

# Comprehensive Medical Image Data Handling for Lung Cancer Stage Screening and Proactive Sustain using Deep learning Techniques

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## Abstract

Lung cancer stage identification and proactive stage sustain is a difficult task to implement using the medical data images alone due to its complex structure and inter component relations. The process of taking the medical images and maintaining it for further processing with sensitive care is an essential part in lung cancer analysis so that it will be properly handled by the appropriate smart techniques in order to perform the effective advisory process for better medical recommendations. Deep learning plays the appropriate smart technique approach for the medical experts for handling this sensitive lung cancer medical image data in an efficient way. This paper presents the comprehensive medical image data handling for lung cancer stage screening and proactive sustain using deep learning techniques. This paper module focuses on the optimal selection of deep learning techniques to identify the types, stage and stage level recognition towards the lung cancer using medical image data sets. The future extension of this paper focuses on automated lung cancer data analysis model to access the lung cancer medical image data directly using opinion learning approaches.

**Keywords**—Deep learning, Lung cancer, Resource, Medical service, Performance

## 1. INTRODUCTION

### a. Deep Learning:

Deep learning is an artificial intelligence (AI) method that teaches computers to process data in a way inspired by the human brain. Deep learning models can recognize complex pictures, text, sounds, and other data patterns to produce accurate insights and predictions.

### b. Lung cancer stages:

#### i. Non-Small Cell Lung Cancer (NSCLC) Stages:

##### \*Stage 0 (Carcinoma in Situ):

Abnormal cells are present in the lining of the lungs but haven't invaded deeper tissues.

##### \*Stage I:

Cancer is limited to the lung, with no spread to lymph nodes or other areas.

##### \*Stage II:

Cancer may be larger, spread to lymph nodes within the lung, or have multiple tumors in the same lobe.

##### \*Stage III:

Cancer has spread to lymph nodes in the chest further from the lung, or there are large tumors that have spread to nearby lymph nodes.

##### \*Stage IV:

Cancer has spread beyond the chest cavity to other parts of the body.

#### ii. Small Cell Lung Cancer (SCLC) Stages:

**\*Limited Stage:** Cancer is confined to one side of the chest and a limited area.

**\*Extensive Stage:** Cancer has spread throughout the lung, to the other lung, to lymph nodes on the other side of the chest, or to other parts of the body.

## II. LITERATURE REVIEW

David Baua , Jun-Yan Zhua , Hendrik Strobel & Agata Lapedriza, "Understanding the Role of Individual Units in a Deep Neural Network", Journal of Towards Data Science vol-21 issue-9 (2020)

This paper deals with the process of accessing the deep learning procedures with its components and actions.

Geetha gowri,"Machine Learning", 9 IJRAR June 2019, Volume 6, Issue 2

In this paper, the application of machine learning approach for the gadgets based on the user experiences.

Mudit varma , " Artificial intelligence and its scope in different areas with special reference to the field of education", International Journal of Advanced Educational Research ISSN: 2455-6157 Volume 3; Issue 1; January 2018; Page No. 05-10

This paper deals with the different data analysis structure and functions followed by the artificial intelligence approaches and applications for medical diagnosis.

## III.METHODOLOGY

The proposed methodology consists of 3 stages, they are

1. Lung cancer image data unification process.
2. Proposed methodology design.
3. Algorithmic approach.

### Stage-1: Lung cancer image data unification process

The data unification process represents the standard format conversion of medical images to DICOM format.

The data sources of lung cancer medical image data are,

- i. Physical data collection.
- ii. X-ray images.
- iii. Scan images.

The revert back medical data image formats are,

The following image formats are used for import and export DICOM images handling process:

1. JPEG (Joint Photographic Experts Group)
2. TIFF (Tagged Image File Format)
3. PNG (Portable Network Graphics format)
4. GIF (Graphics Interchange format)

The DICOM tools are,

The tools for medical image data conversion are,

- i. PostDICOM,
- ii. Horos,
- iii. RadiANT,
- iv. Miele LXIV, and
- v. Navegatum

