Artificial Bee Colony (ABC) optimization Algorithm based Automatic Segmentation and Detection of Suspicious Lesions in Lung CT Images

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ABSTRACT
With the increasing reporting cases of lung cancer there is an increasing demand for the detecting of the tumor at the initial state. With various computer aided algorithmized detection schemes doing a better job in the detection, the accuracy of these detection schemes could be always improved by introducing the newer optimization algorithms. The Artificial Bee Colony (ABC) optimisation algorithm is a novel optimisation technique that proceeds with the assumption of the existence of operations that resembles the biological behaviours of the honey bee in searching for food. For instance, each solution represents the food source locations and the bees are involved in finding the best solution. The fitness value, strongly linked to the solution, refers to the quality of the solution. With this optimisation algorithm the threshold levels are determined which then segments the various pixels into clusters thereby as a result the tumour region is correctly segmented with a better accuracy than the other algorithms. The artificial bee colony algorithm demonstrates robustness to image variability, evidenced by its high accuracy of 97.94%. Additionally, it provides detailed visualization of the shape of abnormal tissue around the lesion area.

Keywords
Tumour segmentation, Lung CT image, ABC algorithm.

1. INTRODUCTION
Despite significant advancements in the medical field and ongoing research for cancer diagnosis and treatment, cancer remains a substantial threat to society. In the early twentieth century, lung cancer was rare; however, it has since become increasingly prevalent, almost reaching epidemic proportions and causing more deaths than colorectal, breast, and prostate cancers combined. Over decades of development and validation, computed tomography (CT) imaging has emerged as a crucial tool, capable of generating high-resolution, low-distortion, and high-contrast images of chest anatomy, essential for detecting lung cancer. Consequently, hospitals accumulate a vast number of medical CT images that require thorough analysis by radiologists. However, manually screening these images is time-consuming and prone to errors due to radiologist fatigue. To address this challenge, there is an urgent need for computerized systems to assist in the detection process. These systems primarily focus on lesion detection, lesion body segmentation, and pathological analysis by employing image processing techniques and soft computing algorithms. With the development of the evolutionary swarm-based algorithms the segmentation of the lesion is improved with greater accuracy, and hence detecting the cancer in initial stage thereby increasing the life span. This paper deals with a metaheuristic algorithm that helps in the segmentation of the lung lesions which turn out to be the initial stage of lung cancer.

The ABC algorithm comprises three classes of bees: employed bees, onlooker bees, and scout bees. Employed bees are tasked with investigating food sources and conveying information to recruit onlooker bees. Subsequently, onlooker bees make decisions regarding food source selection based on the strength of each source, determined by honey bee movements. Onlooker bees favour food sources of higher quality over those of lower quality. When a food source is found to be low quality by both employed and onlooker bees, the corresponding employed bee associated with the food source is converted to a scout bee role. Consequently, the exploitation of food sources is managed by employed and onlooker bees, while scout bees maintain exploration, facilitating both global and local search functionalities. By using the optimization algorithm, threshold values for pixels at each segmentation level are determined, enhancing the segmentation process. This iterative approach allows for efficient exploration of the solution space, ultimately improving the segmentation algorithm's performance.

The existing various methods of extracting the lung nodule from the CT images are described in section 2. Section 3 gives a detail understanding of the theoretical basics behind the morphological operations and the ABC algorithm which are used in extraction of the nodule. The segmentation result of the algorithm is evaluated with its performance criteria in section 4.

2. RELATED WORK
Segmenting the cancer nodules is done with the help of various supervised and unsupervised learning techniques. Adaptive threshold segmentation is superior to normal thresholding [1]. In Otsu thresholding the threshold is fixed after analysing all the pixels. Further enhancements are employed to the concept of Otsu thresholding to achieve the improved classification.

K-NN (K Nearest Neighbour) algorithm is a well-accepted algorithm used for clustering [2]. KNN partitions the input pixels into K clusters, with each pixel being assigned to the nearest cluster. The algorithm segments the CT image into K levels of pixel intensity based on the probability of occurrences. The level of pixel intensity with the least probability denotes the tumor nodule, which also include the airways, which are normally differentiated by their size as they are cylindrical. With the aid of the different morphological filters like opening by reconstruction the K means clustered image the disintegration operation is applied on it with a suitable structuring element thereby removing the airways that are segmented together with the nodules [3]. The morphological processed K-means clustered an accuracy of 98% was achieved by training a multilayer perceptron network [4].

