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# Multi-Modal Data Fusion and Dual Validation for Lung Lesion Detection and Optimization

Ranjitha U N[1], Shanthi D L[2], Rajesh I S[3], Maithri C[4], Sumit Gupta[5], Chandrappa S[6]
[1]Associate Professor, Department of CSE, REVA University, Bangalore, India. email: ranjitha.un@gmail.com
[2]Assistant Professor, Department of CSE, BMSIT&M, Bangalore, India. email: gopalaiahshanthi@bmsit.in
[3]Assistant Professor, Department of AI & ML, BMSIT&M, Bangalore, India. email: rajeshaiml@bmsit.in
[4]Professor & HoD, Dept. of CSE, KIT, Tiptur, Karnataka, India. email: maithri.c.prashanth@gmail.com
[5]Research Head, R&D Dept., Xsys Software Technologies, India. email: sumit@xsyssoftwaretechnologies.com
[6]Assistant Professor, Dept. of CSE, Jain(Deemed-to-be University), Bengaluru, India. email: chandrucs21@gmail.com

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**ABSTRACT**

The research proposes Dual Data Validation (DDV) and Whale Optimization Algorithm (WOA) which combines CT and Ultrasound patterns to boost medical imaging effectiveness and precision during lung lesion detection. CT lung datasets undergo Deep Neural network (DNN) framework processing during the primary stage to extract critical features by means of attribute co-relationship mapping. The WOA optimization of the feature matrix leads to effective feature selection while enabling primary decision-making to produce an optimized trained dataset for dual feature verification. The parallel processing system extracts features from ultrasound samples through MOTIF feature extraction while using Swarm Optimization Terminology for extensive multi-modal validation. The DDV technique starts through threshold mapping techniques applied to obtained datasets to calculate Regions of Interest (ROI) and undertake optimization processes for precise decision-making. The proposed method reaches an 87.32% accurate decision support rate through evaluation on a dataset of 1794 CT and Ultrasound images from Kaggle. The technique achieves a 12.73% better prediction accuracy than regular uni-processing approaches because it combines dual modality data with optimization methods to enhance lung lesion detection.

**Keywords**: Lung Lesion Detection, MOTIF, Dual Data validation, Whale Optimization Algorithm

## I. Introduction

Lung cancer is life-threatening and requires immediate medical attention for curing and treatment. The diagnosis phase should be initiated immediately and henceforth requires modern tools and technological support in diagnosis and predictive result generation. According to the World Health Organization (WHO) 2019 survey, 1.76 million deaths were reported, and 2.09 million new cases were registered for treatment post-confirmation [1]. Usually, men are at higher risk due to their chronicle habits. The usage of modern techniques and diagnosis tools enables early and exact detection of lung cancer at its initial stages. These medical evaluation processes follow two main approaches by collecting information in a structured format

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or generating medical datasets including MRI, PET, CT and Ultrasound. These datasets lack internal evaluation systems which would speed up diagnosis support while medical experts are absent.

Developing nations experience a misbalance between doctor-physician resources compared to patient needs because of insufficient infrastructure and limited funding. The diagnosis of patients through distant consultations requires evaluation of various research scenarios that span from simple cases to complex situations. Consultants must receive independent self-contained reports about their distant patient population. The diagnostic reports function through either medical infrastructure or environmental factors which creates a mismatched system for diagnosis. A study conducted by [2] applies CT imaging techniques together with [3] and [4] which provides historical information about early 1980s lung cancer diagnostic processes performed by traditional radiologists.

The scope of this study is to detect and predict the occurrences of lung cancer via multiple data training and validation approaches. The proposed technique, i.e. Dual Data Validation (DDV) is based on dual datasets processing. The CT and ultrasound datasets are processed independently and result in a collective evaluation towards accurate decision making and support framework. The technique is aided by Whale Optimization Algorithm (WOA) for feature set selection and process validation of DDV datasets. The later section of this article discusses on results and research outcomes of the proposed framework with a supportive conclusion.

