Revista Argentina de Clínica Psicológica
2021, Vol. XXX, N°3, 149-159
DOI: 10.24205/03276716.2021.5017

Advanced Lung Cancer Detection using Juxta-Pleural Nodule Extraction and Optimization by PSO Algorithms

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Abstract
In this proposed work the diagnosis of Lung Cancer, for speedy and accurate analysis in the recognition of Lung Nodules by the radiologists for the early detection and increases the survival rate of the people. In the detection and classification of the Lung nodules, the segmentation process is considered to be the mandate requirement. The process of separating out the lung nodules from the other tissues is the segmentation. The traditional conservative methods used for the segmentation process does not yield accurate results and mostly depends on the features generated by the radiologists. In this proposed work, a computerized algorithm is designed with specified features for identifying the lung nodules and analyzing the nature of the segmented output with the ground truth images. Also the particle swarm based optimization algorithms are used for the improved detection mechanism. The advantageous feature of our proposed work is the detection of the juxta pleural lung nodules present very close to the wall of the lungs. The work also aims at reducing the time constraint of radiologists, since manual detection is time consuming and leads to false detection. The key goal of the proposed work is to obtain the accurate results by using the advanced contrast enhancement and the region growing segmentation algorithms. The performance is analyzed by using accuracy, specificity and sensitivity values. The above implementation is done for CT lung image database. On equating with the three algorithms, CPSO, WPSO and PSO, the accuracy of the malignant tumor detection and extraction is comparatively very much improved in case of CPSO with the enhanced accuracy of 95.80%. Also the algorithm has shown an improved accuracy of 90% in all the 20 sample images taken. The CPSO Algorithm shows an enhanced accuracy of 90% in the 4 out of 10 datasets.
Keywords- Median filter, Adaptive histogram equalization, Particle Swarm Optimization (PSO), Inertia Weight PSO, Chaotic PSO

Introduction

Lung Cancer is considered to be the second leading cause of death globally and is responsible for a death rate of 9.6 Million in 2018 (WHO, 2021), which is based on a survey conducted by the World Health Organization. The Malignant tumor characterized by an uncontrolled growth of cells in the tissues of the lung is termed as Lung Cancer or Carcinoma (Jiang et al., 2018). In men, the prostate cancer is considered to be the most commonly occurring type of cancer, whereas in case of women, breast cancer is the most occurred. According to the statistics released by the American Cancer Society in 2021 (American Cancer Society, 2021),in the world about 235,760 new cases of lung cancer reported out of which 131,880 deaths. The majority of the cases around 85% reported are due to the long term tobacco smoking and also the people around 10 – 15% are infected without any smoking habits were due to various factors like genetic background or exposure to radon gases, asbestos and air pollution.

The Lung Cancer is visually interpreted by the Chest Radiographs and Computed Tomography (CT) Scans. The analysis or the identification of the cancerous nodules is carried out by biopsy, performed by either bronchoscopy or CT guidance (Silvana et al., 2020). The major ways of preventing risk factors incudes avoidance of smoking habits and some primary methods to prevent air pollution. The treatment for the detected or identified tumors depends on the type of cancer, stage in which the disease is identified and the overall vital statistics of the patient (Feragen et al., 2014). Based on the

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severity, the treatment plans may vary between surgery, Chemotherapy and Radiotherapy Procedures.

Related Work

In order to minimize the issues related to the juxta- pleural nodule extraction, a novel segmentation method is implemented using the Chan-Vese (CV) model, which is based on the Bayesian approach for active lung contours (Chung et al., 2018). The CV model evaluates the lung images with reference to the previous frame of the image or the neighboring upper frame. The paper emphasis on the early detection of the Lung Cancer (Huang & Hu, 2019). In this proposed method, Genetic K-Nearest Neighbour (GKNN) Algorithm is used, which is a non- parametric method. The optimization algorithm allows physician to identify the nodules at an early stage. Since the manual interpretation are time consuming and very critical, the genetic algorithm combined with the KNN algorithm classifies the cancerous nodules in an optimal time and also efficiently (Graham et al., 2010).

In this paper (Mathews & Jeyakumar, 2020), machine learning methods compared while detect lung cancer nodule. We applied Principal Component Analysis, K-Nearest Neighbors, Support Vector Machines, Naïve Bayes, Decision Trees and Artificial Neural Networks machine learning methods to detect anomaly. An automated system is proposed in this paper for identifying lung cancer from the analysis of computed tomography images by performing nodule segmentation using an optimal critical point selection algorithm (OCPS) which improves the detection of shape- and size-based juxtapleural nodules located at the lung boundary (Liu et al., 2014). A suspect area of nodule is obtained with the help of a bidirectional chain code (BDC) approach and the OCPS.

