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Exhortative Medical Image Data Handling For Lung Cancer In Proactive Survival Rate Improvement Using Deep Learning Techniques

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Lung cancer acts as a horrible disaster to any human being in this world due to its painful impact of daily life routine and emotional break down for expecting the death at any time. The collection of taking the medical images and maintaining it for further analysing with proper medical assistance is an important role in proactive survival rate improvement. The role of Deep learning in this key area plays an effective part in the treatment of lung cancer patients with corresponding and essential approaches in a vital manner. This paper presents the exhortative medical image data handling for lung cancer in proactive survival rate improvement using deep learning techniques. This module concentrates on the proper usage of deep learning techniques to treat the lung cancer patients based on the type, stage and stage level towards the proactive survival rate improvement from lung cancer using medical image data sets. The future development of this module can be extended on automated lung cancer survival rate improvement model to help the lung cancer medical data domain using soft computing approaches.

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

I. INTRODUCTION

a. Deep Learning:

Deep learning is a type of machine learning that uses artificial neural networks to learn from data. Artificial neural networks are inspired by the human brain, and they can be used to solve a wide variety of problems, including image recognition, natural language processing, and speech recognition.

b. Lung cancer survival rate for 5 years:

The two types of cancer comprise the following survival rates for next 5 years.

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

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

The survival rate is 90% and it can be improved significantly if properly treated.

***Stage I:**

The cancer is still in the lung and hasn't spread. 5-year survival rates range from 65% to 90%, with higher rates for younger individuals.

***Stage II:**

The cancer has spread to nearby tissues or lymph nodes. Survival rates are around 40-60%.

***Stage III:**

The cancer has spread to lymph nodes but not on distant organs. 5-year survival rates are around 15-40%, according to Cancer Research UK.

***Stage IV:**

The cancer has spread to other parts of the body. 5-year survival rates are very low, around 5%.

ii. Small Cell Lung Cancer (SCLC) Stages:

***Limited Stage:**

The survival rate is 10% only with exception.

***Extensive Stage:**

The survival rate is 5% only with exception.

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 accesing 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 6 stages, they are

Stage-1: Lung cancer image data handling process.

Stage-2: Diagnosis test design.

Stage-3: Gene mutation mapping computation.

Stage-4: Select Treatment for survival rate improvement by Boltzmann machine learning inspiration

Stage-5: Proposed methodology design.

Stage-6: Algorithmic approach.

Stage-1: Lung cancer image data handling process

The following steps are included in the lung cancer image data handling process as classic neural network layer to layer form as in fig-1.

- **Step-1: The data handling process represents the standard format collection of physical data, X-ray and scan reports of medical images to DICOM format.**
- **Step-2: Selection of standard to DICOM image conversion tools**
  The DICOM tools such as Post DICOM, Horos, RadiANT, etc. are used for conversions.
  Step-3: The reverse conversion process of DICOM to jpg, TIFF, png is through DICOM tools itself, if not needed then the actual storage retained.
  Step-4: Cloud storage acts as the primary copy and Local storage acts as the backup copy.

The following fig-1 illustrates the entire process.

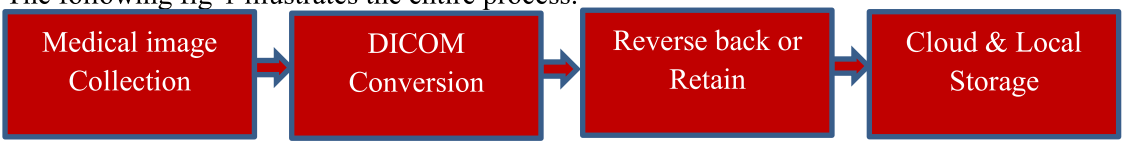

Fig-1: Medical image data handling process as in classic neural network layers.

Stage-2: Diagnosis Test design using convolutional grid based deep learning approach

The diagnosis test design for the proposed schema incorporates the deep learning based decision making system to culminate the lung cancer type and stage with proper suggestive analysis in order to improve the survival rate through proper care.

The convolutional grid learning design is as follows in the table-1.