## II. Literature Reviews

Lung cancer detection and diagnosis is primarily processed using image processing and data analysis techniques. Cancer science has improved its approaches with the improvisation of technological enhancements. These enhancements have led to the design of techniques and algorithms bounded with CT images, rather than typical X-Ray datasets. These CT images provide much more reliable and accurate results in evaluation compared to X-rays as discussed in [5]. The author discusses a basic image processing, segmentation, and feature extraction technique from MATLAB. This research can be considered as an initial process of considering CT datasets. Further, the author [7] has discussed various image processing techniques for lung cancer decision-making. This study includes image quality, resolution, and dataset format.

With the introduction of machine learning terminology, concepts such as neural networking, fuzzy logic, and intelligent computing being put together result in much more reliable and efficient processing systems. Typically, the development of a neural networking model for lung cancer detection is discussed in [8] concerning dependencies of inter-connected feature sets for decision support. The challenge in feature extraction with relevance to ultrasound signals is the extraction of most repeated patterns and evaluating schemas for processing named MOTIF. The author [9] has discussed MOTIF extraction of sequential data streams with each passing pattern recurrence mapping and reporting. These recursive patterns are internally co-related to frame a structural unit of feature dependencies.

With the inclusion of clustering and demand for classifying the data streams, the author of [10] has included a study towards the detection of lung cancer using clustering of patterns via a DNN framework. The approach is to provide a reliable framework for the extraction of most alike features under demand-based classification. The arguments are supported by [11] with an improved DNN framework. The overall unit is to provide reliable feature selection and evaluation of decision-making via trained and threshold library updating using a repeated medical multi-dimensional data technique as in [6]. These techniques discuss multi-clustering approaches to process multi-dimensional medical datasets. Ranjitha et. al [12] introduced a novel approach for lung nodule segmentation and classification using the Chronological-African Vultures Optimisation (CAVO) algorithm. Lung nodule segmentation is performed using a Bi-

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directional ConvLSTM-U-Net (BCDU-Net), while classification is carried out with an ensemble of Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), and Deep Residual Network (DRN). Another work by Ranjitha et al. [13], proposes a hybrid segmentation model that integrates K-means clustering with morphological operations. It also presents a comparison of different process sequences, broadening its application to the volumetric quantification of lung tumors.

The process of development in this survey is to provide a structural analysis of current research trends and technical enhancements. The study has observed the pattern and need for processing over multiple streams and dimensions of datasets. Typically, the research problem objective is streamlined and processed concerning dual data processing and validation approaches.

## III. Methodology

The proposed method is developed to make efficient predictions about lung cancer on the available datasets. The method mostly gathers raw data from datasets of CT and ultrasound devices. These datasets are independently processed under Phase I and Phase II respectively as shown in below Figure 1. Under Phase I: the datasets of CT are considered for processing with respect to attribute extraction. The attributes are a series of interconnected parameters of data, resulting in a reflective approach to data-dependency matrix. The approach is internally collected via a stream of attribute indexing. These indexing results in the generation of validated segments of inter-connected attributes. This results in generating aligned datasets of CT images towards attribute optimization.

In parallel, Phase II computation is processed via ultrasound signal samples. These samples are directly converted into signals and MOTIFs are extracted. MOTIFs are typically a set of series of repeated signal patterns. The MOTIF attributes result in an accurate ROI detection and evaluation. The resultant attributes matrix is retrieved from framed segments of patterns and the occurrences of individual MOTIF signals with a considered interval of time. These signals are fragmented into smaller radical instances such as ROI patterns to ensure a pixel-based labeling of datasets.

These independently processed datasets are combined and fragmented to retrieve attribute inter-dependency evaluation matrix using a Deep Neural Networking (DNN) model for correlation mapping. The DNN aided design is to ensure the features combined in the process of attributes are extracted via independent computation. The extracted feature matrix is then processed via a Whale Optimization Algorithm (WOA) to evaluate interdependent features and their rational parameters. The Ultrasound data-samples are then processed using a swarm based 'Ant Colony' optimization for feature selection. The independently processed datasets as shown in Fig. 1 are combined under a functional paradigm of proposed Dual Data Validation (DDV) technique. This technique is supported by a generated dual dataset database. The dual datasets DB is termed as multi-dimensional model of attributes and feature representation in a 2D approach.