This paper presents a novel shape based Genetic Algorithm Template Matching (GATM) method for the automated detection of lung nodules (Wang & Guo, 2016). The GA process is employed as an optimization method to effectively search for the location of nodule candidates within the lung area (Azzawi et al., 2016). To define the fitness function for GATM, 3D geometric shape feature is calculated at each voxel and then combined into global nodule intensity distribution. The identification stage includes pattern matching and confirmation to increase accuracy, performed by fuzzy logic, support vector machine, statistical classifiers. The categorization stage involves matching characters (texture, shape and density) of the detected nodules to characters of normal cells (texture, shape and density) of nodules with known condition of disease (confirmed by sample extraction techniques) (Chen et al., 2019).

Methodology

The following flow diagram explains the methodology used for the identification of the cancerous nodules in the CT input images.

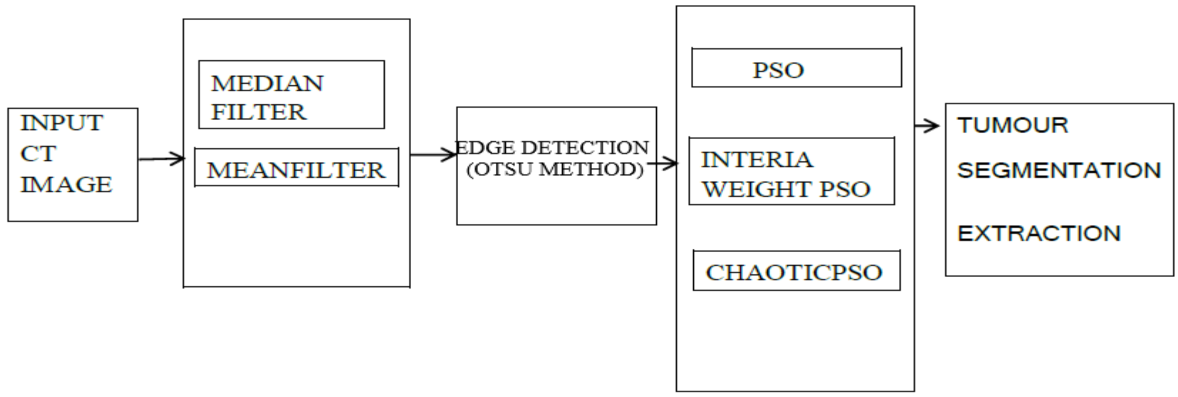


FIG 1: **Algorithm Flow Diagram**

The CT images inputs are denoised by both the spatial and the transform domain in which the image for the edge detection is extracted from the noisy image. De- Noising is considered to be the preliminary step in the filtering process. The methods of denoising is adapted is such a way the edges of the images are preserved and the valid information are not lost. Conventionally used models are Linear and Non- linear models, but mostly the non- linear noise removing models are used, in which the edges are handled in a much better manner compared to that of the linear noise removal models. The major limitation of these linear models is the improper recognition of the discontinued edges also has a trade off in preserving the edges. But compared to the nonlinear models, the linear models are considered to be the faster method.

In the Median filter, the values of the pixels are replaced by the median of the gray levels and creates an excellent noise reduction capabilities, which will produce an output which will possess less blurring effects (Priya & Jawhar, 2020). The median filter in an order specific filter because it is based on statistics derived from ordering the elements of a set rather than taking the mean.

$$SSI = \frac{\sqrt{Var(I_f)}}{Mean(I_f)} * \frac{Mean(I_o)}{\sqrt{Var(I_o)}} \quad \textbf{(1)}$$

Where, I_f= Filtered image

I_0= Noisy image

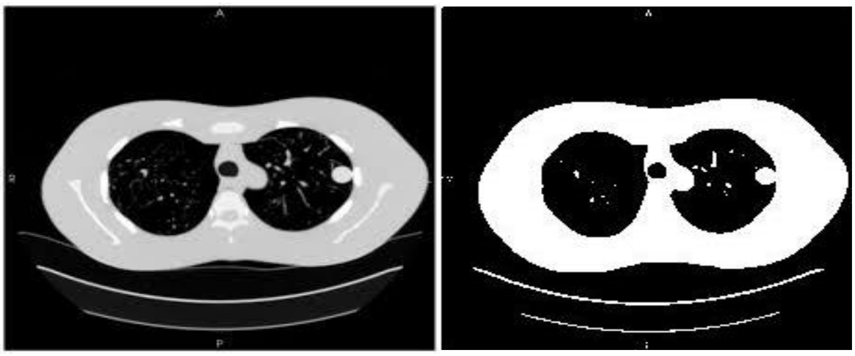
The Suppression Index should be always less than 1, the speckle noise is reduced, which in turn gives out better filtered output.

