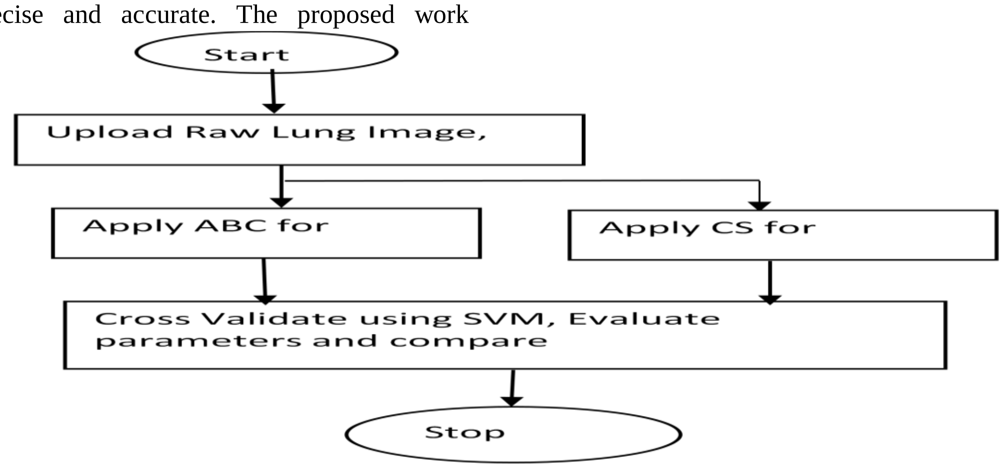

Fig.2 The proposed work Flow

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K-Means clustering algorithm is an unsupervised learning technique that is utilized for solving well-known clustering issues and it is used to segment the interest area from the background. **k-**means algorithm is applied on the raw image itself by providing two centroid regions. The architecture of k-means algorithm is as follows

1. Take every point 'p' from the point list P_{List}
2. Initialize two Cluster with centroid value Cd1 and Cd2
3. Calculate Euclidean distance of each point 'p' from both the centroids using Equation(1)
4. Ed= $D(p,(Cd1,Cd2))$ (1) where D is the ecludeian calculation function
5. Rearrange P_{List} as the closest distance measure from the centroids

The k-means algorithm extracts the foreground and background to a good extent but if the classification design has to be completely automated with preciseness, may be good extent is not good enough. It is observed often that the k-means algorithm put quite some points of background to foreground and vice versa. Figure 3 shows the distorted result of k-means algorithm.

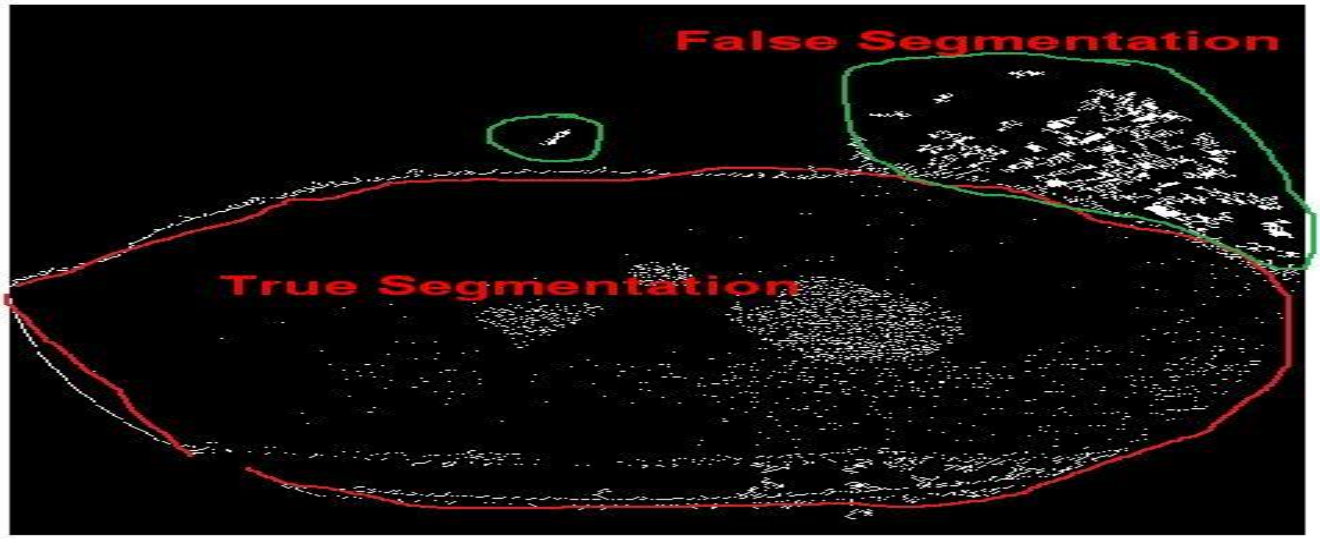

Fig.3 k-means segmentation result

It is also observed that k-means is not able to judge the foreground and background part as correct data labels. The proposed algorithmic structure calculates the area of both clustered region. The background always has the higher area as compared to foreground and hence the proposed algorithmic architecture selects the region with lower area value. In order to improve the performance of the k-means clustering algorithm, the proposed structure uses ABC and CS. Both these algorithms takes the clustered value as input and further applies the architecture of ABC and CS to them.The ordinal measures of ABC and CS are as follows

Table I: Ordinal measure of ABC

Population Size of ABC	**Element Count in each Cluster**
Employed Bee	Cluster Element Value
Onlooker Bee	Average Cluster Value
Incremental Value of Employed and Onlooker	.1

Table II: Ordinal measures of CS

Egg Count in Nest	Element Count in each Cluster
Cuckoo Egg Value	**Cluster Element Value**
Cuckoo threshold	**Average Cluster Value**
Travel Time of Bird	**Random**

For both the optimization algorithms, same fitness function is used for the processing as mentioned in Equation (2).

$$Fitness_{Value} \Rightarrow Accepted\ If\ \frac{\sum_{i=1}^{n} Cluster_{Bitvalue}}{n} < Cluster_{Bitvalue(i)} \quad (2)$$

If the cluster bit value does not meet the average value then the bit is replaced by the average bit value. Both the algorithms returns optimized image which is further passed to Support Vector Machine (SVM) with supplied two classes namely "Average Bit Value" and "Below Bit Value" as shown in Figure 4.