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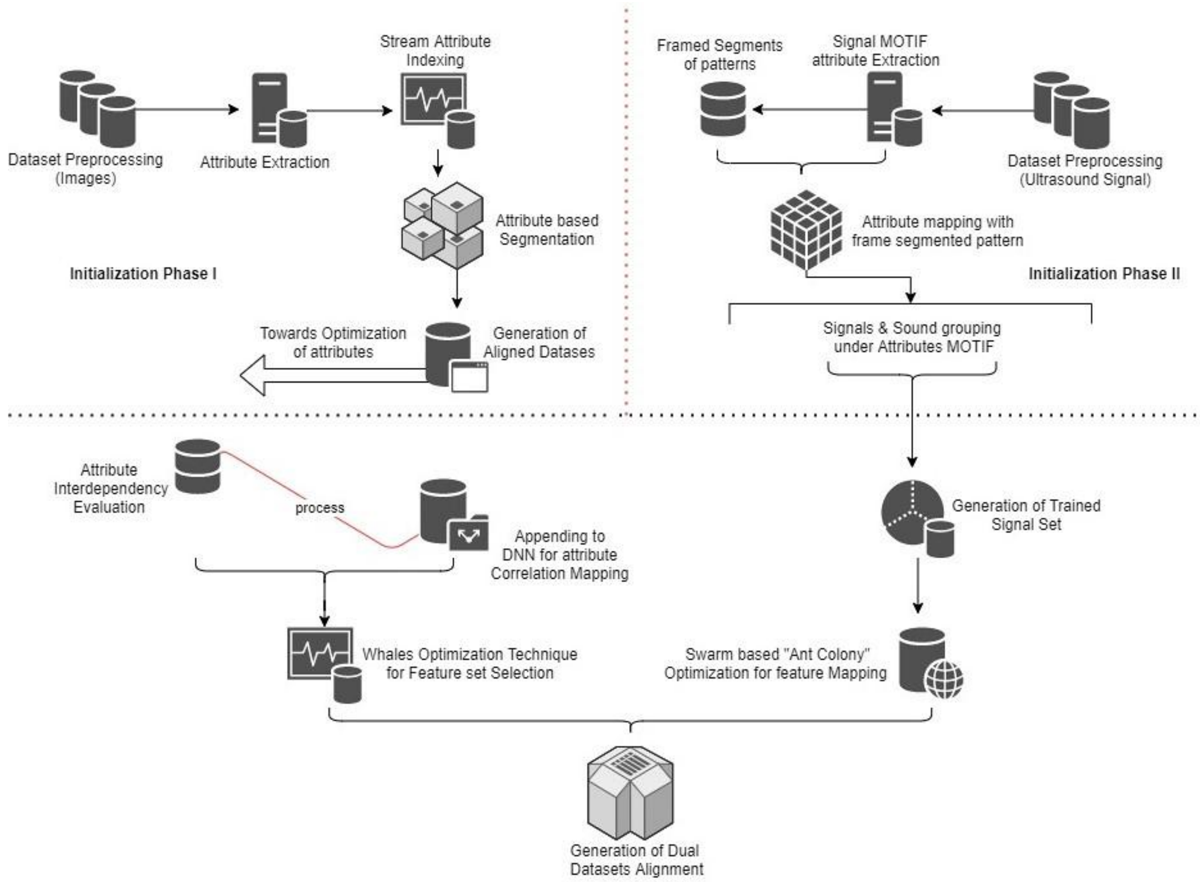


*Fig. 1: Dual data generation framework for lung cancer datasets.*

The dual datasets generation is further expanded and computed as shown in Fig. 2. The evaluation parameter is considered and computed via multi-dimensional spaces, typically in 2D model of DDV framework. The threshold values are generated and processed via a multiple streams of inter-connected segments values. These values are synchronized via a hierarchical indexing technique via a supportive "Feature selection based on WOA". The threshold values are reconsidered to attain a much accurate slot of processing, named as ROI or Region of Interest. The ROI synchronizes with trained (pre) [6] datasets for validation of results and data feature occurrence. This supports the decision and generation of reports in much accurate and reliable format. In the proposed DDV technique, the datasets are computation and validation plays an important role as demonstrated mathematically in section IV.