Contrast Enhancement

Contrast enhancement techniques enhance the image quality of the low contrast image, in which the ratio between the brightest and the darkest pixel intensities were determines over a dynamic range (Choi & Choi, 2014). For better contrast enhancement in case of the medical images, the best used contrast enhancement algorithm is the Adaptive Histogram Equalization because of its effectual representation of all contrast present in the image taken for analysis purpose. Otsu algorithm searches the pixels possessing analogous intensity values of the image and also finds the varied pixels in the particular threshold intensity (Wang & Guo, 2016). In order to detect the edges the sum of the foreground pixels and the background pixels should be maximum, in which the mean weight and variance are evaluated. With the obtained values the class variance is calculated which helps in detecting the edge in the region of Interest. The Fig 2(a) and 2(b) shows the Filtered image input and the contrast enhanced output image using the Otsu Edge detection Algorithm.

```
Input: Filtered Image Input
Output: Contrast Enhanced Image using Otsu Edge detection Algorithm
Start
    For every pixel in the input image, calculate the weight, mean and variance for both the foreground
    and background pixels
Stop for
    Evaluate the class variance within all the pixels, calculate the maximum values of the same, with which
    the edges to be segmented can be identified.
Stop
```

Algorithm 1: **Otsu Algorithm**

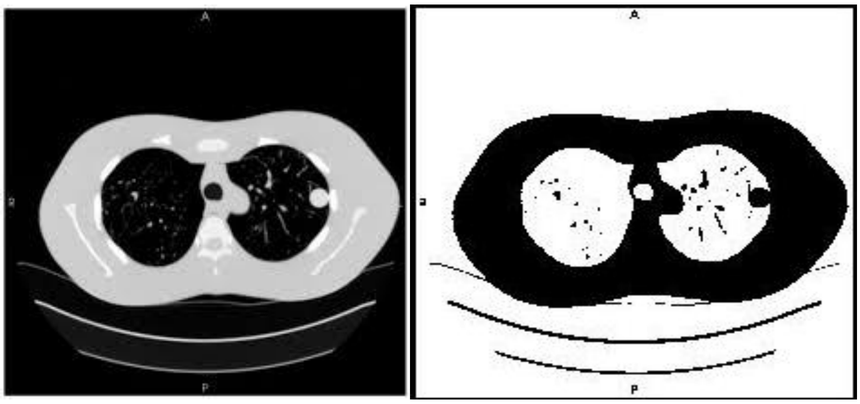


(a) **(b)**

Fig 2**: (a) Input image (b) Contrast Enhanced CT Image**

Global Region Based Segmentation Algorithm

The region growing algorithm is most commonly used method in the segmentation of the lung images. The contrast enhanced CT images are segmented using the Region Growing algorithm. The pixels in the CT image are partitioned and the coordinates are assigned using the global region segmentation algorithm (Kalpana & Rajini, 2016). Once the pixels are selected, the nearest neighborhood of the pixels are formed by the region mean, which is carried out using the pixel connectivity concepts and the gray scale difference of the image, which in turn detects the infected lung nodules efficiently. The pseudocode for the lung nodule segmentation is explained in the Algorithm 3. The Fig 3(a) shows the contrast enhanced CT image and the Fig 3(b) shows the segmented output using the algorithm.



(a) (b)

Fig 3**: (a) Contrast enhanced CT Image (b) Segmented output**

Input: Contrast Enhanced CT Image
Output: Segmented CT Tumor Nodules
Start
Initial grouping by naming the Seed Points
Neighbors of the seed points are grouped sequentially and sorted, while the ssl is not empty, clear the point y from the SSL
Check the neighboring points of y, whether all the points are labelled except the boundary label
Calculate and update the mean of the added region of y, set or already in the SSL to the SSL value of the δ
Else y with boundary index
Stop

Algorithm 2: **Global region based segmentation algorithm**

Particle Swarm Optimization

PSO optimizes the problem by consecutively iterating to improve the particle solution with respect to the quality. The PSO Algorithm solves any problem by having a population of candidate solutions and moving these particles around in the search- space according to simple mathematical expressions over the particles position and velocity. The topology of the particles swarm defines the subset of particles with which each particle can exchange information. In general, the global topology is used as the swarm communication structure. This topology allows all particles to communicate with all the other particles, enabling them to share the same best g position and p position for a single particle. The convergence of the solution can be explained in which all the particles converge to a point in the search- space which may be an optimal solution or may not be an optimal one. It can be attained alternatively where the local optimum value can be achieved by approaching the best p and g values.

$$Y_{id}(t+1) = V_{id}(t) + N_1 * q_1[pbest - K_{id}(t)] + N_2 * q_2 [gbest - K_{id}(t)] \quad \textbf{(2)}$$

$$K_{id}(t+1) = V_{id}(t) + Y_{id}(t+1) \quad \textbf{(3)}$$

$V_{id}(t)$ - Current Velocity, $V_{id}(t+1)$ - new velocity, $K_{id}(t)$ - current position, $K_{id}(t+1)$ - new position, q_1 & q_2 - even distributed random numbers, interval [0,1] and N_1& N_2 - acceleration coefficients, N_1 - factor that influences the cognitive behavior, in which the particle follows the own best position, N_2 - factor for social behavior, in which the particles produces the Swarm's best Solution.