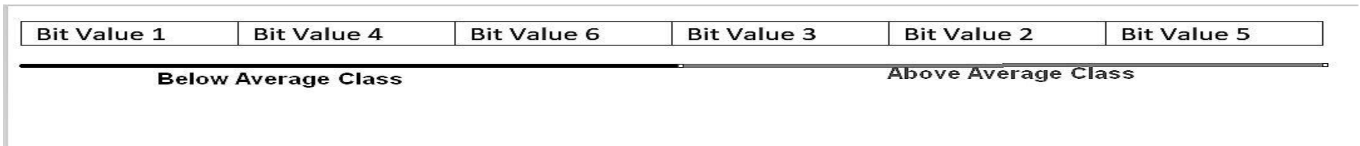

Fig.4 Bit Value Segmentation

The segregated group is then further passed to SVM as shown in Figure 5

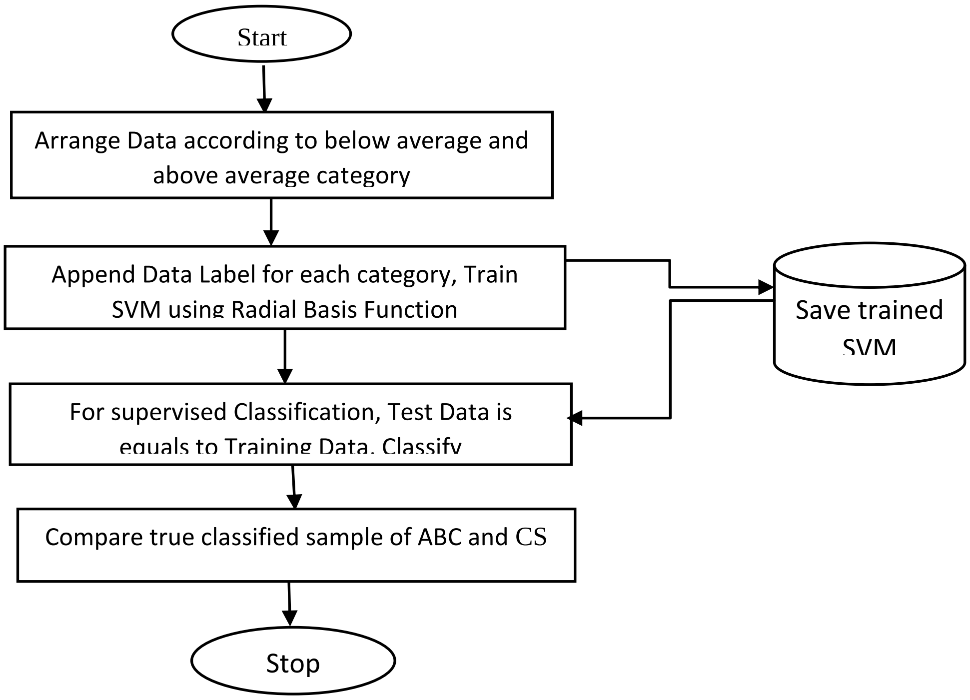

Fig.5 Training and Classification using SVM

Pseudo Code 1.

Pseudo Code 1: Training and Classification using SVM

1. *Initialize TrainingData and Associated LabelClass as Empty*
2. *TrainingData. Append* (*Below Average Class. Bit Value*)
3. *Associated LabelClass. Appen* (1);
4. *TrainingData. Append* (*Above Average Class. Bit Value*)
5. *Associated LabelClass. Append* (2);
6. *Initialize SVM Training with kernel type* "*Radial Basis Function* (*rbf*)"
7. *Store SVM Training Structure to db*
8. *TestData* = *TrainingData*
9. *Classify and Choose maximum classified value*

The training of SVM using RBF kernel which supports Neural Training within the SVM class value. Figure 6(a) and (b) demonstrates the training and classification architecture of SVM.