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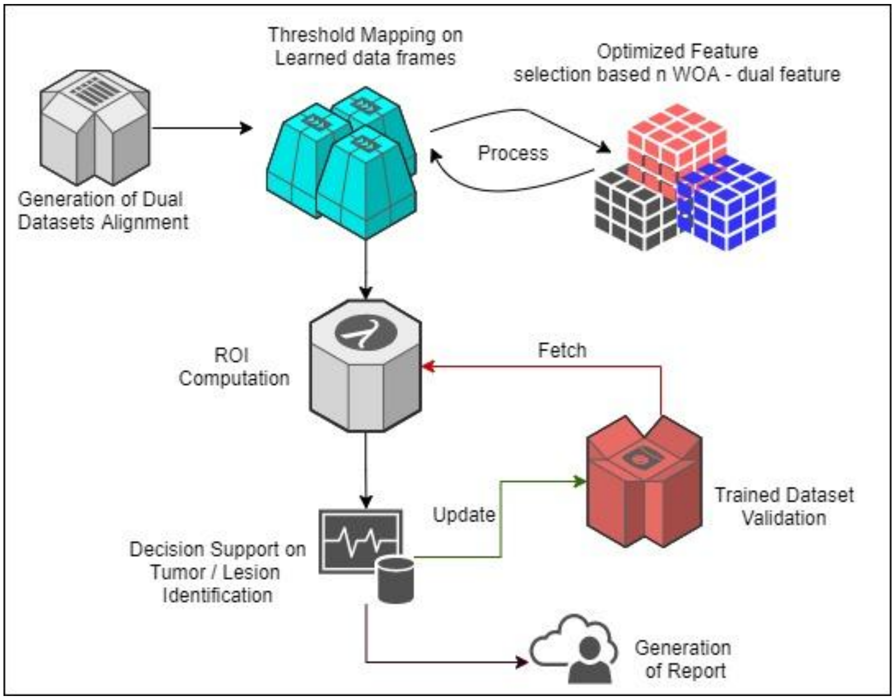


*Fig. 2: Framework for DDV technique's decision support*

## IV. Mathematical Modeling

The lung lesion or cancer is typically identified via an image processing techniques using the given datasets $U_D$, consisting of CT and Ultrasound data formats. Each dataset $(U_D)_i$has a usual association of attributes as $U_D = \{(U_D)_{A1}, (U_D)_{A2}, (U_D)_{A3}, (U_D)_{A4} \ldots (U_D)_{An}\}$ where each of attribute $(U_D)_{Ai}$ is reflecting to an independent array of attribute sets. The resultants of these datasets are dual progressively aligned with ultrasound $(U_T)$ signals of user's in-order to reflect the dependencies with two independent monitoring systems as $\left((U_D \simeq U_T)/\forall A_1, A_2, A_3 \ldots A_n \in U\right)$ where $U$ is a universal set of attributes. The table of notation is as follows:

**Table. 1: Notations and description**

| Notation | Description |
|---|---|
| $U_D$ | Dataset with CT and ultrasound images |
| $U_r$ , $A_i, A_j$ | Ultrasound signal vector, Individual attribute sets |
| $A_Z$ | Intersected attribute set between CT and Ultrasound datasets |
| $U$ | Universal set of all possible attributes |
| $\delta(\,)$ | Derivative or rate of change of a variable |
| $\Delta t$ , $\Delta Tf$ | Time interval, Threshold function used for feature mapping |
| $M(U_D)_{\{A_i\}}$ | Mapping function applied to attribute $A_i$ from CT dataset |
| $U_Z$ | Combined/intermediate dataset from CT and Ultrasound attributes |
| $D$ | Feature vector optimized using WOA |
| $U_{\overrightarrow{Z+1}}$ | Next-generation optimized feature set vector |
| $F$ | Final optimized feature set combining CT and Ultrasound features |
| $T_M$ | Threshold vector from Ant Colony Optimization (ACO) |

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| | |
|---|---|
| $T$ | Final decision threshold combining ultrasound and CT features |
| $f, \Delta f$ | Feature value and its threshold-adjusted bound |
| $\lim(i, j \to n)$ | Limit operation as indices $i$ and $j$ approach $n$ |
| $e^{Aj}$ | Exponential term of attribute $A_j$, used in optimization |

### A. Initialization Phase

Under the phase of initiation, the Phase I is specific to CT datasets and Phase II is specific to ultrasound datasets of Lung. The attributes extraction and dual feature parameter association is computed as each of dataset $U_D$and $U_T$is associated with attribute set, the each attribute order has to be obtained as $A_Z = ((U_T)_{Ai} \cap (U_D)_{Ai})$ where, each of attributes relationship has to be extracted as shown in Eq. 1

$$A_Z = \left(\sum_{i=0}^{n} \sum_{j=0}^{n-1} \left(\frac{\delta(U_T)_{Ai}}{\delta(U_D)_{Aj}}\right)\right) \subseteq U \tag{1}$$

Thus, each of extracted attributes is resultant of independent existence. So, the indexing of functionalities of each inter-correlated attributes are aligned and extracted to form attribute-based segmentation as shown in Eq. 2

$$A_Z = \left[\left(\sum_{i=0}^{n} \sum_{j=0}^{n-1} \left(\frac{\delta(U_D)_i - \delta(U_T)_j}{\delta t}\right)\right) \cap \left(\frac{\delta(U)}{\delta t}\right)\right] \tag{2}$$

$$A_Z = \frac{1}{\Delta t}\left[lim_{i,j\to n}\left(\delta(U_D)_i - \delta(U_T)_j\right) \cap \delta(U)\right] \tag{3}$$

$$A_Z = \frac{1}{\Delta t}\left[lim_{i,j\to n}\left(\frac{(\delta(U_D)_i - \delta(U_T)_j)}{(\delta(A_j))}\right) \cap \left(\left(\delta(A_j)\right)\delta(U)\right)\right] \tag{4}$$

The resultant equilibrium of segments under each attribute is associated with attribute grand set $(A)$ as $(A_Z \subseteq A)$ and thus $\left(\forall A_i \subseteq A_j \subseteq A\right)$ and $(A \in U)$ as an associated parameter of attribute extraction. These attributes result in the generation of aligned datasets of CT images. Similarly, the parameters of ultrasound signals and CT images are combined to form a co-related inter-development parameter of attributes in providing decision support of MOTIF [9] paradigms as each of $\left(\delta(U_D)\right) = |M(U_D)_{Ai}|$ such that $\forall(U_D)_{Ai} \in \cup$ and each of $(A_i \subseteq A)$ as shown in Eq. 3 and Eq. 4 respectively.

### B. Computation and Validation

The extracted and aligned attributes datasets $(U_D \cup U_T) = U_Z$is a co-lateral inter-connected attributes of two independent datasets (i.e.) CT and Ultrasound. These attributes are processed using a DNN Framework for co-relationship mapping as shown in Eq. 5.

$$U_Z = \frac{\Delta Tf}{\Delta t}\left[lim_{i,j\to n}\left(\frac{(\delta(U_D)_i - \delta(U_T)_j)}{(\delta(A_j))}\right) \cap \left[\left(\Delta(A_j)_j\right) - \delta(U)\right] - A_Z\right] \tag{5}$$

$$\therefore \forall U_Z \Rightarrow \left[(U_D)_i \Rightarrow (U_T)_i \triangleq \Delta Tf\left(\frac{\delta(A_Z)_i}{\delta t}\right)\right] \tag{6}$$

From Eq. 6, the $\Delta Tf$, a ratio of threshold function is validated with associated mapping from independent datasets $(U_D)_i$ and $(U_T)_i$ with respect to $A_Z$. The attribute mapping now expands internal fragments of features as shown in Eq. 7 with reference to the Whale Optimization Algorithm (WOA).