The sample DICOM image from standard data resource as in fig-1[8],

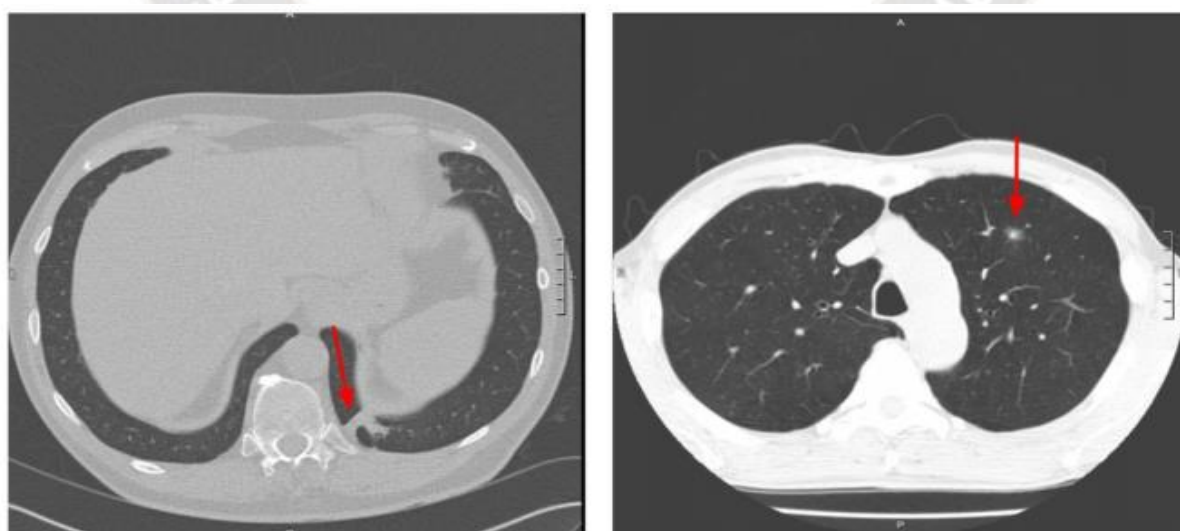
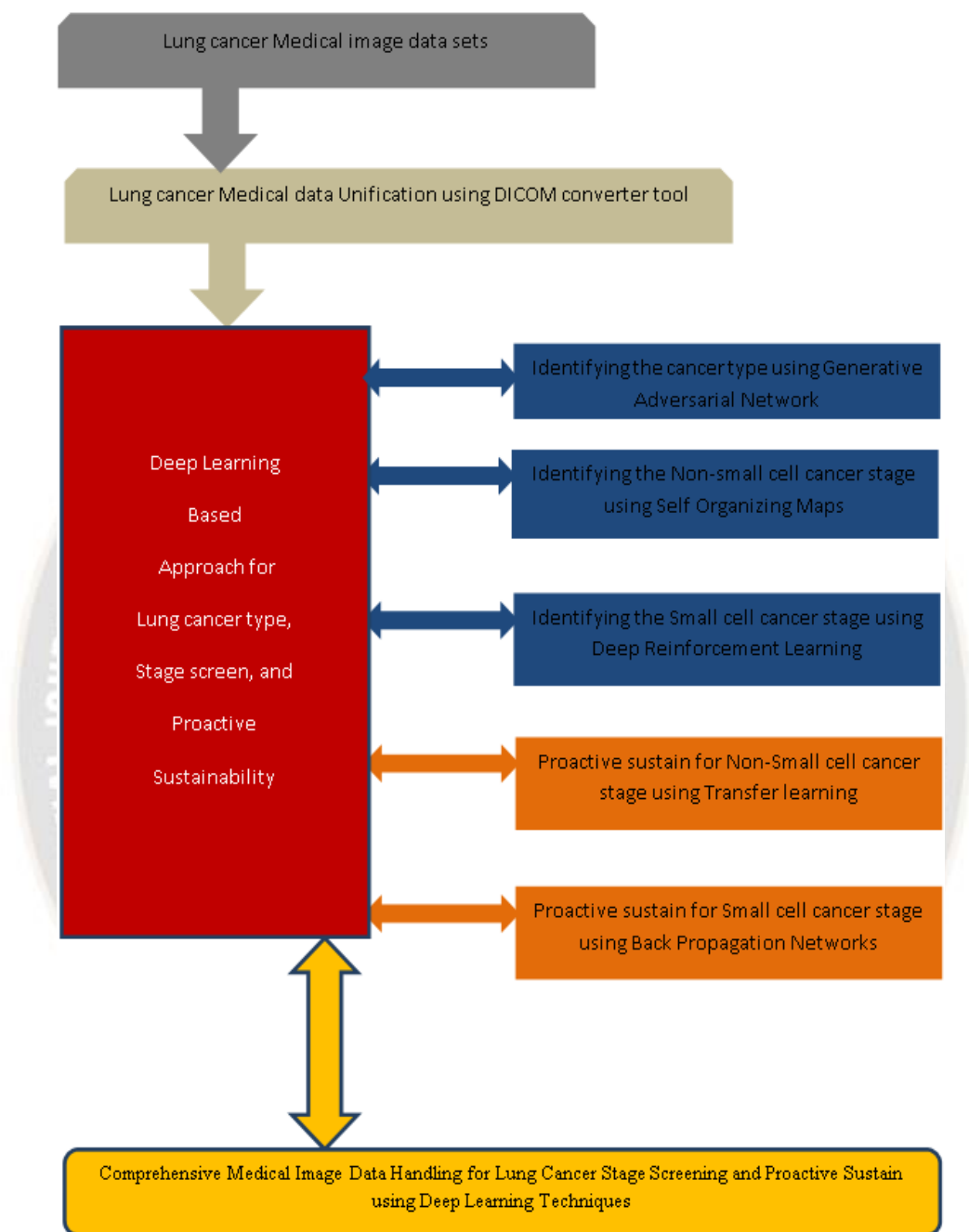