Fuzzy clustering is another unsupervised clustering technique, which has the advantage of assigning the pixel based on its membership function. The binary mask is obtained from the otsu threshold FCM clustered image [5]. This technique reached a good Dice Coefficieny of 0.97.

To improve the clustering accuracy the snake optimization method is employed to separate lung from the background. which is followed by GK algorithm for tumor segmentation in [6]. A snake model is a curve that evolves from an initial position to object boundaries with the input from the user. The energy functions which include both internal and external functions are optimized by Viterbie algorithm. Internal energy is related to the shape of the counter whereas the external is based on the features of the image. By minimizing these functions, the lung region is separated from the background pixels. The GK algorithm focus to minimize the objective function which includes the membership matrix, center matrix, weight related to the degree of fuzziness, a local norm inducing matrix for each cluster and the squared distance matrix. This is iterated till the membership function is optimized. By segmenting to five clusters this method achieved a entropy of 0.89 which is comparatively better than those obtained for FCM or K-Means for the same number of clusters.

Swarm intelligent metaheuristic and nature-inspired algorithms are used to get the optimal threshold value for the segmentation. The Firefly algorithm [7], inspired by the flashing behavior of fireflies to attract mates, communicate, and warn predators, is employed until convergence. This algorithm is utilized to determine centroids, representing levels of threshold intensity. Subsequently, the image is clustered using fuzzy c-means clustering. The dice coefficient of 0.96 was achieved. By using the fireflies to inspect and find the centroids and then clustering via FCM yield an accuracy of 96.63% In traditional Otsu thresholding the threshold value is found by iterating every pixels to find the optimal one, which increases the complexity to about O(L4). To speed up the computational time for the threshold computation a Particle Swarm Optimization (PS)) is employed for the search of the optimal threshold [8]. They replicate the flock of birds in search of food, where each has its individual best and a global best value. The PSO (Particle Swarm Optimization) method conducts the search for the optimal solution using agents known as particles. During each iteration of the algorithm, particles update their positions according to their current velocities, aiming to converge towards better solutions in the search space. Employing PSO the time involved to find the threshold for Otsu thresholding was greatly reduced from 85 seconds for Otsu thresholding to 1.7 seconds [8].

The Otsu thresholding is speed up by using ABC algorithm in the search of the optimal threshold [9] and is utilized for optimization tasks, particularly for determining the optimal threshold value in Otsu thresholding. Once the image is segmented, the FCM clustering is employed to strengthen the segmentation. The Adaptive Artificial Bee Colony algorithm [10] mends together the ABC with the 2D Otsu thresholding to achieve the speed up to determine the threshold value.

Supervised learning like training convolution neural network with the input Ct images and output segmented image is another widely used technique of segmentation. There are various versions of enhanced layers of convolution is developed giving new convolution models. The Convolution neural network (CNN) in a encoder-decoder architecture a simple CNN model was used to segment the lung parenchyma region [11] with an accuracy of 0.95. The CNN is constructed with a pre-processed image input layer, a convolution layer and a pooling layer and two fully connected layer with softmax layer [12]. One convolution layer with six convolution kernals are used to deal with the image patch of 32×32, which is followed by a ReLU unit and a normalisation unit which could prevent the overfitting and accelerate the convergence.

SegNet is indeed an interesting CNN architecture designed for segmentation, particularly where precise pixel-level classification is required, such as in medical image analysis or autonomous driving. [13]. The encoder part captures hierarchical features from the input image via a sequence of convolutional layers, whereas the decoder part reconstructs the segmented output from the encoded features utilizing de-convolutional layers. SegNet typically consists of multiple encoding and decoding layers. In the original SegNet architecture, there are 13 convolutional layers in total, with 5 pooling layers for down sampling and 5 up sampling layers for up sampling the feature maps. By using pooling layers in the encoder, SegNet achieves a sub-sampling rate of 16. The final layer of SegNet typically employs a Softmax activation function, which is commonly used in classification tasks. In the context of SegNet, it helps in generating probability distributions over the classes for each pixel in the segmented output. The reported accuracy of 96% likely refers to the performance of SegNet on a specific dataset and task [13].

The Recurrent 3D Dense U-Net is an adaptation of Convolutional Neural Networks (CNNs) that combines concepts from DenseNet, U-Net, and Convolutional Recurrent Networks. Each encoder block consists of two consecutive 3D-Convolutional layers, followed by Batch Normalization, ReLU activation, and a 2D-Maxpooling operation with a kernel size of (2×2). Additionally, a spatial dropout layer is applied at the end of every encoder block to enhance robustness. The transition sections between the encoder and decoder utilize Convolutional LSTM blocks. These blocks help capture inter-dependencies among the output features of the encoder, thereby producing more reliable features for subsequent decoder blocks. This integration of recurrent connections enhances the model's ability to understand temporal dynamics and context in 3D data [14].