1. Initialize the Particles Position and Velocity.
2. Using the Objective Function, the fitness value of all the particles are calculated.
3. Evaluate the values of pbest and gbest.
4. The particles are updated with the position and velocity.
5. The steps 2 to 4 are repeated until the particle values are converged i.e. in the successive iterations the particles values are not altered.

Algorithm 3: **PSO**

Inertia Weight Pso

Inertia weight significantly affects the convergence and exploration/ exploitation trade off in PSO Process. The Inertia weight predicts the contribution rate of a past particles velocity to the velocity of it in the current time step. It is also called as the deciding factor in the convergence behavior of the PSO. The large inertial weight values results in the delayed convergence of the optimization and low inertial values of weight will result in local trapping of the particles. In order to avoid this improper selection of inertial values, an algorithm is chosed which best suits for satisfying the searching- utilization trade off.

During optimization, effect of inertial weight of the PSO on the optimal placement of distributed generation associated with the PSO technique is used for determination of optimal size of the distributed generation at that location.

For a Multinode network, total active power losses are calculated by the equation

$P_{Loss} = \Sigma\ \Sigma\ [\alpha_{mn} (P_mP_n + Q_mQ_n) + \beta_{mn} (P_mP_n + Q_mQ_n)]$, for all m,n = 1 to N **(4)**

In which the,

$$a_{mn} = \frac{R_{mn}}{v_m v_n} \mathrm{Cos}\ (\delta m - \delta n)$$

$$\beta_{mn} = \frac{R_{mn}}{v_m v_n} \mathrm{Sin}(\delta m - \delta n)$$

N – Total Number of Nodes in the Network

P – Injected Real Power

Q – Injected Reactive Power

V – Magnitude of Voltage

δ – Angle of the Voltage

m – Node Number

The resulting velocity update equation becomes:

$Y_{id}(t+1) = a * V_{id}(t) + N_1 * q_1[pbest - k_{id}(t)] + N_2 * q_2 [gbest - k_{id}(t)]$ **(5)**

Where,

a = inertia weight.

Constant inertia weight: a = N (N = 0.7)

Random inertia weight a = 0.5 + rand ( )/2

1. Initializing the values of the position and velocity for all the particles.
2. Using the objective function obtained from all the particle are used in the calculation of the Fitness value.
3. The newly obtained pbest value is included in the algorithm if the fitness value is better than the old pbest value.
4. Initialize Inertia weight.
5. Using the initialized Inertial weight values, the position and velocity values of all the particles are updated and included in the network.

Algorithm 4: **WPSO**

Chaotic Particle Swarm Optimization (Cpso)

The CPSO optimization algorithm exerts a disordered disconcertion on the global best variable, preventing the particles from early merging. In the PSO algorithm, the convergence velocity will be reduced in the latter stages and the optimal solutions cannot be obtained. In order to overcome this problem the CPSO optimization algorithm is used. Chaotic system is a random process possessing nonlinear characteristics with complex behavior in nature. The logistic map for the global convergence can be explained with the equation shown below.

$N_r (t + r) + m + N_r (t) + (1 + N_r (t))$ **(6)**

Where,

N_r – Chaotic variable,

m – Control parameter

The velocity update equation can be formulated as,

$y(t+1) = y(t) + Nr[pbest(t) – z(t)] + (1– Nr) [gbest(t) –z(t)]$ **(7)**

This method avoids local minima and improves global convergence. The parameters r1 and r2 are modified by the logistic map in CPSO.

1. Initializing the values of the position and velocity for all the particles.
2. Using the objective function obtained from all the particle are used in the calculation of the Fitness value.
3. Calculate the values for pbest and gbest of the algorithm.
4. Update chaotic N_r value using equ (5).
5. Using the calculated update N_r, the values of the position and velocity are updated.
6. The steps from 2 to 5 are repeated until the convergence is attained.

Algorithm 4: **CPSO**

Results and Discussions

The figure 4 depicts the PSO algorithm result of the sample images. The result includes the clustered and the segmented output of the input image. Also the tumor extracted image after the segmentation process is also shown. Similarly the figure 5 and 6 shows the outputs of the WPSO and CPSO Algorithms.