Fig-1: Sample lung cancer negative and positive scan result image.

## Stage-2: Proposed methodology design for Lung cancer Stages Screening and proactive sustain:

The proposed methodology lung cancer screening and proactive sustainis as follows in fig-2.



**Fig-2:Proposed Lung cancer stage screening and sustain design using deep learning approach.**

## Stage-3:Algorithmic approach for the proposed methodology:

The algorithmic approach for the proposed methodology consisting of the following steps:

Step-1: Medical image data sets collection for lung cancer

Step-2: Data unification or revert back for DICOM data using DICOM converter tools.

Step-3: Identifying the cancer type using Generative Adversarial Network

Step-4: Identifying the Non-small cell cancer stage using Self Organizing Maps

Step-5: Identifying the Small cell cancer stage using Deep Reinforcement Learning

Step-6: Proactive sustain for Non-Small cell cancer stage using Transfer learning

Step-7: Proactive sustain for Small cell cancer stage using Back Propagation Networks

Step-8: Store the results with authenticity for recovery options.

End

#### IV. IMPLEMENTATION

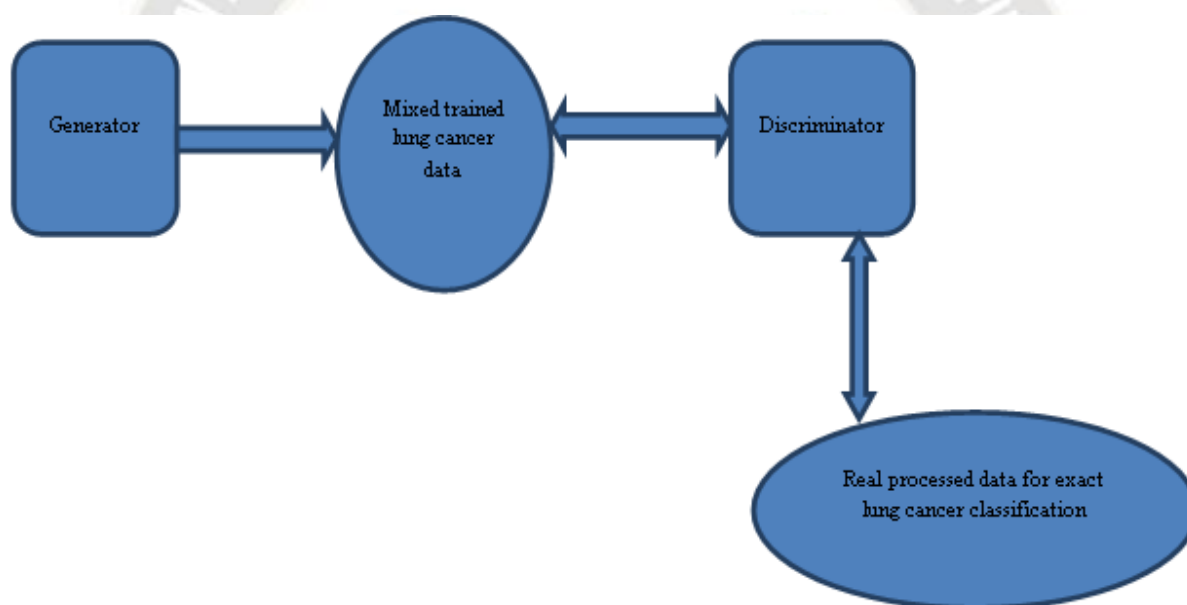


Fig-3:Proposed Deep Learning Generative Adversarial Network

##### ii. Computation logic

The histology results classification produces the lung cancer type classification based on the following computation.