The Hybrid-3D dilated fully convolutional neural network, as described in reference [15] and based on the LungNet architecture, is a model that combines elements of 2D and 3D convolutional neural networks. This model builds upon the original 2D LungNet architecture by incorporating convolutional blocks. Each slice of the input data is applied sequentially to these blocks, which generates 2D feature maps from individual 2D slices. This hybrid approach leverages the benefits of both 2D and 3D convolutional operations, allowing the model to capture both spatial and temporal information effectively for tasks such as medical image analysis.

The artificial bee colony optimisation algorithm has shown promising results in segmenting Brain MR Images [16] and Breast DCR-MR Images [17-19]. This work applies artificial bee colony optimisation algorithm for segmenting the lung CT images.

3. METHODOLOGY

An intelligent segmentation algorithm based of the behaviour of bees is developed to segment the lesions in the lung CT image. The extraction of the tumour involves the following steps: pre-processing, lung parenchyma extraction and ABC algorithm-based clustering thereby extracting the tumour lesions from the CT image. The algorithms and the steps used in the segmentation of the lung lesion are showed in Figure 1.

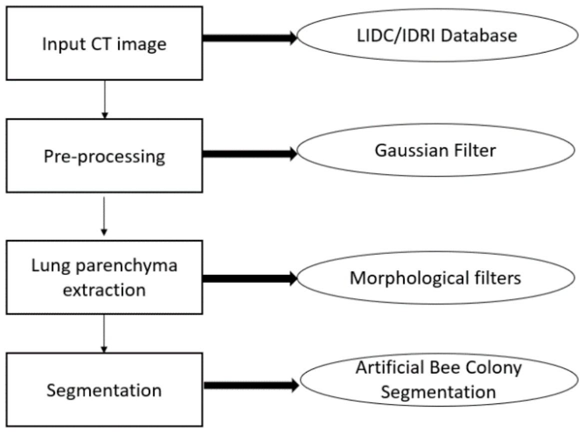


Figure 1: The flow diagram of steps used in extraction of lesion from Lung CT image

3.1 Input Lung CT Image

The CT images of the lung are obtained from the LIDC/IDRI database, which contains helical thoracic CT scans from various patients. These images include annotations of nodules by radiologists, provided in XML format alongside the CT images in DICOM format, a widely used standard in medicine. DICOM files contain detailed imaging parameters such as slice thickness and pixel spacing. For segmentation purposes, ten tumor images are selected, each in DICOM format with dimensions of 512x512 pixels.

To process the DICOM images, they are converted to TIFF (Tagged Image File Format) format, which offers versatility and supports various image sizes, resolutions, and color depths. TIFF images preserve the original image quality. Hence, TIFF images are preferred for processing CT images to ensure no loss of data.

3.2 Image Processing

The CT image is enhanced to remove the noises present in the image and also to enhance the contrast so that the nodules are easily detected. Gaussian filter is used to enhance the image. A 3x3 mask is created and the corresponding gaussian function is laid upon it to generate the enhanced image. The mask performs convolution of the gaussian function over the image, where the center pixel on the mask is replaced by the function performed by the filter to get the gaussian filtered image. The concept behind Gaussian smoothing involves utilizing a 2-D Gaussian distribution as a "point-spread" function. This is accomplished through convolution, where the image is convolved with the Gaussian kernel, effectively applying the Gaussian distribution to the image.

3.3 Lung parenchyma Extraction

There are some others parts like the arteria or the oesophagus which may be segmented as the nodule; therefore, the lung parenchyma is extracted first and the processed separately so that the false negative detection of nodules could be eliminated. This can be performed with the help of the morphological operations and the little knowledge about the lung. The various morphological operations that can be used are the dilation, erosion, image opening, image closing, binarization, filling the holes etc. These morphological operators are used to determine the mask of the lung which is then used to extract the lung parenchyma from the CT image. In figure 2, the lung parenchyma extraction process is illustrated, depicting the various steps involved in the procedure.