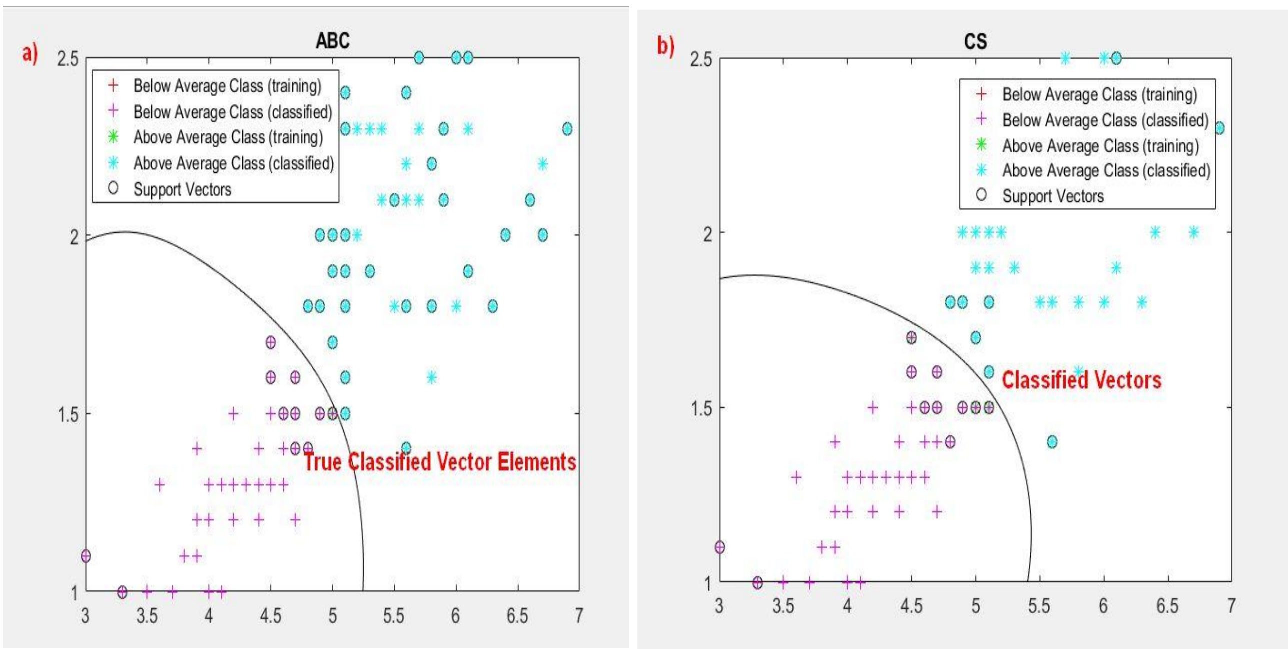

Fig.6 Classified Vector of ABC and CS

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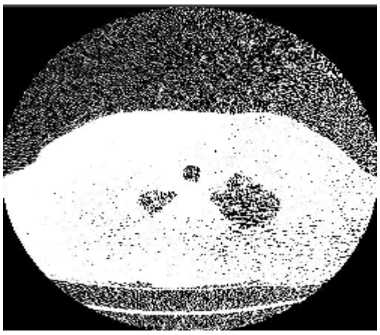
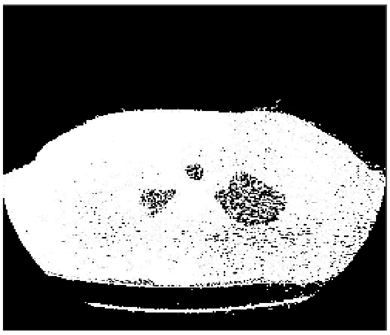
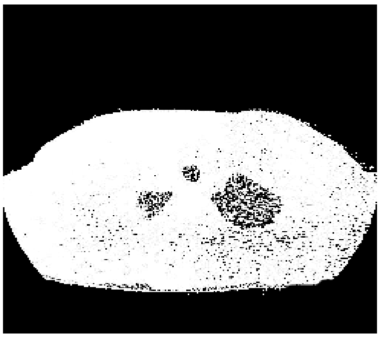
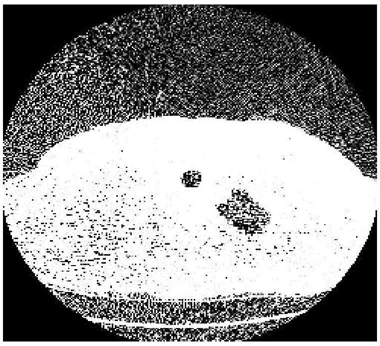
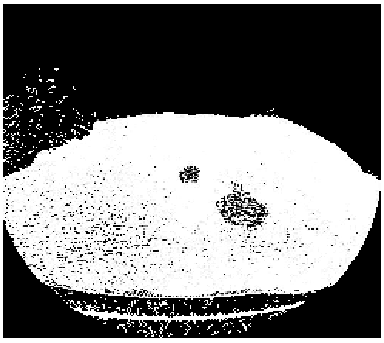
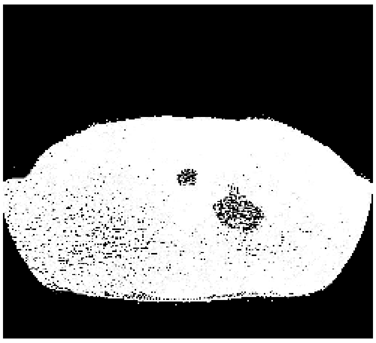
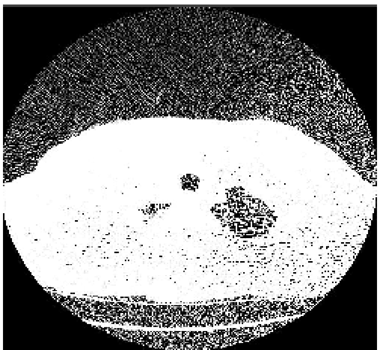
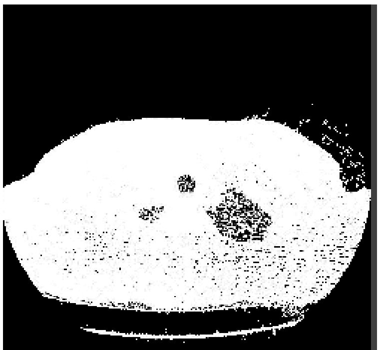
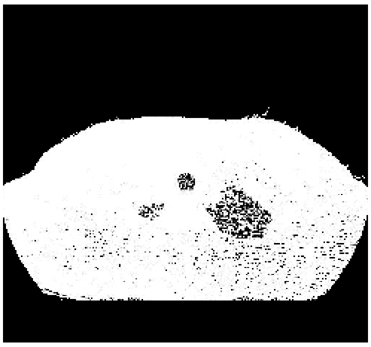
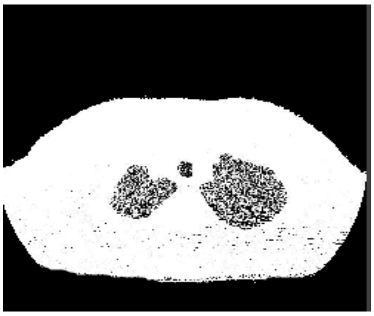
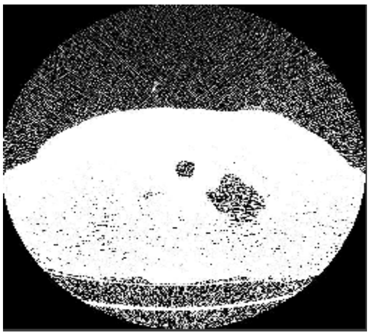