*If histology result (biopsy)=Non small cells and biomarker=No gene alter for small cells then*

*Lung cancer type= Non Small Cell Lung Cancer (NSCLC)*

*Else if histology result (biopsy) = Small cells and biomarker = gene alter for small cells then*

*Lung cancer type= Small Cell Lung Cancer (SCLC)*

The implementation of the proposed methodology contains separate sub modules with deep learning treatment for attaining the results in an optimized manner.

##### a. Identifying the cancer type using Deep Learning Generative Adversarial Network

###### i. Concept

Generative Adversarial Network contains two key components generator and discriminator. Generator generates the trained data with mixed authenticity whereas discriminator identifies the real dataas in fig-3.

The different pathology results of histology data are given as inputs with little variations or modification on training data.

The discriminator identifies the real data each time and produces the authentic data by avoiding the false data.

*Else*

*Lung cancer type= other type*

##### b. Identifying the Non-small cell cancer stage using Deep Learning Self Organizing Maps

###### i. Concept

Self-organized map represents the clustering and mapping techniques to map multidimensional data onto lower-dimensional values used for easier interpretation as in fig-4.

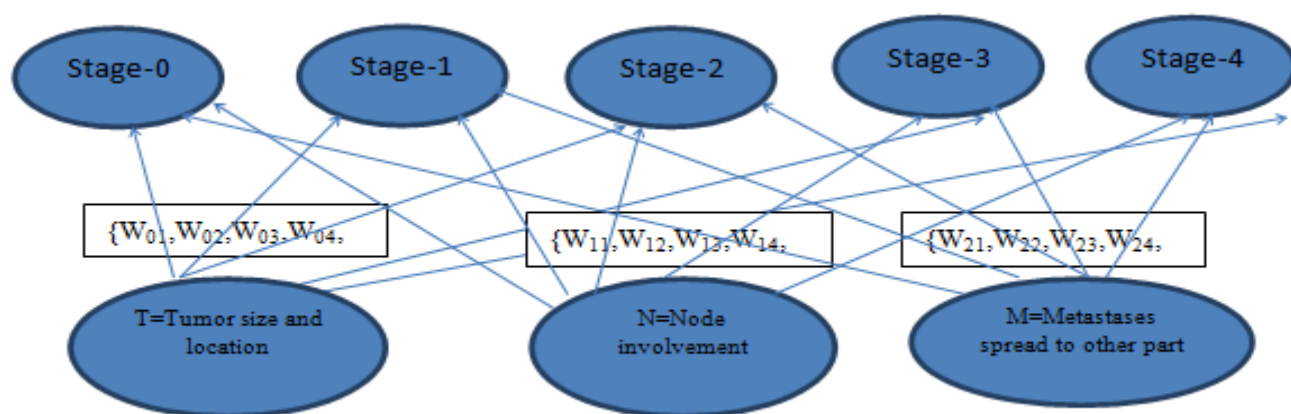


Fig-4: Proposed Deep Learning Self Organizing Maps

## ii. Computation logic

The computation logic is represented in the following table-1.

Table-1: Computation logic table for NSCLC Lung cancer stages by SOM

Parameter/Value	0	1	1a	1b	2	3	4
T	---	surrounded by lung or visceral pleura	Dim $\leq 2$	$2 \leq \text{Dim} \leq 3$	$3 \leq \text{Dim} \leq 7$ Invasion of the main bronchus	Tumor invades the chest wall	Tumor invades the mediastinum, diaphragm, heart
N	No regional lymph node	Regional lymph node	---	---	Other lymph node also	---	---
M	No distant metastasis	Distant metastasis	---	---	---	---	---

## c. Identifying the Small cell cancer stage using Deep Reinforcement Learning

### i. Concept

Deep reinforcement learning takes the input as reward for the set of all states so that the agent presumes the action for the reward towards the environment in a recurrent manner until the desired classification obtained as in fig-5.