Input CT Image	Grouped Image	Image Segmented Output	Extraction of Tumor

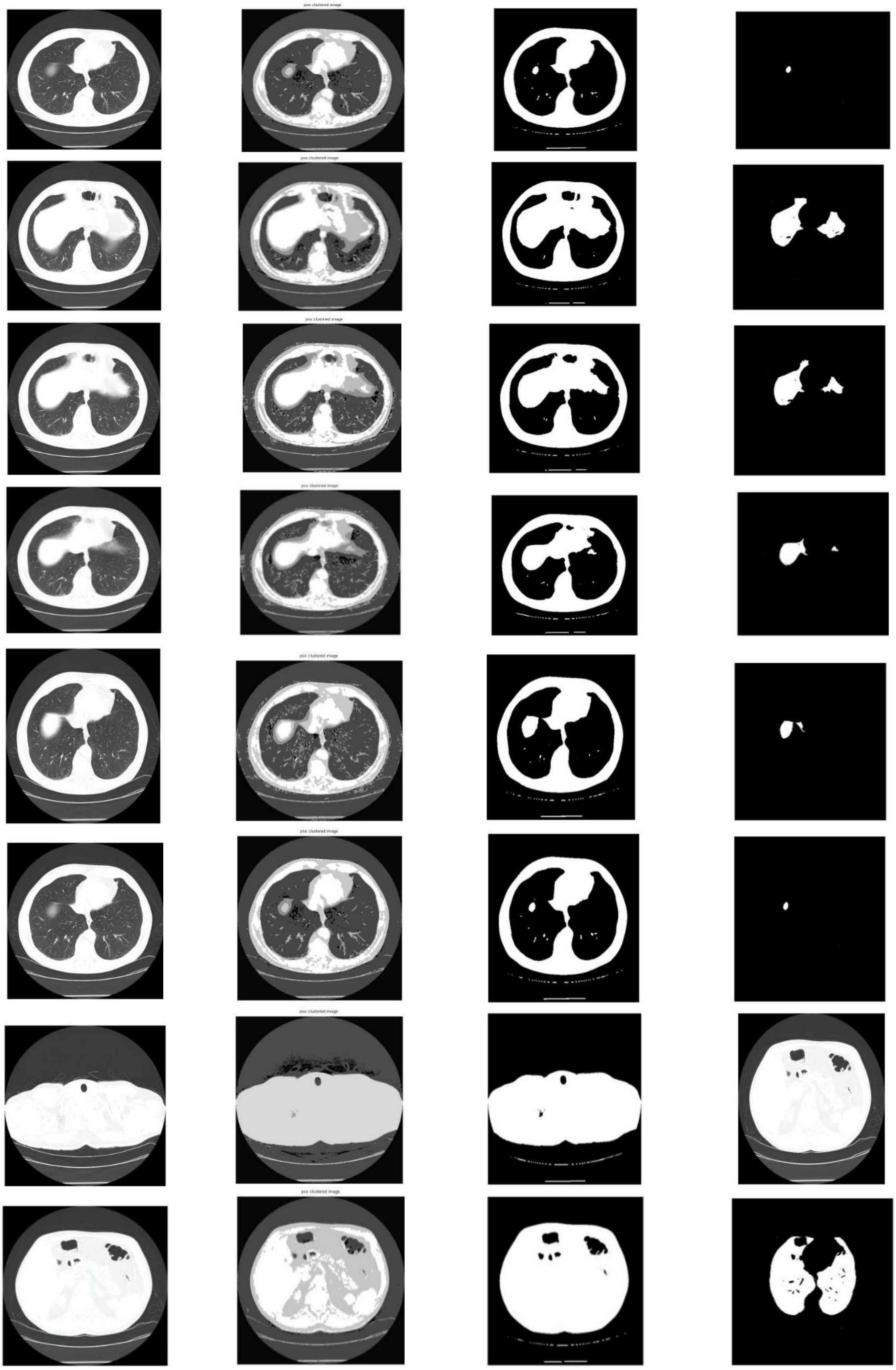


Fig 4: **PSO OUTPUT**

Input CT Image	Grouped Image	Image Segmented Output	Extraction of Tumor

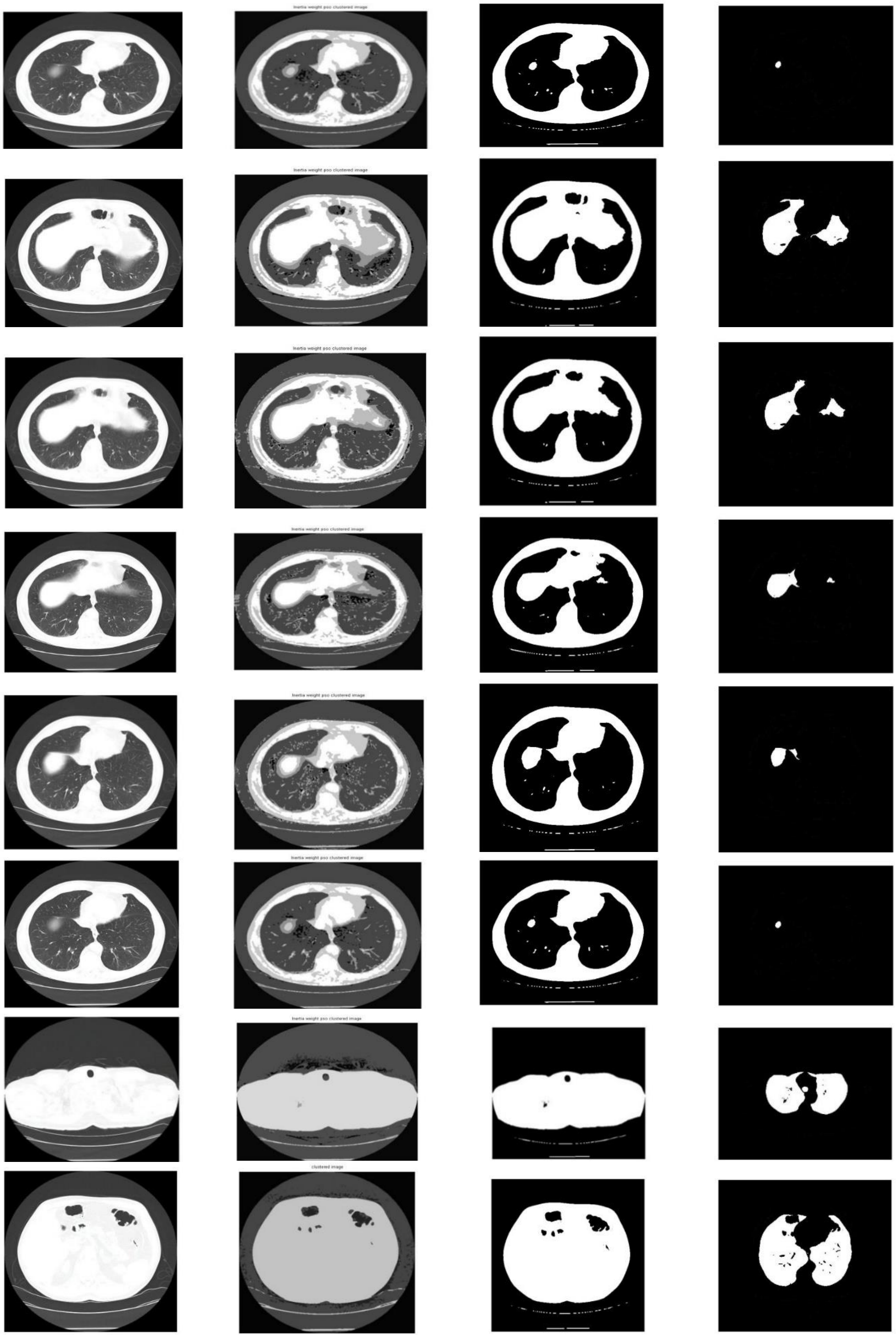


Fig 5: **WEIGHTED PSO OUTPUT**

Input CT Image | Grouped Image | Image Segmented Output | Extraction of Tumor

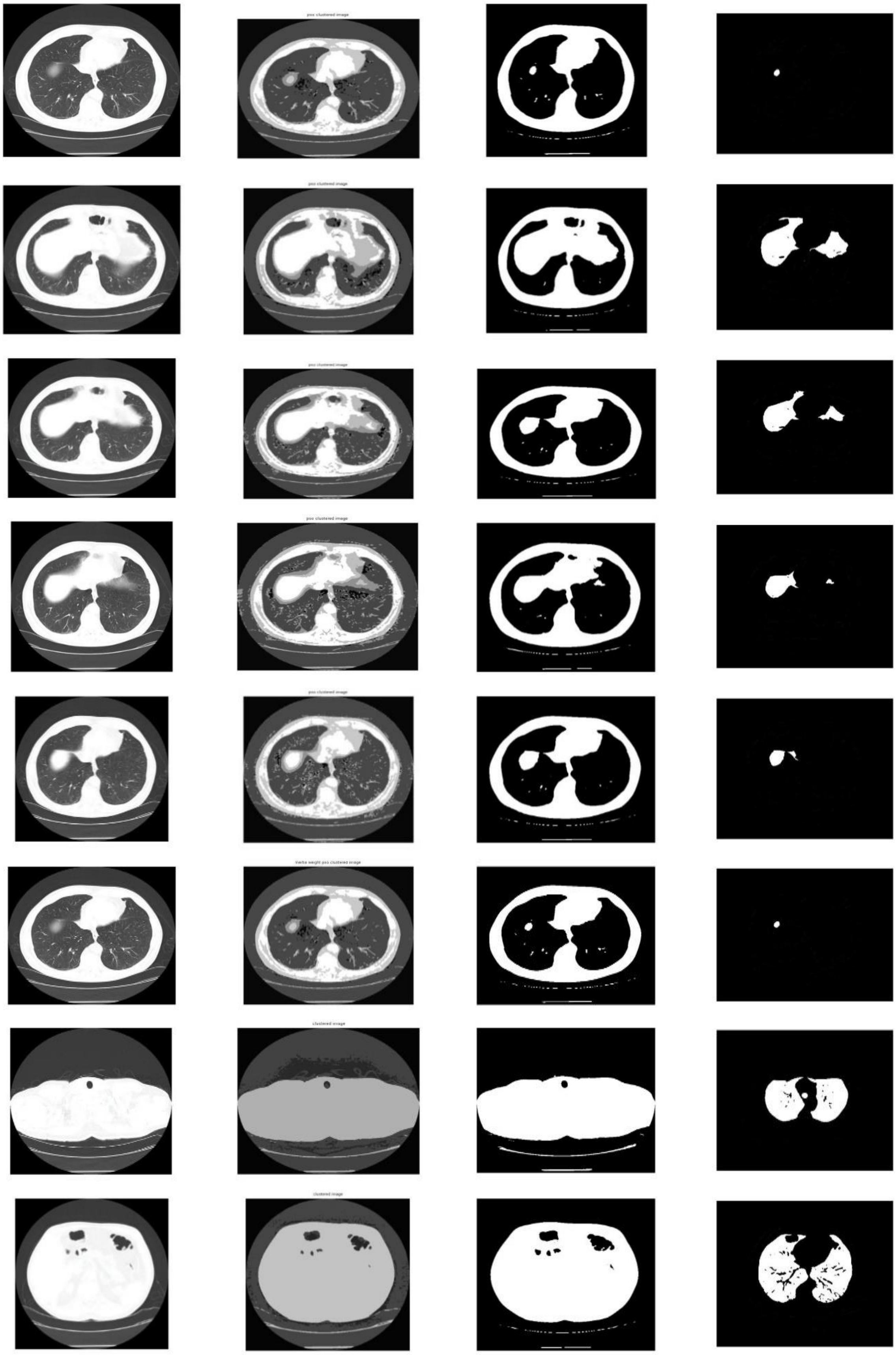


Fig 6: **CHAOTIC PSO OUTPUT**

Performance Parameters

The optimization algorithms PSO, WPSO and CPSO are analyzed and their performance are evaluated using the parameters Accuracy, Sensitivity and Specificity along with the classification parameters True Positive rate (TPR), True Negative Rate (TNR), False Positive Rate (FPR) and False Negative Rate (FNR) with the formulas,