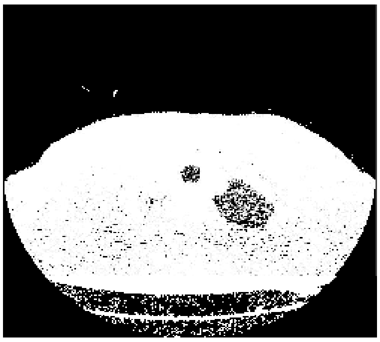
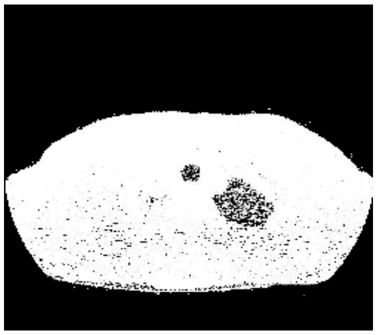
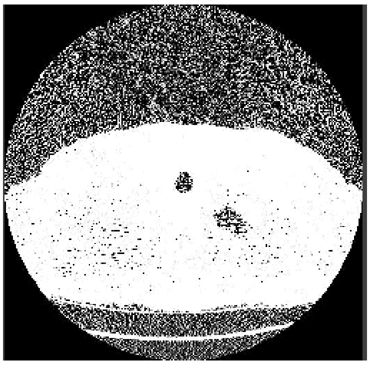
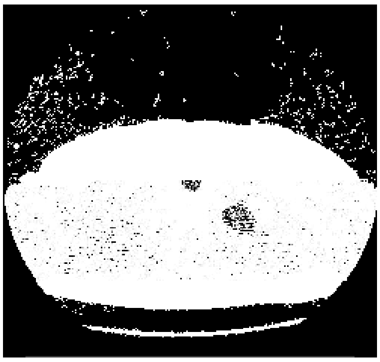
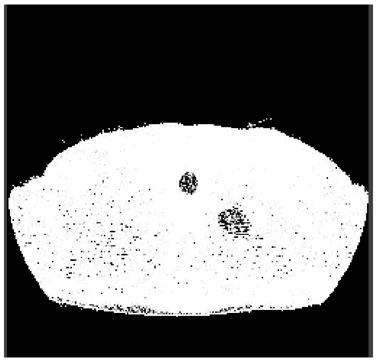
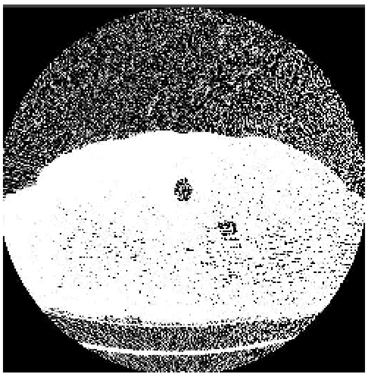
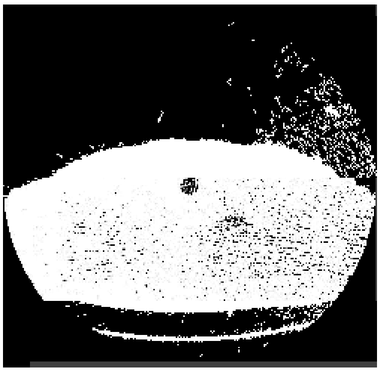
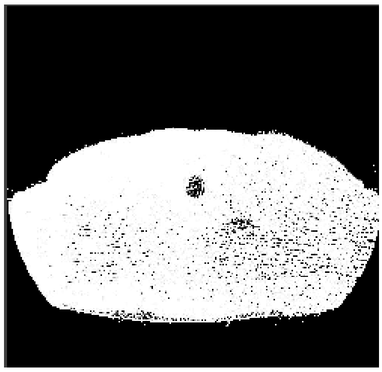
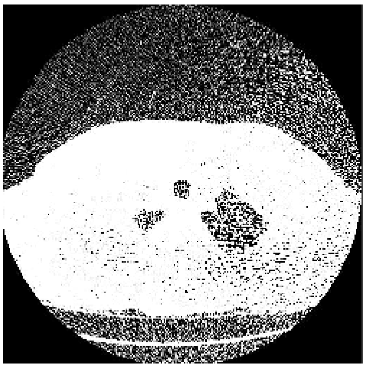
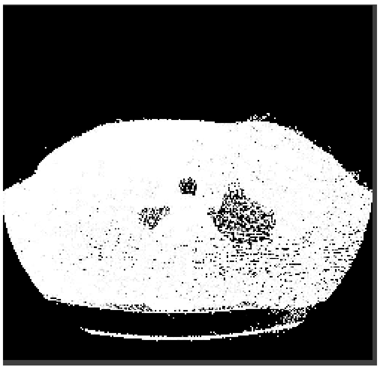
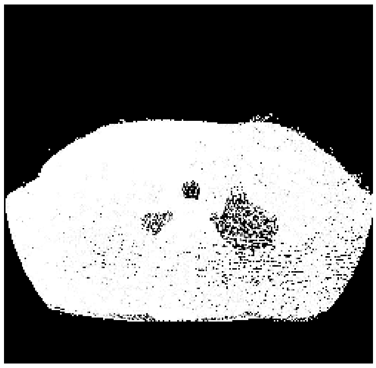
IV. RESULT

This section illustrates the results along with the sampled segmented images. The results of both CS and ABC is demonstrated as shown in Table 3.