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$$D = \left|\left(\overrightarrow{U_Z} \in \cup\right) - A_Z\right| \tag{7}$$

$$\left[\delta\left(\overrightarrow{U_{Z+1}}\right) + \delta\left(\vec{t}\right)\right] = \left|\left(\left(\overrightarrow{U_Z}\right)_{rand}\right) - A_Z D\right| \tag{8}$$

Where, each of $\overrightarrow{U_Z}$ represents the initial feature associated with an attribute with reference to functional values of segmentation of WOA technique parameters *(D)*. such that, on extension with each feature it forms $\left(\overrightarrow{U_Z} \Rightarrow \overrightarrow{U_{Z+1}}\right)$ with a ratio of $\delta t$ in dependency. Thus $\left(\overrightarrow{U_Z}\right)_{rand}$ value is a threshold data point of attribution with each vector is independently associated in searching of prey (optimized feature) leading to the generation of customized datasets (trained) as shown in Eq. 9 and 10 respectively.

$$\left|\overrightarrow{U_{Z+1}} - D\right| \leq min\left|\overrightarrow{U_Z} - D\right| \leq min\left|\left(\overrightarrow{U_Z}\right)_{rand} - D\right| \tag{9}$$

$$where\ \left(U_{i,j}\right) = \begin{matrix} 1 & if\left|\overrightarrow{U_{Z+1}} - D\right| \leq min\left|\overrightarrow{U_Z} - D\right| \\ 0 & if\left|\overrightarrow{U_Z} - D\right| \leq min\left|\left(\overrightarrow{U_Z}\right)_{rand} - D\right| \end{matrix} \tag{10}$$

### *C. Multi-data Processing and Optimization (Dual Data Validation Technique)*

The ultrasound $\overrightarrow{U_S}$ signals are processed and optimized under swarm-based optimization algorithms for feature mapping in functionary attributes as shown in Eq. 11.

$$\left|\overrightarrow{U_D} \times D\right| - |U| \Rightarrow \forall\left(\overrightarrow{D}^{\rceil} e^{Aj} \times cos\left(2\pi A_j\right)\right) + \overrightarrow{U_{Z+1}} \tag{11}$$

Where, each functional attribute $Aj$ is redefined and retrieved with a co-related functional parameter $e^{Aj}$with respect to $\overrightarrow{U_S}$. The collective attributes are further expanded into a series of features co-relationship mapping over independent set of data to feature each willingness or fitness of searched attributes as shown in Eq. 12.

$$F = \left[\left(\frac{\delta(U_Z)}{\delta t}\right) \cup \left(\frac{\delta(U_S)}{\delta t}\right)\right] \Rightarrow \left[\left(\frac{\delta(A_Z)}{\delta t}\right) \Delta Tf \left|\left(\overrightarrow{U_Z}\right)_{rand}\right|\right] \tag{12}$$

$$\therefore \forall F \Rightarrow \frac{\Delta Tf\left|\left(\overrightarrow{U_Z}\right)_{rand}\right|}{\delta t}\left\{\left(\delta(U_Z) \cup \delta(U_S)\right)\right\} \tag{13}$$