Table-1: Case Study for diagnosis

Patient Id:	**CSGATS00001**				
Patient Name:	**ASDFGJK**				
Gender	**Male/Female**				
Country	**ABC**				
State	**DEF**				
Zip code / Pin code	**123456**				
Hospital	**GHIJ**				
Medical Expert	**KLMN**				
DATE	**XX/XX/XXXX**				
Test	**R=Result**	**SLR=Supervised Learning Result**	**EOR=Experts Opinion Result**	**CA=Computed Average**	**Decision=CA or any two {R, SLR, EOR} holds well.**
Examination & Observation	$0.1 < X < 0.5$	$0.1 < X < 0.5$	$0.1 < X < 0.5$	$0.1<X<0.5$	Apply CT Scan.

Remarks	X > 0.7	X > 0.6	X > =0.5	X>=0.5	Apply MRI Scan.
	X > 0.8	X > 0.7	X > 0.6	X>0.5	Apply PET Scan.
	X > 0.9	X > 0.8	X > 0.7	X>0.5	Apply PET/CT Scan.
CT Scan	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Suspect state, if X>=0.3 then apply MRI Scan
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Apply General Biopsy.
MRI Scan	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Suspect state, if X>=0.3 then apply PET Scan
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Apply Bronchoscopy.
PET Scan	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Suspect state, if X>=0.3 then apply PET/CT Scan. For X>0.6 identify and confirm type and stage if possible.
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Apply Endo Bronchial Ultra Sound. For X>0.6 identify and confirm type and stage if possible.
PET/CT Scan	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Suspect state, if X>=0.3 then apply Video assisted Thoracoscopy. For X>0.6 identify and confirm type

					and stage if possible.
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Apply Wedge resection. For X>0.6 identify and confirm type and stage if possible.
General Biopsy	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Repeat with proper interval. For X>0.6 identify and confirm type and stage if possible.
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Confirm lung cancer type and stage. For X>0.6 identify and confirm type and stage if possible.
Bronchoscopy	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Repeat with proper interval. For X>0.6 identify and confirm type and stage if possible.
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Confirm lung cancer type and stage.
Apply Endo Bronchial Ultra Sound	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Repeat with proper interval. For X>0.6 identify and confirm type and stage if possible.
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Confirm lung cancer type and stage.

Video assisted Thoracoscopy.	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Repeat with proper interval.
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Confirm lung cancer type and stage.
Wedge resection.	0.1 < X < 0.5	0.1 < X < 0.5	0.1 < X <0.5	0.1<X<0.5	Repeat with proper interval.
	X>=0.5	X>=0.5	X>=0.5	X>=0.5	Confirm lung cancer type and stage.

Stage-3: Gene Mutation mapping using association learning

The following fig-2 illustrates the Gene mutation mapping structure with impact level for Non-Small Cell Lung Cancer impact in human health conditions.