Table III. Segmentation images obtained using k-means, K-ABC and K-CS

Number of Samples	Original Image	Segmented Images	
		k-means with ABC	*k-means with CS*
1			
2			
3			
4			

5			
6			
7			
8			

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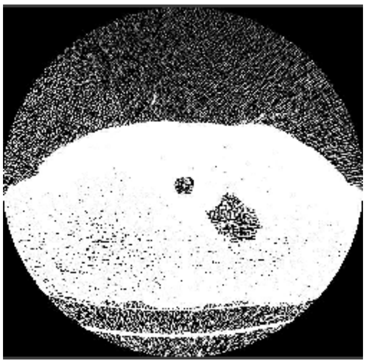
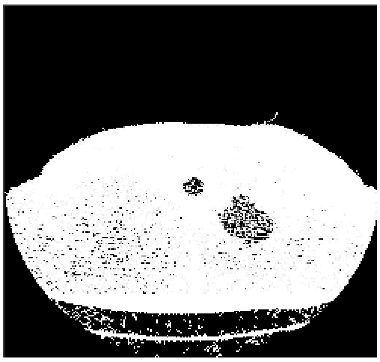
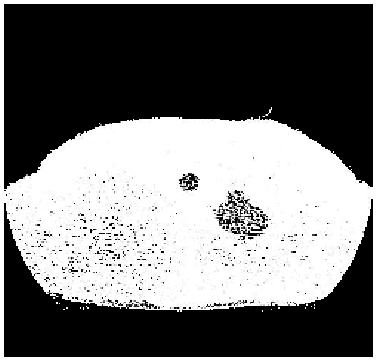
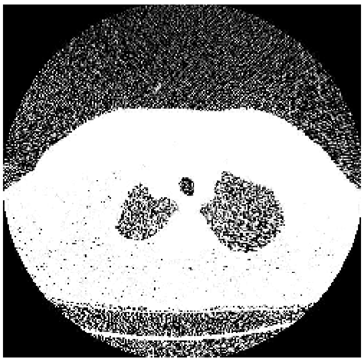
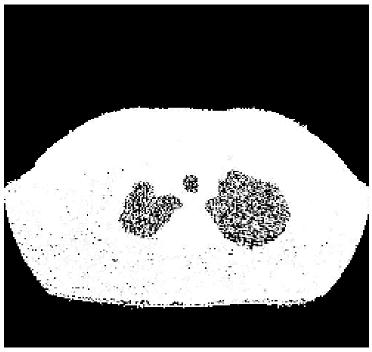
9			
10			

Table 3 summarizes the results obtained as a result of segmentation performed on the 10 original lung cancer images. Visualization of the segmented images clearly show that the RoI is better cropped and highlighted in case of segmentation performed with hybrid k-CS. Here it is concluded that hybrid k-CS provides better results than k-ABC when it comes to selecting the RoI.

1. EXPERIMENTAL CALCULATIONS

The evaluations of the experimental calculations are based on Accuracy, Precision, Recall, F-Measure, Execution time, and Error Rate.

Accuracy: It is the measure of extraction of RoI in the sample images for being correct, exact and not prone to any sort of defect. It is calculated as follows:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \qquad (2)$$

Error: It is the extent that is left to be covered by accuracy. In other words it is the amount of inaccuracy. Percent error can be calculated as follows:

$$Error = 1 - \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \qquad (3)$$

Precision: It is the measure the fraction of relevant pixels of the sample among all the retrieved instances and results. It corresponds to the usefulness of the analysis results. Mathematically, it is calculated as presented in equation (4)

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \qquad (4)$$

Recall: It is also referred as the sensitivity or the True Positive Rate. Recall is defined as the fraction of relevant pixels extracted that have been retrieved over the total amount of relevant pixels. It is important parameter that corresponds to the completeness of the analysis and is calculated as follows:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad (5)$$

F-Measure: It is measured to find the effectiveness of the proposed models in detecting the ROI. It is calculated as the harmonic average of recall and precision as follows:

$$Fmeasure = 2 \cdot \frac{precision \cdot recall}{precision + recall} \qquad (6)$$

V. ANALYSIS OF THE RESULTS

The experimental values corresponding to the accuracy, percentage error, time taken for image segmentation, precision, recall and f-measure are summarized in this section to compare and evaluate the proposed hybrid models. Table 4 shows the tabulated results obtained for accuracy, error and segmentation time for each in case of segmentation performed with k-means, k-means with ABC (k-ABC) and k-means with Cuckoo Search (k-CS). A comparative study is performed by plotting these experimental values for each model, i.e., k-means, k-ABC and k-CS on Y-axis against the 10 image samples taken along X-axis.

Table IV. Result of Accuracy, Error and Segmentation Time

Number of Samples	k-means	k-means with ABC	k-means with Cuckoo Search

	Accuracy (%)	Error (%)	Time (sec)	Accuracy (%)	Error (%)	Time (sec)	Accuracy (%)	Error (%)	Time (sec)
1	84.84	15.16	2.58	88.67	11.33	8.57	94.28	5.72	5.85
2	87.56	12.44	4.54	89.43	10.57	9.65	96.18	3.82	8.87
3	86.67	13.33	2.76	93.78	6.22	11.86	95.58	4.42	7.56
4	85.05	14.95	4.76	95.97	4.03	10.97	99.27	0.73	9.65
5	89.34	10.66	5.35	89.36	10.64	9.87	96.37	3.63	7.86
6	85.27	14.73	4.98	96.43	3.57	12.45	98.28	1.72	6.45
7	86.23	13.77	3.76	93.28	6.72	10.54	97.74	2.26	8.47
8	88.67	11.33	4.23	90.62	9.38	11.86	98.29	1.71	9.04
9	85.27	14.73	3.68	87.23	12.77	8.98	95.23	4.77	8.97
10	87.28	12.72	4.79	94.12	5.88	7.28	96.29	3.71	6.86