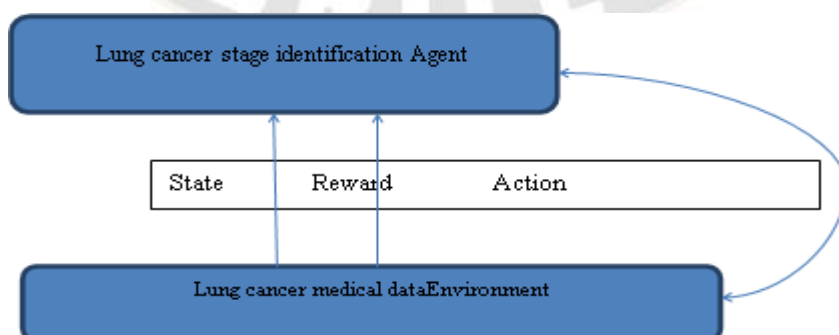


Fig-5: Proposed Deep Learning based Reinforcement learning lung cancer schema



## ii. Computation logic

The deep reinforcement learning computation is as follows in table-2.

**Table-2: Computation table for lung cancer using reinforcement learning**

Sl.No	Component	Functionality
1	Agent	Decision making in Lung cancer stage for SCLC.
2	Environment	Medical image data sets and result storage for Lung cancer SCLC stages.
3	State-0	Initial pre examination state for lung cancer SCLC stage
4	State-m	Suspicious stage state
5	State-n	Confirmed stage state
6	Reward	A scalar feedback signal for positive or negative classification for weight adjustment.
7	Action	Decisions from the agent based on Policy P.
8	Experience replay	Stored prior experiences for improved decision making

### Policy P:

*If Tumour=one side of chest and spread=minimal lymph nodes then*

*Stage=Limited stage*

*Else if Tumour=both sides of chest and spread=max lymph nodes then*

*Stage=Extensive stage*

*Else*

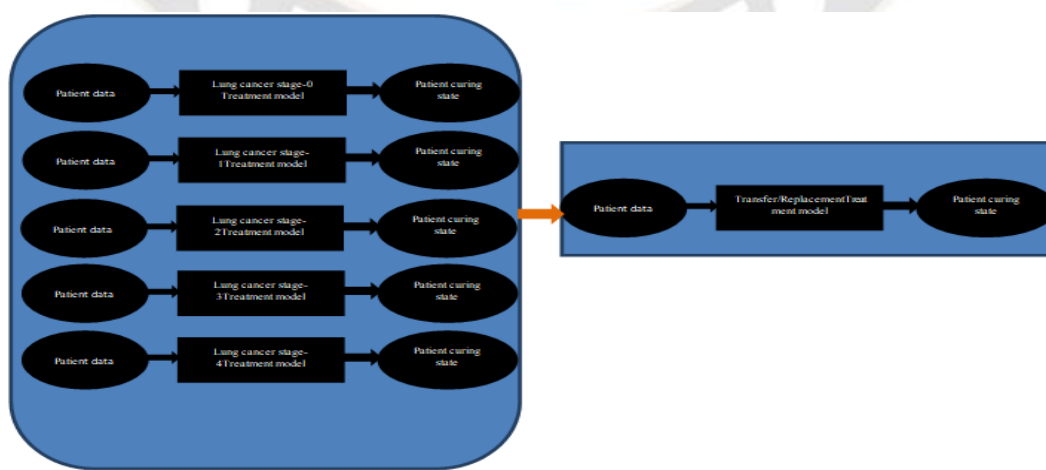
*Stage=Otherwise*

The deep reinforcement learning schema identifies the SCLC lung cancer stages in an effective manner.

### d. Proactive sustain for Non-Small cell cancer stage using Deep Transfer learning

#### i. Concept

Transfer learning represents the knowledge trained from one model is used for other relatable models to improve efficiency as in fig-6.



**Fig-6:Proposed Deep Learning based Transfer learning lung cancer schema**

ii. Computation logic

The computation logic for the transfer learning in proactive lung cancer NSCLC stages is represented in the following steps.

Step-1: Pre-trained model selection

The pre trained model for NSCLC cancer stages 0 to 4 are selected and ready to available for the network component transition.

Step-2: Pre-trained model availability

The pre trained model must be configured to each individual case of the NSCLC cancer stage so that passing input variations the model is ready to process the treatment.

Step-3: Preserve pre-trained layers

The initial weights for the pre trained models are 0/null so that the layers are inactive during off state, but the knowledge is in preserve state as it is.

Step-4: Release the last layer

The last layer is always set to specific task, so it must be released based on the new task requirement.

Step-5: New layer replacement

The new layer with new functional adoption must be placed on the top of the model for expected results.