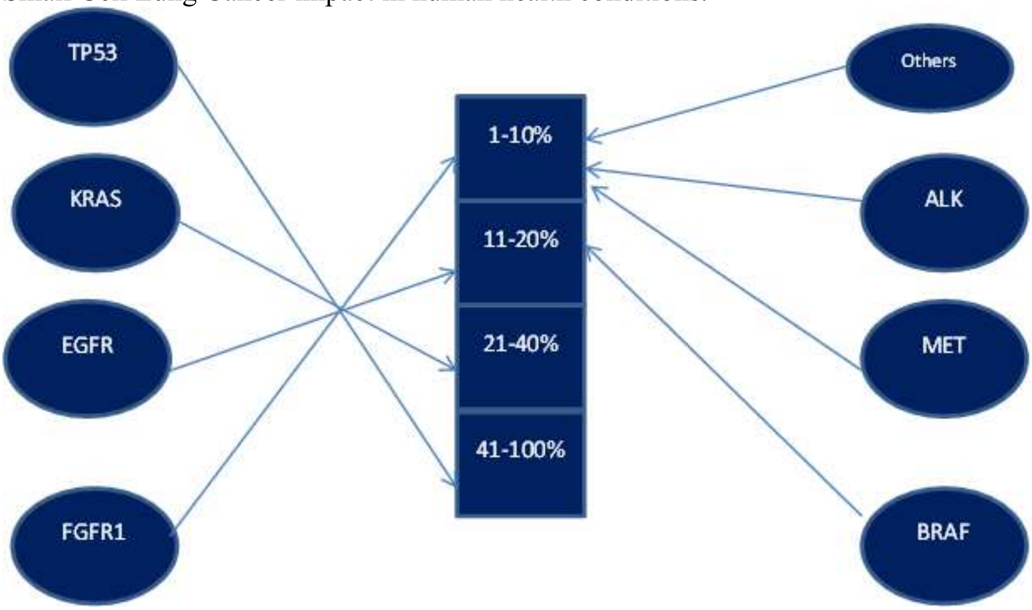

Fig-2: Gene Mutation level mapping

The association learning approach for the gene mutation mapping is as follows:

If Smoke=T/F & Age=any & Gender=M/F & Diagnosis result=true then
Gene mutation=TP53 Impact percentage >= 51%
Else if Smoke=T & Age=any & Gender=M/F & Diagnosis result=Organ cancer (Adenocarcinoma) then
Gene mutation=KRAS Impact percentage <= 40%

Else if Smoke=F & Age=any & Gender=F & Diagnosis result=Organ cancer (Adenocarcinoma) then
Gene mutation=EGFR Impact percentage <= 20%
Else if Smoke=T/F & Age=any & Gender=M/F & Diagnosis result=Organ cancer (Adenocarcinoma) then
Gene mutation=FGFR Impact percentage <= 10%
Else if Smoke=F & Age=Younger & Gender=M/F & Diagnosis result=true then
Gene mutation=ALK Impact percentage <= 7%
Else if Smoke=T/F & Age=any & Gender=M/F & Diagnosis result=true then
Gene mutation=MET Impact percentage <= 5%
Else if Smoke=T & Age=any & Gender=M/F & Diagnosis result=true then
Gene mutation=BRAF Impact percentage <= 3%
Else Smoke=T/F & Age=any & Gender=M/F & Diagnosis result=true then
Gene mutation=Others Impact percentage <= 1%

Stage-4: Select Treatment for survival rate improvement by Boltzmann machine learning inspiration

The Boltzmann deep learning network for lung cancer treatment in improving the survival rate contains two units, visible and hidden units.

Visible units=V_i = Lung cancer type such that

- V1=Stage1Type1
- V2= Stage1Type2
- V3= Stage1Type3
- V4= Stage1Type4
- V5= Stage2Type1
- V6= Stage2Type2

Hidden units=H_j=Lung cancer treatments such that

- H1=Wedge Resectomy(Smaller part of lung removal surgery)
- H2=Segmentectomy (Larger part of lung removal surgery)
- H3=Lobectomy (Entire lobe of 1 lung removal surgery)
- H4=Pneumonectomy(Entire single lung removal surgery)
- H5= Radiation therapy
- H6= Chemotherapy
- H7= Stereotactic body radiotherapy
- H8= Targeted therapy
- H9= Immunotherapy
- H10= Palliative care
- H11=Combined vector Level1
- H12=Combined vector Level2
- H13=Combined vector Level3

δ= Fuzzy membership values for primary variants as represented in table-2

Table-2: Computation table

Health	**Type**	**Size**	**Position**	**Stage**
Excellent	NSCLC	Small	Central	T1Stage-1
Good	SCLC	Medium	Peripheral	T1Stage-2
Ok		Large	Proximity	T1Stage-3
Satisfactory			Invasion	T1Stage-4
Unfit				T2Stage-1
				T2Stage-1

The conditional probability value determines the treatment corresponding to the Lung cancer patient with respect to its current state to improve the survival rate as effective as possible, such that

Probability P (V/H) = **δ (π P (Vi/∑Hj); i=1 to m, j=1 to n. ---------------------------------Eq-1**

The computation logic for the Survival rate improvement treatment selection is as follows:

If P (V/H) > 0.5 then

Apply Survival treatment Hj;

Else

Revaluate;

End if

Stage-5: Proposed methodology design for Lung cancer proactive survival rate improvement

The proposed methodology lung cancer screening and proactive sustain is as follows in fig-3.