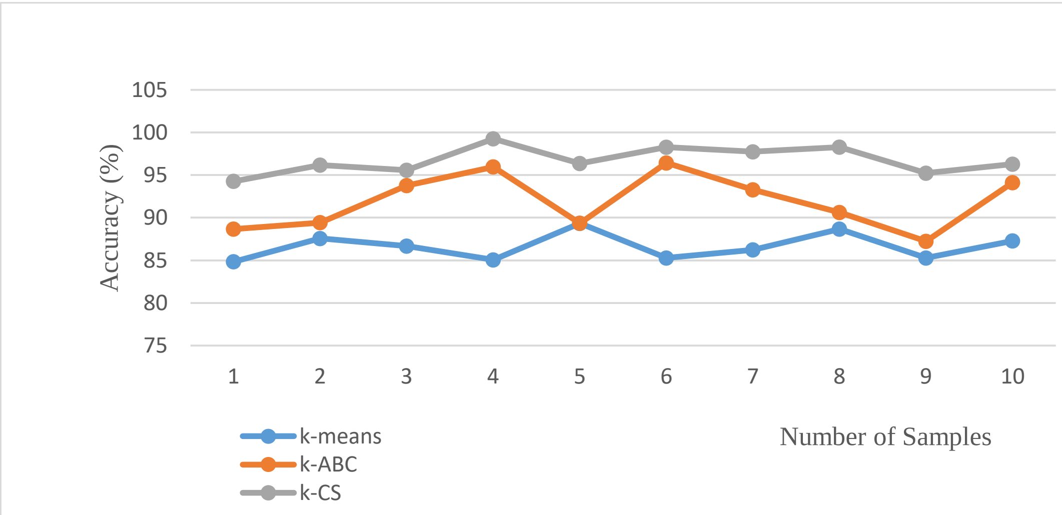


Fig.7 Accuracy Graph of k-means and the Hybrid Model

Fig.7 shows the accuracy of the proposed work lies in between 84.84% to 99.27%. It is clearly seen that average accuracy obtained with k-means is 86.62%, k-ABC is 91.89% and with k-CS is 96.76%. The figure also depicts that the hybrid model with k-CS shows 10% higher accuracy when compared with k-means model and 5% higher accuracy than k-ABC hybrid model because CS has better threshold selection ability than ABC.

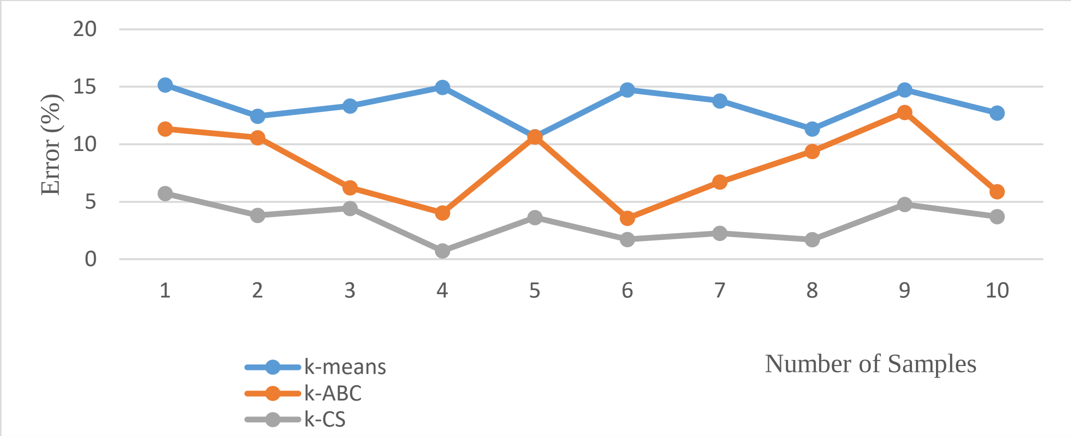


Fig.8 Error Graph of k-means and the Hybrid Models (K-ABC and K-CS)

The calculation of percentage error obtained during lung cancer image segmentation in the three models is plotted in Fig.8 . It is observed that the average error obtained in case of model based on k-means is highest and accounts to 13.39% whereas the average error value for K-ABC is 8.12% which is still higher than that of 3.25% obtained for k-CS hybrid model over the segmentation performed on 10 samples. Due to better accuracy, CS has comparatively less average error value. This results k-CS model into a better model for segmentation process and likely to less prone to error to perform image segmentation.