TPR = TP / (TP + FN) **(7)**

TNR = TN / (FP + TN) **(8)**

FPR = FP / (FP + TN) **(9)**

FNR = FN / (FN + TP) **(10)**

The Table 1 gives the TPR, TNR, FPR, FNR and Accuracy of sample images using the PSO Algorithm. Also, the Table 2 and Table 3 show the performance parameters of sample images using the WPSO and CPSO Algorithms.

Table 1: **Pso Output**

IMAGES	TPR	TNR	FPR	FNR	ACCURACY
SAMPLE IMAGE 1	88.6524	91.2307	10.9915	13.5698	90.1735
SAMPLE IMAGE 2	87.0723	87.0723	9.659	9.659	90.08
SAMPLE IMAGE 3	83.903	90.9425	11.2797	18.3192	87.5961
SAMPLE IMAGE 4	82.2382	89.8949	12.3273	19.984	86.1078
SAMPLE IMAGE 5	83.7454	88.5106	13.7116	18.4768	86.141
SAMPLE IMAGE 6	83.0107	86.4011	15.8211	19.2115	84.6692
SAMPLE IMAGE 7	82.8392	81.206	21.0162	19.383	82.0549
SAMPLE IMAGE 8	81.5293	81.1832	21.039	20.6929	81.3682

Table 2: **Wpso Output**

IMAGES	TPR	TNR	FPR	FNR	ACCURACY
SAMPLE IMAGE 1	88.576	91.4383	10.7839	13.6462	90.0924
SAMPLE IMAGE 2	87.3061	90.9237	11.2985	14.9161	89.2921
SAMPLE IMAGE 3	84.0458	90.0733	12.1489	18.1764	87.2129
SAMPLE IMAGE 4	82.5396	88.3124	13.9098	19.6826	85.4695
SAMPLE IMAGE 5	84.0134	87.5051	14.7171	18.2088	85.7742
SAMPLE IMAGE 6	83.2176	85.6256	16.5966	19.0046	84.3987
SAMPLE IMAGE 7	83.2472	80.2855	21.9367	18.975	81.8175
SAMPLE IMAGE 8	81.4385	81.4966	20.7256	20.7837	81.4655
SAMPLE IMAGE 9	83.5296	81.5035	20.7187	18.6926	82.5742
SAMPLE IMAGE10	82.188	80.7076	21.5146	20.0342	81.5054