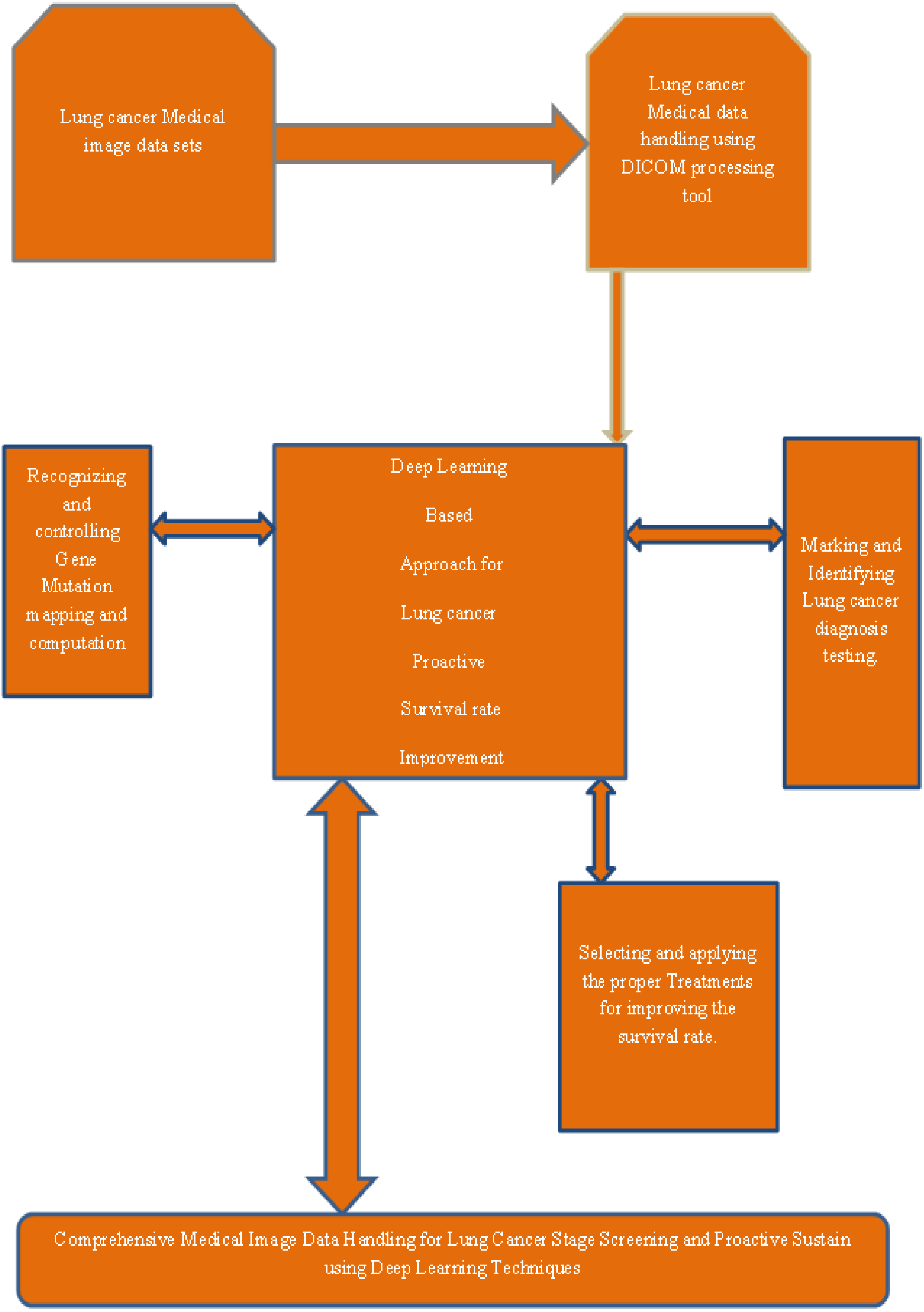
Lung cancer Medical image data sets
Lung cancer Medical data handling using DICOM processing tool
Recognizing and controlling Gene Mutation mapping and computation
Deep Learning Based Approach for Lung cancer Proactive Survival rate Improvement
Marking and Identifying Lung cancer diagnosis testing
Selecting and applying the proper Treatments for improving the survival rate.
Comprehensive Medical Image Data Handling for Lung Cancer Stage Screening and Proactive Sustain using Deep Learning Techniques

Fig-3: Proposed Lung cancer proactive survival rate improvement.