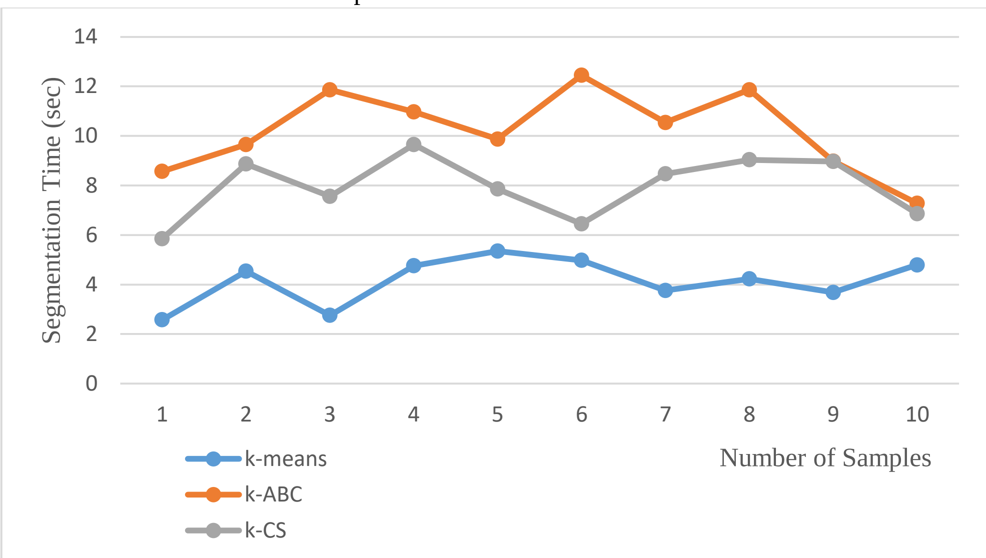


Fig.9 Segmentation Time Graph of k-means and the Hybrid Models (k-ABC and k-CS)

During comparative analysis of the models, segmentation time is also calculated to compare the speed of segmentation performed by various models. The Fig.9 shows that segmentation carried on with k-mean took only 2.76 seconds to 4.79 seconds and is the fastest among the three. There is an increase in average segmentation time when k-means is combined with ABC and CS. The average time consumed for segmentation increases from 5.43 seconds (k-means) to 7.96 seconds in case of k-CS and to 10.21 seconds in case of k-ABC. On an average k-ABC took 3 seconds less than k-ABC for segmentation of 10 samples of lung cancer CT image due to the fact that both k-means and CS are robust algorithms.

Table V. Result of Precision, Recall and f-measure

Number of Samples	k-means			k-means with ABC			k-means with Cuckoo Search		
	Precision	Recall	f-measure	Precision	Recall	f-measure	Precision	Recall	f-measure

1	0.835	0.783	0.809	0.863	0.825	0.844	0.927	0.894	0.911
2	0.845	0.838	0.842	0.885	0.838	0.861	0.957	0.908	0.932
3	0.856	0.797	0.826	0.873	0.849	0.861	0.973	0.901	0.936
4	0.865	0.781	0.821	0.948	0.827	0.884	0.958	0.895	0.926
5	0.846	0.832	0.839	0.895	0.847	0.871	0.991	0.978	0.985
6	0.886	0.818	0.851	0.908	0.816	0.86	0.938	0.928	0.933
7	0.854	0.806	0.83	0.951	0.859	0.903	0.968	0.905	0.936
8	0.885	0.847	0.866	0.907	0.869	0.888	0.995	0.987	0.991
9	0.826	0.829	0.828	0.959	0.883	0.92	0.958	0.943	0.951
10	0.835	0.783	0.809	0.863	0.825	0.844	0.989	0.963	0.976

Table 5 shows the results obtained for precision, recall and f-measure for the 10 lung cancer image samples for each in case of segmentation performed using k-means, k-ABC and k-CS. For comparison of the algorithms, results are plotted against 10 samples taken on X-axis and the values for precision, recall and f-measure on Y-axis.

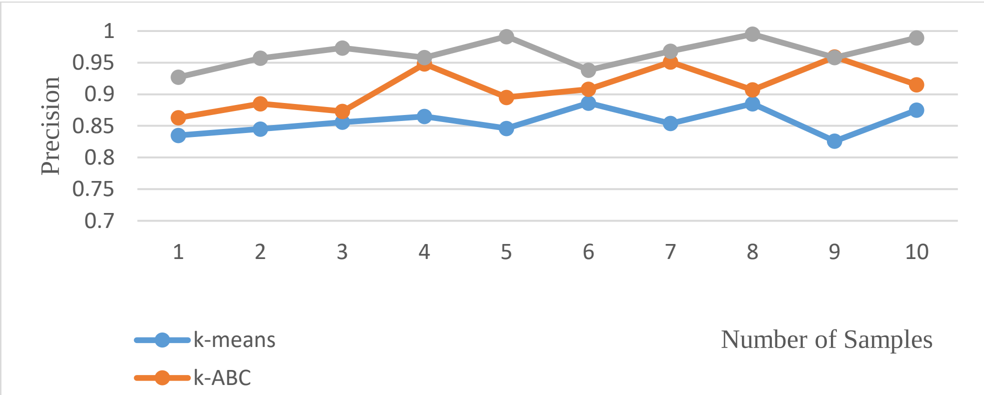


Fig. 10 Precision Graph of k-means and the Hybrid Models (k-ABC and k-CS)

The Fig.10 shows the precision values plotted against 10 lung cancer image samples. The average precision of the proposed work models k-ABC and k-CS are 0.92 and 0.97 respectively and that of k-means is 0.86. The improved precision percentage of the proposed models is 11% (k-CS) and 6% (k-ABC) over the native k-means. The k-CS has better ability to correctly recognise the RoI and hence a high precision of 97% is achieved.

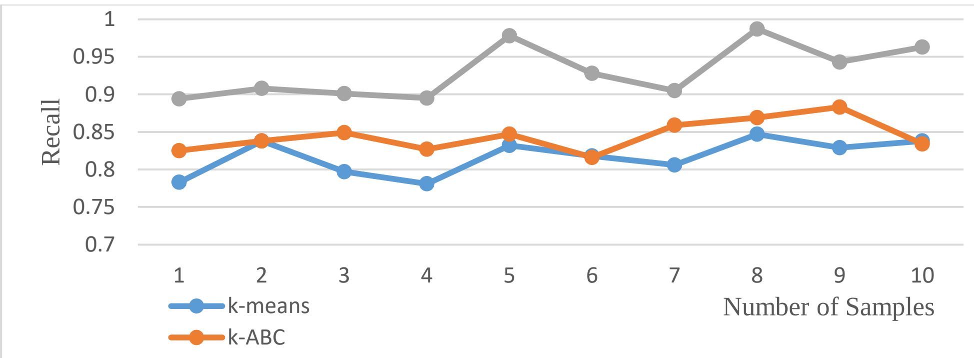


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Fig.11 Recall Graph of k-means and the Hybrid Models (k-ABC and k-CS)

The Fig.11 corresponds to the comparison of recall values obtained in the three cases. Recall value reflects the effectiveness of the models to extract ROI. It is clear from the above graph that average recall value in case of segmentation performed using k-mean is 0.82, k-ABC is 0.85 and k-CS is 0.94. The proposed models show an improvement in recall from 3% to 12% with k-ABC and k-CS respectively. The k-CS shows the better performance of 94% in terms ROI extraction from the original data hence it is better than the k-ABC and k-means.