Table 3: **Cpso Output**

IMAGES	TPR	TNR	FPR	FNR	ACCURACY
SAMPLE IMAGE 1	91.6158	100	0	8.3842	95.8079
SAMPLE IMAGE 2	90.9563	100	0	9.0437	95.4782
SAMPLE IMAGE 3	88.8404	100	0	11.1592	94.4204
SAMPLE IMAGE 4	87.2946	100	0	12.7054	93.6473
SAMPLE IMAGE 5	87.3583	100	0	12.6417	93.6792
SAMPLE IMAGE 6	86.1567	100	0	13.8433	93.0784
SAMPLE IMAGE 7	83.4867	100	0	16.5133	91.7434
SAMPLE IMAGE 8	83.1082	100	0	16.8918	91.5541

Table 4: **Performance Measures of Image Segmentation**

Sl.No	Parameters	PSO	WPSO	CPSO
1	Accuracy	84.9127375	83.84914	93.6761125
2	True Positive Rate	83.0127125	82.89908	87.352125
3	True Negative Rate	85.9440625	84.67606	100
4	False Positive Rate	13.369575	15.32394	0
5	False Negative Rate	16.300925	17.10092	12.647825

The correctness of the segmentation process is analyzed using the metric Accuracy, which is given by the expression,

Accuracy = $(T_p + T_n) / (T_p + T_n + F_p + F_n)$ **(11)**

If the values of the True Positive and True Negative are maximum than the False Positive and False Negative, it signifies that the given sample image is segmented accurately as foreground and background and its value is almost near to 1.

It is the metric used to identify the number of diseased cases in the dataset, can also be termed as True Positive Rate. The relationship is given by

Sensitivity = $T_p / T_p + F_n$ **(12)**

In the analysis of the severity of the tumor in the segmented images, in order to identify the normal cases in the set of images the True Negative Rate metric is used. It can also be termed as Specificity.

Sensitivity = $T_n / F_p + T_n$ **(13)**

Overlap index or Dice coefficient is the factor defining the similarity index between the compared results. Dice coefficient also defines the relationship among the input images and ground truth images. It also compares the sum of the nonzero features in the processed data and the ground truth images.

Dice Coefficient = $(2 \times T_p) / (T_p + F_p + F_n)$ **(14)**

Table 5: **Comparative Analysis of Performance Parameters**

S.No.	Parameters	PSO	WPSO	CPSO
1	Accuracy	82.61361	85.88736	92.273
2	Sensitivity	81.78102	84.99338	86.84288
3	Specificity	100	100	100

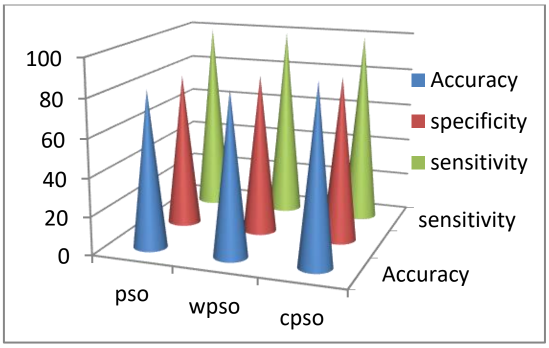


Fig 7: **Comparative Analysis of Performance Parameters**

Conclusion

In this proposed work, we evaluated the various optimization algorithms, for the detection of tumor in the CT Lung Images. The images taken for detection and analysis of the tumor from the database images, requires formerly the preprocessing steps then the processed images are taken for the numerical analysis. Primarily the datasets undergo a usual preprocessing steps and Median filter replaces the value of a pixel by the median of gray levels in the neighborhood of the pixel considered for the analysis purpose in the meantime, the median filtering is reflecting a non-linear digital filtering technique, most commonly practiced for the elimination of unwanted noise from the image. The mean weight and variance of the contrast enhanced input CT images are calculated using the OTSU Algorithm for segmentation. For the segmentation of infected lung areas in the CT images taken for analysis the region growing algorithm is deployed, in which the regions are segmented based on connectivity and gray scale difference. In order to validate the algorithms used in this proposed work the PSO, Inertia Weight PSO and Chaotic PSO are used to optimize the algorithms and on comparing the performance factors of the above mentioned algorithms, the Chaotic particle swarm optimization algorithm shows an improved accuracy of 95% and also in the sample 20 images shows an accuracy of 90%. Also, the Comparative Analysis of the Parameters like Accuracy, Sensitivity and Specificity are considerably good in case of the CPSO Optimization Algorithm with 92%, 87% and 100% respectively. The CPSO algorithm establishes an accuracy of 90% in all the 20 datasets considered for the segmentation and the analysis purposes, compared to the previously adapted algorithms. The proposed algorithm can be extended by deploying neural network classifier to improve accuracy and classify the cancerous and non cancerous nodule using deep learning methods.

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