Stage-6: Algorithmic approach for the proposed methodology
The algorithmic approach for the proposed methodology consisting of the following steps:
Step-1: Medical image data sets handled for lung cancer
Step-2: Diagnosis Test design using convolutional grid based deep learning approach
Step-3: Gene Mutation mapping using association learning
Step-4: Select Treatment for survival rate improvement by Boltzmann machine learning inspiration
Step-5: Store the results with authenticity for recovery options.
End

IV. IMPLEMENTATION

The implementation of the proposed methodology includes the following steps with deep learning treatment for attaining the results in an effective manner.

Step-1: Medical image data sets handled for lung cancer
The process of handling lung cancer medical images contains the following procedures. The ordinary scanned results of multiple scanned angles combined to gather to form a complete DICOM image for lung cancer image data handling approach as in fig-4.a and 4.b.
a. A sample scanned image file for lung cancer diagnosis.

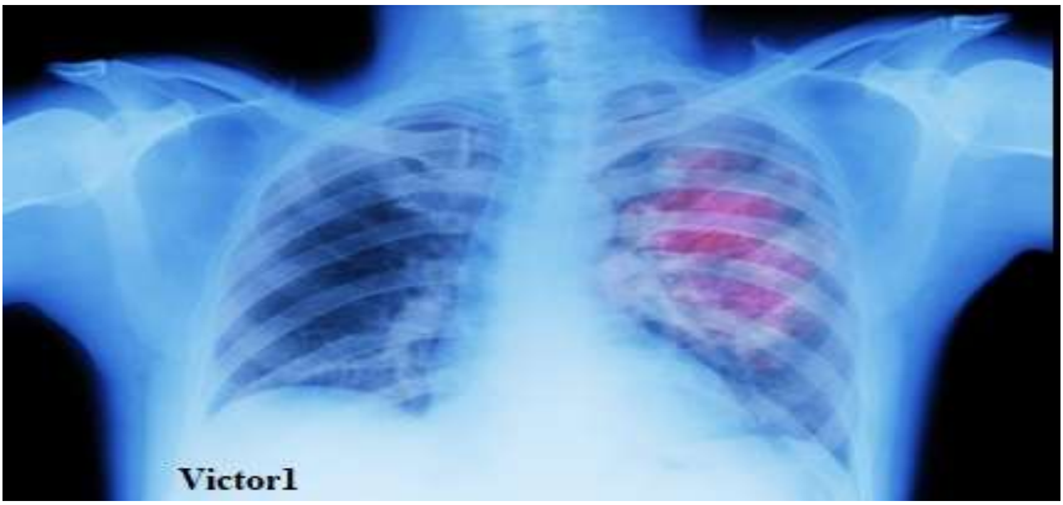

Fig-4.a: Scanned image

b. The conversion of DICOM image format for the scanned image.