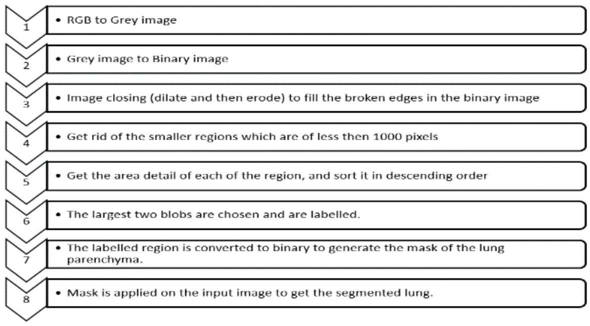


Figure 2: steps involved in parenchyma extraction process

3.4 Artificial Bee Colony Algorithm

The segmentation of various pixels in the extracted lung parenchyma is achieved through a clustering technique. This technique groups the data based on their similarity, which is measured using the Euclidean distance between the pixel intensity and the cluster center. The algorithm aims to minimize this clustering metric by searching for appropriate cluster centers (c1, c2, ..., ck). The optimization of cluster centers is performed using the ABC algorithm, this approach facilitates the optimization of cluster centers, leading to effective segmentation of lung parenchyma pixels based on their similarities.

The basic steps of ABC clustering operation are:

Step 0: Start.

Step 1: Initialize the population of the solutions Xi where i=1.... N.

Step 2: Involves evaluating the fitness of the population of solutions. This is achieved by employing Equations (1) and (2) as follows:

$$fit_i = \left\{ \begin{array}{ll} \dfrac{1}{1+f_i} & if\ f \geq 0 \\ 1+abs(f_i) & if\ f < 0 \end{array} \right\} \quad (1)$$

$$f = \sum_{i=1}^{N} 100(x_i - x_i^2) + (x_i - 1)^2 \quad (2)$$

Step 3: initialize the cycle counter to 1.

Step 4: involves repeating the following process while the stopping criteria are not met.

Step 5: new solutions are produced.

Step 6: involves selecting solutions for neighbourhood search based on information in the neighbourhood of the present solution.

Step 7: entails recruiting bees for the selected solutions, with more bees allocated to the best e sites. The fitness values of the recruited bees are evaluated, and the probability values P_i for the solutions are calculated using Equation (3).

$$P_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{3}$$

Step 8: The fittest bee from each solution is selected.

Step 9: involves assigning the remaining bees to search randomly and evaluating their fitness values.

Step 10: updates the cycle counter by incrementing it and this process continues until the maximum number of cycles is reached.

Step 11: Stop.

At the initialization stage, a set of employed bees is randomly selected, with one for each cluster. The initial clusters are constructed by finding the minimum Euclidean distance between each input data pattern and all cluster centres. The cluster centres are then replaced by the actual centroids. This initialization process is repeated whenever a new solution is formed. The fitness evaluation process is performed for each solution visited by a bee using Equation (1), which employs the Rosenbrock function given in Equation (2) to evaluate the fitness. After the fitness evaluation, a new population of solutions is formed, a crucial step in optimization. The algorithm designates the m solutions with the highest fitness as selected solutions, chosen for neighbourhood search. More bees are assigned to search in the neighbourhood of the best e solutions. Identification and choosing of the best e solutions can occur directly based on their fitness values; it can determine the probability of selection using Equation (3). The bee that discovers the solution with the maximum fitness value joins the next bee population of solutions. The left behind bees is arbitrarily allocated in the region of the search space to explore for new potential solutions. At the end of each iteration, the colony will have two stages in its new population: representatives from the selected solutions and scout bees conducting random searches. Ultimately, each pixel is assigned to one of the clusters. The output image from the honeybee clustering process is then edge-enhanced, followed by efficient extraction of the tumour or region of interest (ROI) from the segmented image output.