Where, $F$ is the feature-set co-relationship of independent datasets $\delta(U_Z)$ and $\delta(U_S)$ for a rational vector of $\Delta Tf\left|\left(\overrightarrow{U_Z}\right)_{rand}\right|$ in searching the optimized relationship attribute for maximum decision making and support system development. Using swarm based "Ant Colony" optimization technique, the multiple thresholding vector is generated as shown in Eq. 14

$$T_M = |\forall F - (U_Z U_S \subseteq Aj)| \times \left(\frac{\delta(\Delta Tf)}{\Delta t}\right) \tag{14}$$

$$\therefore T_M \Rightarrow \left(\Delta T_{Uf} \cup \Delta T_{Us}\right) \triangleq T \tag{15}$$

The threshold vector $T_M$ generated to form an inter-related coefficient matrix and hence, $(\Delta Tf)$ remains a major independent factor for evaluation. The ROI is computed with a feature selection i.e. $\left(f \leq \Delta f \times \delta(U_Z)\right)$ and minimization values point matrix. The evaluation of features with respect to threshold values are computed and data is aligned for selection using a vector-based classification of ranges

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to support decision-making. Additionally, the process of correlating multiple features across two independent datasets through a generalized data standardization technique is discussed.

## V. Results and Discussions

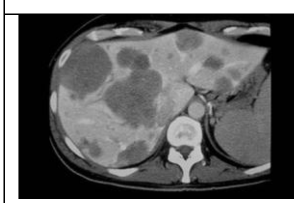
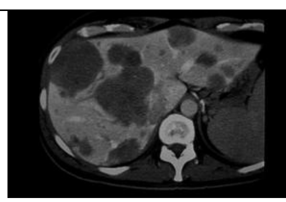
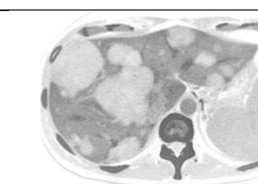
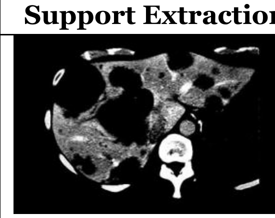
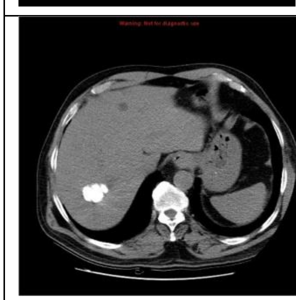
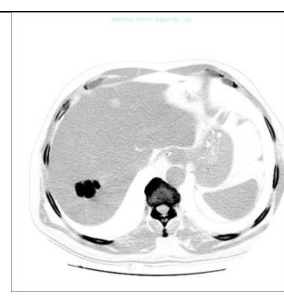
The purpose of DDV technique is to refine and provide a reliable sum of decision making and process evaluation toward the detection of lung cancer. Typically, the proposed DDV technique is refined and evaluated using CT and Ultrasound datasets. The decision support is novel as it includes the dual data dimensional parameters evaluation. The DDV technique achieves a higher reliability of informative evaluation computed to conventional techniques and algorithms as discussed in literature. The Table.2 demonstrates performance and outcome evaluation with reference to decision support.

**Table. 2: Comparative output parameter evaluation**

| | **Precision** | **Efficiency** | **Reliability** | **Accuracy** |
|---|---|---|---|---|
| Basic Image processing technique | 72.21 | 82.30 | 68.21 | 79.923 |
| Neural Networking techniques (Cumulative) | 74.98 | 88.28 | 52.23 | 62.12 |
| Neural Networking (Trained Schema) | 74.23 | 87.98 | 72.12 | 67.32 |
| Deep Neural Networking techniques (Cumulative) | 79.37 | 89.23 | 77.32 | 82.33 |
| Dual Data Validation Technique (Proposed) | 79.34 | 88.42 | 79.23 | **87.32** |

The decision support for evaluation and parametric observation of multiple streams and approaches are reliable and has provided a higher-order of accuracy and performance reliability compared to conventional processing techniques as per current literature. Table. 3 demonstrates the internal processing Dual Processing Technique (DDV) with reference to defined approaches as per Fig. 1 and Fig. 2 respectively.