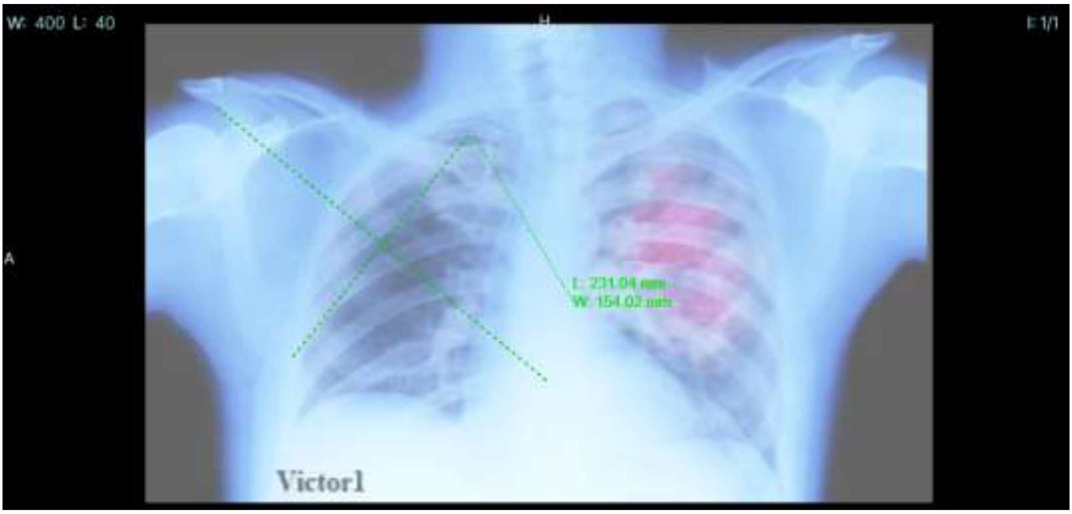

Fig-4.b: DICOM image conversion

Step-2: Diagnosis Test design using convolutional grid based deep learning approach
Consider the following 3 cases for lung cancer diagnosis as in Table-3, 4 and 5.
Case-1:

Table-3: Case-1 Diagnosis result

<table>
<tr><th colspan="2">Patient Id:</th><th colspan="4">CSGATS00001</th></tr>
<tr><th colspan="2">Patient Name:</th><th colspan="4">SUJATVLK</th></tr>
<tr><th colspan="2">Gender</th><th colspan="4">Female</th></tr>
<tr><th colspan="2">Country</th><th colspan="4">MNO</th></tr>
<tr><th colspan="2">State</th><th colspan="4">PQR</th></tr>
<tr><th colspan="2">Zip code / Pin code</th><th colspan="4">123456</th></tr>
<tr><th colspan="2">Hospital</th><th colspan="4">QGHIJK</th></tr>
<tr><th colspan="2">Medical Expert</th><th colspan="4">ZKLMN</th></tr>
<tr><th colspan="2">DATE</th><th colspan="4">XX/XX/XXXX</th></tr>
<tr><th>Test</th><th>R=Result</th><th>SLR=Supervised Learning Result</th><th>EOR=Experts Opinion Result</th><th>CA=Computed Average</th><th>Decision=CA or any two {R, SLR, EOR} holds well.</th></tr>
<tr><th rowspan="2">Examination & Observation Remarks</th><td>0.4</td><td>0.4</td><td>0.5</td><td>0.43</td><td>Apply CT Scan.</td></tr>
<tr><td></td><td></td><td></td><td></td><td>Apply MRI Scan.</td></tr>
</table>

					Apply PET Scan.
					Apply PET/CT Scan.
CT Scan	0.4	0.4	0.5	0.43	Suspect state, if X>=0.3 then apply MRI Scan
					Apply General Biopsy.
MRI Scan	0.5	0.4	0.5	0.46	Suspect state, if X>=0.3 then apply PET Scan
					Apply Bronchoscopy.
PET Scan	0.9	0.9	0.9	0.9	Suspect state, if X>=0.3 then apply PET/CT Scan. For X>0.6 identify and confirm type and stage if possible.
The convolution grid based decision making by deep learning approach for lung cancer diagnosis test result.			**Patient identified with type 1 cancer with stage-2 condition.**		

Case-2:

Table-4: Case-2 Diagnosis result

Patient Id:	**CSGATS00002**
Patient Name:	**SPVictor2**
Gender	**Male**
Country	**ABC**
State	**DEF**
Zip code / Pin code	**123456**
Hospital	**GHIJ**
Medical Expert	**KLMN**

DATE		XX/XX/XXXX			
Test	**R=Result**	**SLR=Supervised Learning Result**	**EOR=Experts Opinion Result**	**CA=Computed Average**	**Decision=CA or any two {R, SLR, EOR} holds well.**
Examination & Observation Remarks	0.2	0.2	0.2	0.2	Apply CT Scan.
					Apply MRI Scan.
					Apply PET Scan.
					Apply PET/CT Scan.
CT Scan	0.3	0.3	0.3	0.3	Suspect state, if X>=0.3 then apply MRI Scan
					Apply General Biopsy.
MRI Scan	0.3	0.3	0.2	0.27	Suspect state, if X>=0.3 then apply PET Scan
					Apply Bronchoscopy.
The convolution grid based decision making by deep learning approach for lung cancer diagnosis test result.			**Patient is in suspicious state for earlier lung cancer detection. Patient is in observable state for specified y interval of time for re-examination.**		