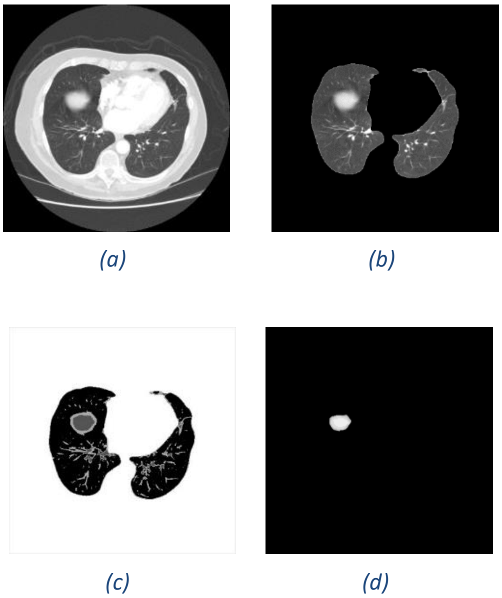
4. RESULTS AND DISCUSSION

The implementation of the novel ABC algorithm to segment the lung nodules from the CT image has shown appreciable results. The images are taken from the LIDC database which is an online database of the CT images which is open for research and studies. The images are classified as malignant or benign by the radiologist. The images from the database are available in DICOM format which is converted to TIFF format for processing ensuring that the details are not lost. The initialization of parameters in the ABC algorithm is critical for guiding the optimization process. Each of these parameters plays a significant role in determining the behaviour and performance of the algorithm during optimization. Proper initialization and tuning of these parameters are essential for achieving efficient convergence and finding optimal solutions. Table 1 shows the initialised initial parameters required for the algorithm.

Table 1. Parameters used in ABC clustering algorithm

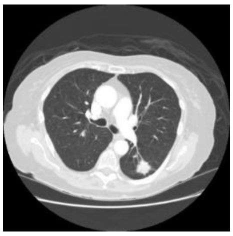
Parameters	Values
Number of scout bees, n	25
Number of solutions selected for neighborhood search, m	10
Number of best elite solutions out of m selected solutions, e	3
Number of bees recruited for best e solutions, nep	7
Number of bees recruited for the other (m-e) selected solutions, nsp	3
Limit	100
Maximum number of cycles R	2000

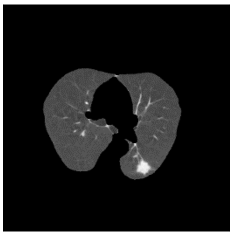
These values are chosen from trial-and-error methods which guarantee for the best result. The performance of the developed segmentation algorithm is assessed using the Dice similarity coefficient, which quantifies the overlap between the segmented lesion region and the ground truth. The output for the converted TIFF input CT image, extracted lung parenchyma image, the various stages in the segmentation of the tumour region from different input CT image are shown in fig 3-6. The respective input image after converting to the TIFF format is shown in (a). The output of the extraction of the lung parenchyma with the various morphological filters is shown in (b). The parenchyma extraction image after the segmentation is shown in (c). The ABC segmented tumour region after separation of it from the other region is shown in (d).

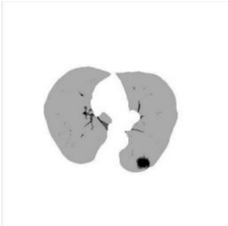


(a) *(b)* *(c)* *(d)*

Figure 3: Artificial bee colony clustering algorithm output


(a)

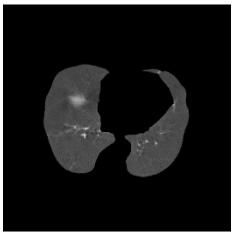

(b)


(c)


(d)

Figure 4: Artificial bee colony clustering algorithm output


(a)


(b)


(c)

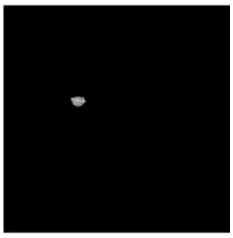
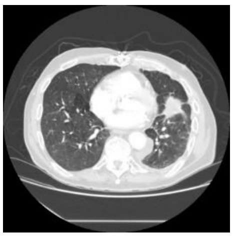
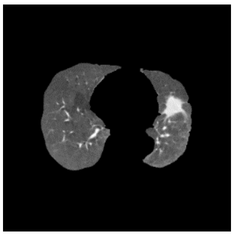
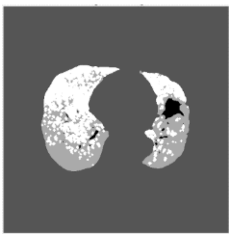

(d)

Figure 5: Artificial bee colony clustering algorithm output


(a)


(b)


(c)

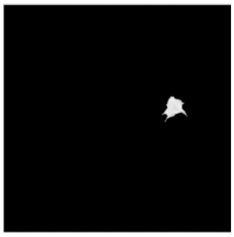
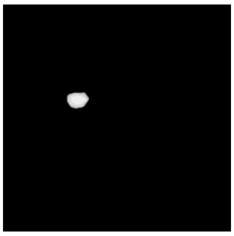
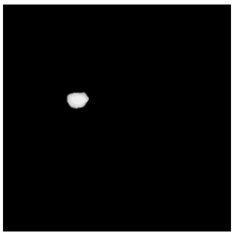
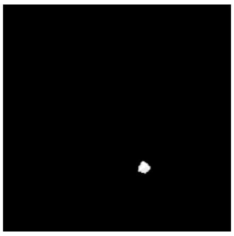

(d)

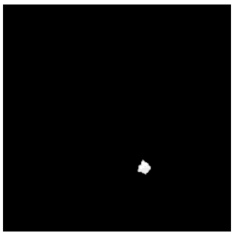
Figure 6: Artificial bee colony clustering algorithm output.