**Table. 3: DDV technique processing**

| **Input Sample** | **Data Alignment** | **Feature Selection** | **ROI and Decision Support Extraction** |
|---|---|---|---|
|  |  |  |  |
|  |  |  |  |

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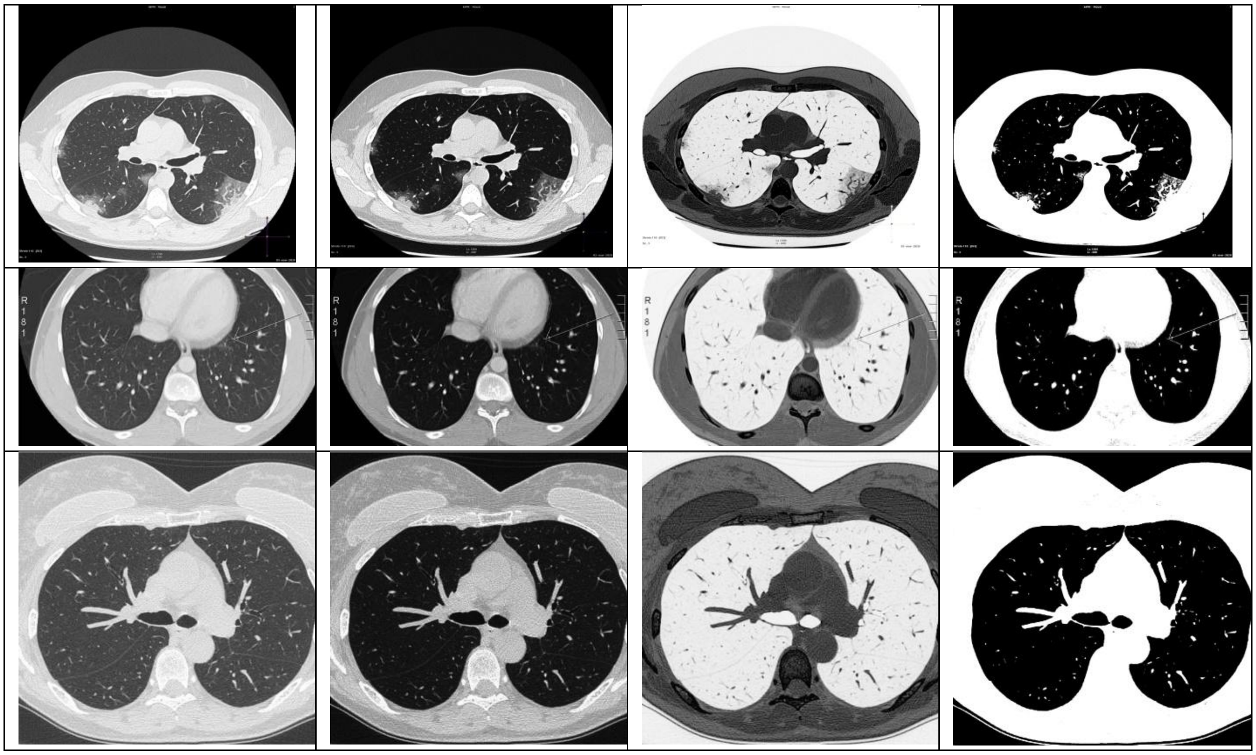

## VI. Conclusion

The proposed technique of dual data validation (DDV) is designed with a scope of prediction, detection and support of evaluation using CT and Ultrasound datasets of lung cancer. The DDV technique processes parallel CT images and Ultrasound signals in the phase of initialization to form inter-dependent attributes set. These attributes are optimized using the Whale Optimization Algorithm (WOA) for feature set segmentation resulting in a functional set of $\left(\overrightarrow{U_Z}\right)_{rand}$ vector. The proposed technique has achieved data segmentation and feature set categorization using swarm based Ant Colony optimization algorithm. The extracted feature set has obtained an efficiency of 87.32% over the dual-data processing and optimization. The decision support has a prediction ratio of 12.73% compared to basic processing and single mode dataset supporting algorithms.

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