Step-6: Target domain adjustment

Train the model for new target achievement by adjusting the hyper parameter of the model.

Step-7: Finalize the result

The filtered results are matched with the target and desired value, and the model will be adjusted until the target reaches the desired value.

e. Proactive sustain for Small cell cancer stage using Deep Learning Back Propagation Networks

i. Concept

The back propagation network represents the error correction it learns through the loss function by difference between the input and the output variance as in fig-7.

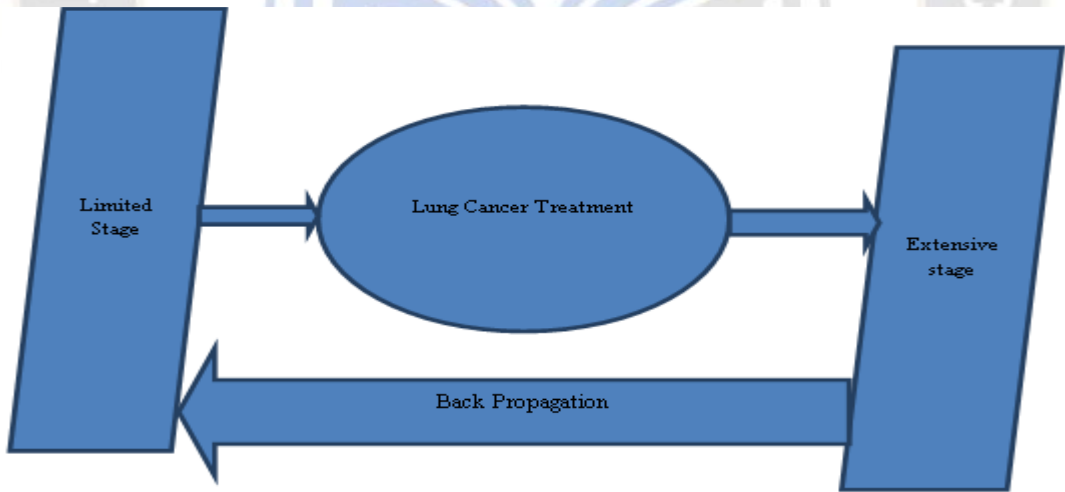
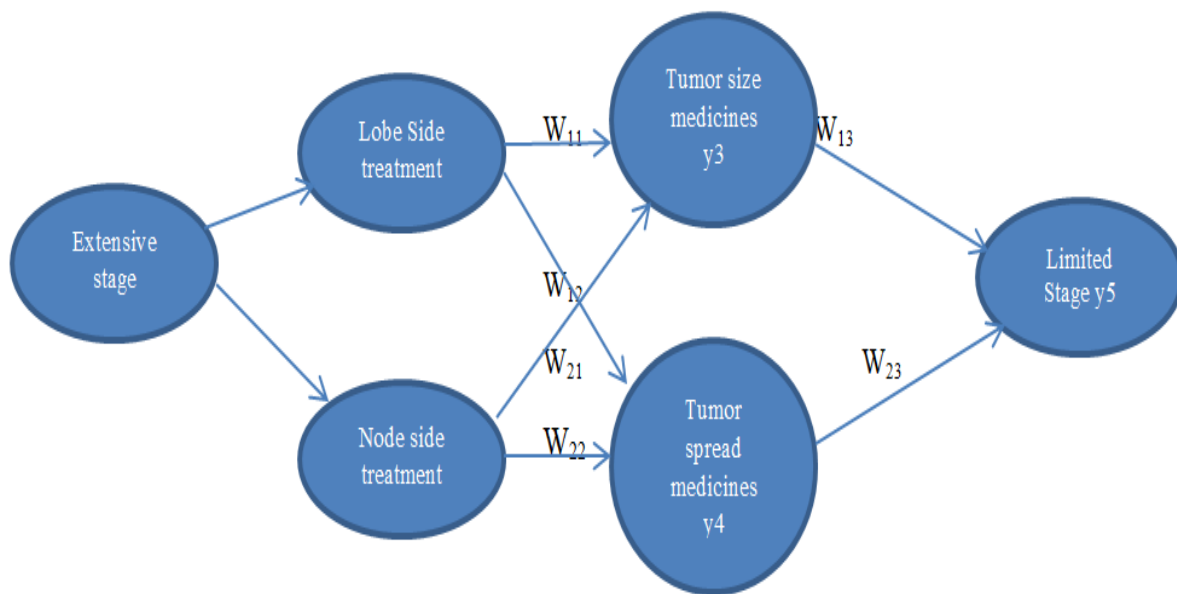


Fig-7: Proposed Deep Learning based BPN lung cancer schema

ii. Computation logic

The computation logic for the proactive sustain for small cell cancer stage using deep learning back propagation network is as follows in fig-8:



**Fig-8: Proposed Deep Learning based BPN lung cancer computation structure**

The computation table is as follows in table-3.