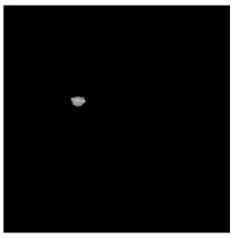
4.1 Comparison of Segmented tumour output with provided ground truth


Ground truth figure 3

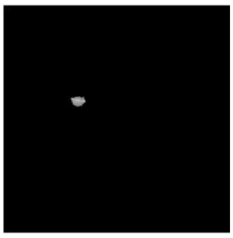

Segmented tumour for image in figure 3


Ground truth figure 4

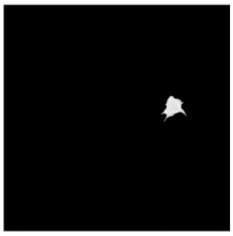

Segmented tumour for image in figure 4



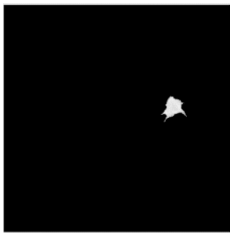
Ground truth figure 5



Segmented tumour for image in figure 5



Ground truth figure 6



Segmented tumour for image in figure 6

For evaluation of the segmentation output by the artificial bee colony algorithm the segmented tumour region is evaluated with reference to the segmented tumour produced by the experts with the help of Dice coefficient which is a statistical measure of the similarity between the two samples. It is calculated using the formula shown in (4).

$$DSC = \frac{2|x \cap y|}{|x|+|y|} \quad (4)$$

'x' and 'y' are the sample sets, here 'x' denotes the ground truth of the tumour region and 'y' denotes the segmented tumour region by the ABC algorithm. The DSC value of 1 represents the accurate the segmentation, with the variation in the segmented output from the ground truth the DSC value decreases. The ground truth and the segmented results for the respective images at figures 3-6 are shown in figures 7-10 and their dice coefficient are given in table 2.

Table 2. Dice Similarity Coefficient index for ABC algorithm

Input image	Dice Similarity Coefficient index
Image 1	0.9757
Image 2	0.9831
Image 3	0.9769
Image 4	0.9771

Among the various algorithms that are used for the segmentation of the nodule the ABC algorithm provides a better DSC compared to that of the others. Table 3 shows the DSC for various algorithms.

Table 3. The Dice Similarity Coefficient Index for various algorithms

S.No	Algorithm	DSC
1	Fuzzy C means Clustering	0.9710
2	Firefly algorithm followed by FCM	0.96
3	Convolution neural network	0.9502
4	Artificial Bee Colony	0.9794

The above analysis from the existing works have showed that the implemented Artificial Bee colony algorithm has a better segmentation result than the others, thereby capable of more accurately detecting the lesions in the lung CT image.

For the above segmented image, the DSC of 0.97 is achieved which indicate that the algorithm is able to cluster the various pixels present in the image into regions thereby effectively segmenting the lung lesion of the CT image.

5. CONCLUSION AND FUTURE SCOPE

With the aid of image processing techniques, the CT images are analyzed and the details of the nodules are extracted. This terms to be an addition support to the doctors in analyzing the result where there is a huge need for human interpretation to read the images and conclude if it is malignant or not. The segmentation algorithm by means of optimization has increased the performance of the detection of the nodules. Further as the image is segmented to remove only the lung parenchyma separately before giving it to the segmentation algorithm, the false positive rate is decreased. Unwanted parts are prevented from being grouped into nodules. The ABC algorithm which resembles the foraging action of the bees has an advantage as it performs both global and local search and segments the lung lesions better than that of the other existing algorithm. The performance analysis showed that the ABC algorithm has a good DSC index, thereby is capable of segmenting the cancer nodules perfectly from the CT image.

We used only Artificial bee colony algorithm for segmentation. In future we will use different segmentation methods on various datasets. We will develop a thorough end-to-end nodule segmentation system in the future that is going to be able to identify and classify the nodule malignancy using various datasets.

6. ACKNOWLEGMENT

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