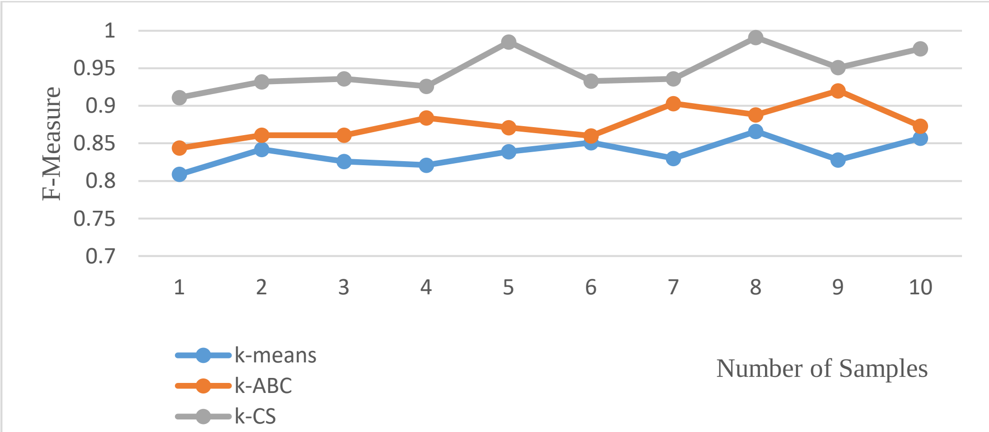

Fig. 12 F-Measure Graph of k-means and the Hybrid Models (K-ABC and K-CS)

Fig.12 shows the graph for f-measure values obtained by plotting k-means, k-ABC and k-CS on X-axis against 10 lung cancer images taken along Y-axis. The f-measures range from 0.82 to 0.99. The average f-measure value obtained using k-means is 0.84, k-ABC is 0.88 and k-ABC is 0.95. High precision for the extraction of RoI have been achieved with k-CS and f-measure is directly proportional to precision. Hence f-measure is also high in case of k-CS. In this paper comparative study is performed to evaluate the performance of native K-means clustering against the proposed hybrid k-ABC and k-CS algorithms. An enhanced overall accuracy of the system of 96.76% is achieved with k-CS as compared to 91.89% with k-ABC and 86.62% with k-means. The precision for the proposed hybrid algorithms also shows an increase from 6% to 11% with k-ABC and k-CS respectively. The average recall value obtained with K-CS hybrid algorithm is 0.94 as compared to 0.85 for k-ABC, accounting to 3% to 12% improvement. The f-measure for k-means alone is 0.84 as compared to k-ABC which is 0.88 and k-CS which is 0.95. These values show 4% to 11% improvement in results with respect to k-means alone.

VI. CONCLUSION AND FUTURE SCOPE OF PROPOSED MODELS

This paper introduced a combination of k-means and CS algorithm where the CS is applied as a post segmentation improvement algorithm. For a comparative analysis, k-means is also combined with ABC algorithm. A new fitness function is designed which takes the average bit value of the image for the post segmentation process in both CS and ABC algorithm. The proposed model is applied over 10 different samples of the dataset and it is concluded that the combination of k-means and CS algorithm performs better than the k-means alone as well as the combination of k-means and ABC algorithm. An enhanced overall accuracy of the system of 96.76% is achieved with k-CS as compared to 91.89% with k-ABC and 86.62% with k-means. The precision for the proposed hybrid algorithms also shows an increase from 6% to 11% with k-ABC and k-CS respectively. In addition to that, SVM also used as a cross validator to classify the results of post segmentation for both ABC and CS. The average recall value obtained with k-CS hybrid algorithm is 0.94 as compared to 0.85 for k-ABC, accounting to 3% to 12% improvement. The f-measure for k-means alone is 0.84 as compared to k-ABC which is 0.88 and k-CS which is 0.95. These values show 4% to 11% improvement in results with respect to K-means alone. This paper introduced a combination of k-means and CS algorithm where the CS is applied as a post segmentation improvement algorithm. For a comparative analysis, k-means is also combined with ABC algorithm. A new fitness function is designed which takes the average bit value of the image for the post segmentation process in both CS and ABC algorithm. The proposed model is applied over 10 different samples of the dataset and it is concluded that the combination of k-means and CS algorithm performs better than the k-means alone as well as the combination of k-means and ABC algorithm. An enhanced overall accuracy of the system of 96.76% is achieved with k-CS as compared to 91.89% with k-ABC and 86.62% with k-means. The precision for the proposed hybrid algorithms also shows an increase from 6% to 11% with k-ABC and k-CS respectively. In addition to that, SVM also used as a cross validator to classify the results of post segmentation for both ABC and CS. The average recall value obtained with k-CS hybrid algorithm is 0.94 as compared to 0.85 for k-ABC, accounting to 3% to 12% improvement. The f-measure for k-means alone is 0.84 as compared to k-ABC which is 0.88 and k-CS which is 0.95.

These values show 4% to 11% improvement in results with respect to K-means alone.

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