**Table-3: Computation table for BPN based lung cancer schema**

Sl.No	Component	Notation	Computation
1	Weighted sum for node 4	$a_3$	$(W_{1,1} * LST) + (W_{2,1} * NST)$
2	Weighted sum for node 5	$a_4$	$(W_{1,2} * LST) + (W_{2,2} * NST)$
3	Weighted sum for node 6	$a_5$	$(W_{1,3} * LST) + (W_{2,3} * NST)$
4	State Value for node 4	$y_3$	$1 / (1 + e^{-a_3})$
5	State Value for node 5	$y_4$	$1 / (1 + e^{-a_4})$
6	State Value for node 6	$y_5$	$1 / (1 + e^{-a_5})$
7	Error	$E$	$y_{target} - y_5$
8	Weight Adjustment	$\Delta w_{ij}$	$\eta * \delta * O$
9	Learning rate	$\eta$	1
10	Error term	$\delta$	$\delta_5 = y_5(1 - y_5)(y_{target} - y_5)$
11	Output Value	$O$	Desired value of 0.5 to convert extensive to limited stage

The final computation produced the results for back propagating from extensive stage to limited stage transfer in lung cancer based on treatment weight adjustments.

## V. RESULTS AND DISCUSSION

The proposed methodology handles the approaches with the standard data sets collected from NLST Lung cancer data dictionary and also from the collection of real time images consisting of 3500 images. The experimental results are

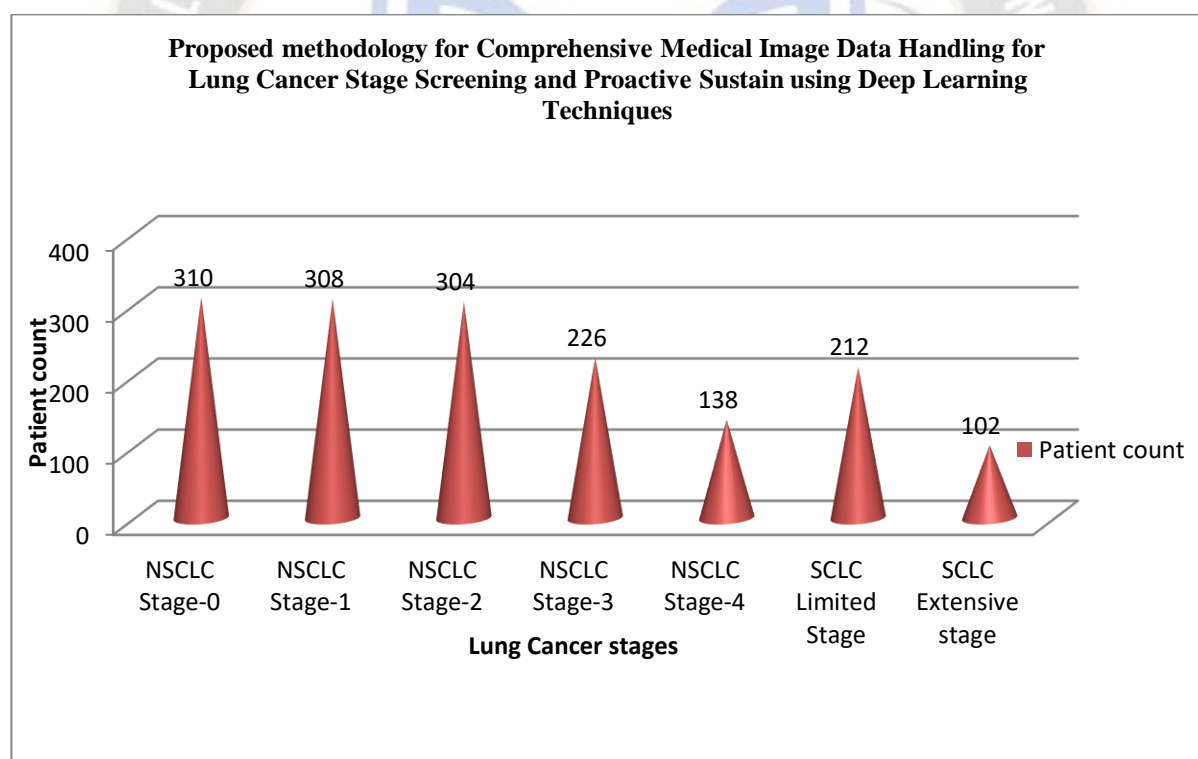


tabulated with main focus on 1602 patients in the below format as in table-4.

**Table-4: Result computation summary structure**

No	Lung Cancer stage	Patient count
1	NSCLC Stage-0	310
2	NSCLC Stage-1	308
3	NSCLC Stage-2	304
4	NSCLC Stage-3	226
5	NSCLC Stage-4	138
6	SCLC Limited Stage	212
7	SCLC Extensive Stage	102

The following graph as in fig-9 shows the proposed methodology result achievement process based on the values in table-4.



**Fig-9: Proposed methodology for lung cancer stage screening**

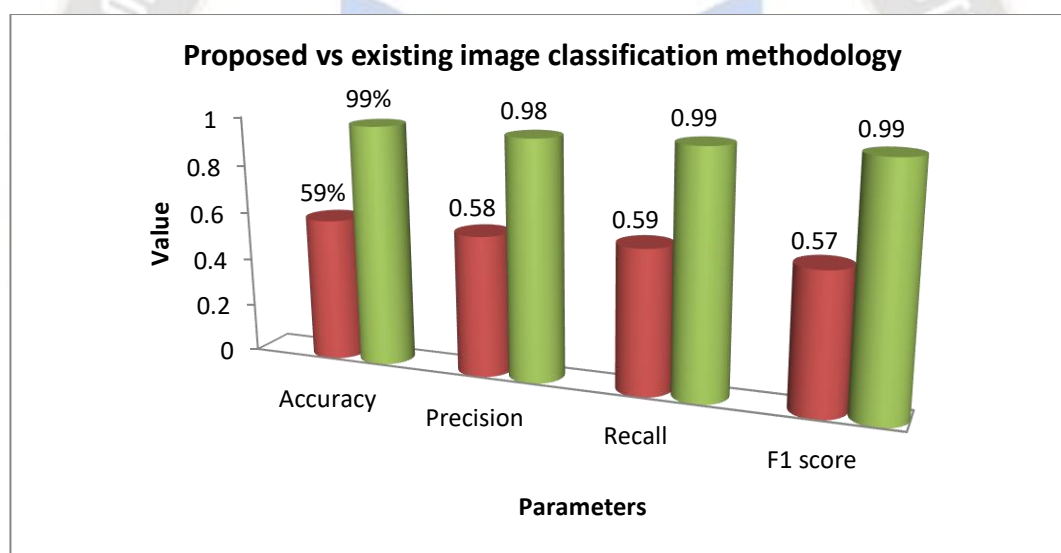
While comparing the proposed methodology results with existing image processing approaches which produces only 920 out of 1600 lung cancer stage screening tests of success which achieves only 57.5% of success rate whereas the proposed methodology produces 98% results of 1600 out of 1602.

The parametric comparison between existing and proposed methods with precision, accuracy etc. are represented in the below format,

**Table-5: Proposed methodology parametric comparisons**

No	Approach	Accuracy	Precision	Recall	F1 score value
1	Image classification method	59%	0.58	0.59	0.57
2	Proposed comprehensive medical image data handling for lung cancer stage screening and proactive sustain using deep learning techniques	99%	0.98	0.99	0.99

The following fig-10 shows the performance comparison between the proposed and existing methodologies.



**Fig-10:Proposed vs. existing image classification methodology performance comparisons**

## VI.CONCLUSION

Deep learning plays the vital role in lung cancer type identification along with the stages recognition in an efficient manner. The implementation of deep learning in the lung cancer medical field is an important achievement for the better treatment to the lung cancer patients. This research module focuses on the comprehensive medical image data handling for lung cancer stage screening and proactive sustain using deep learning techniques. The initial module focuses on the lung cancer type identification followed by the lung cancer NSCLC type stages recognition and with the SCLC

stages and followed by the proactive stage sustainability for the NSCLC and SCLC stages with appropriate treatment selection procedures. The experimental results for the proposed methodology produces 1600 out of 1602 patient data lung cancer stage recognitions in correct manner using lung cancer image data component analysis for the patients. This research will be further enhanced with soft computing based automated lung cancer stage classification system.

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