Case-3:

Table-5: Case-2 Diagnosis result

Patient Id:	**CSGATS00001**
Patient Name:	**ASDFGJK**
Gender	**Male/Female**

Country	**ABC**				
State	**DEF**				
Zip code / Pin code	**123456**				
Hospital	**GHIJ**				
Medical Expert	**KLMN**				
DATE	**XX/XX/XXXX**				
Test	**R=Result**	**SLR=Supervised Learning Result**	**EOR=Experts Opinion Result**	**CA=Computed Average**	**Decision=CA or any two {R, SLR, EOR} holds well.**
Examination & Observation Remarks	0.2	0.2	0.2	0.2	Apply CT Scan.
					Apply MRI Scan.
					Apply PET Scan.
					Apply PET/CT Scan.
CT Scan	0.3	0.3	0.3	0.3	Suspect state, if X>=0.3 then apply MRI Scan
					Apply General Biopsy.
MRI Scan	0.4	0.4	0.3	0.37	Suspect state, if X>=0.3 then apply PET Scan
					Apply Bronchoscopy.
PET Scan	0.4	0.4	0.4	0.4	Suspect state, if X>=0.3 then apply PET/CT Scan. For X>0.6 identify and confirm type and stage if possible.
					Apply Endo Bronchial Ultra Sound.

PET/CT Scan					Suspect state, if X>=0.3 then apply Video assisted Thoracoscopy. For X>0.6 identify and confirm type and stage if possible.
	0.6	0.6	0.6	0.6	Apply Wedge resection.
Wedge resection.					Repeat with proper interval.
	1.0	1.0	1.0	1.0	Confirm lung cancer type and stage.
The convolution grid based decision making by deep learning approach for lung cancer diagnosis test result.			**Patient is confirmed with type-1 cancer with stage-1 condition.**		

Step-3: Gene Mutation mapping using association learning

Consider the following 3 cases for the possible gene mutations using the association learning approach as follows in table-6:

Table-6: Gene mutation mapping

Sl.No	Patient ID	Age	Gender	Smoke	Gene Mutation possibility
1	Case-1	Older	Male	YES	**TP53**
2	Case-2	Younger	Male	NO	**ALK**
3	Case-3	Middle	Female	NO	**EGFR**

Step-4: Select Treatment for survival rate improvement by Boltzmann machine learning inspiration

Considering the Lung cancer patient cases, the following table provides the survival rate improvement by Boltzmann machine learning inspiration as follows in table-7 and 8:

Table-7: Case-1 survival rate improvement result

Sl.No	P(V/Hi) Component	P(V/Hi) Value	Proposed Survival rate improvement by Boltzmann machine learning inspiration
1	H1	0.1	
2	H2	0.2	
3	H3	0.2	
4	H4	0.3	
5	H5	0.3	
6	**H6**	**0.6**	**Apply Chemotherapy**

Table-8: Case-2 survival rate improvement result

Sl.No	P(V/Hi) Component	P(V/Hi) Value	Proposed Survival rate improvement by Boltzmann machine learning inspiration
1	H1	0.1	
2	H2	0.2	
3	H3	0.2	
4	H4	0.3	
5	H5	0.6	Selected for combined vector level1
6	H6	0.7	
7	H7	0.4	
8	H8	0.5	
9	H9	0.4	
10	H10	0.5	
11	H11	0.9	Apply Combined therapy level1

The survival rate improvement for the lung cancer patients with different types and stages are achieved with proper impact of the proposed methodology.

V. RESULTS AND DISCUSSION

The proposed methodology concentrates on the standard data sets collected from NLST Lung cancer data dictionary and also from the collection of real time images consisting of 4000 images.

The experimental results are tabulated with main focus on the results obtained from the proposed model and the actual medical treatment implemented for the current survival rate improvement for comparisons as in table-9. There are 17 patients exists in the current scenario in which the treatment modifications were obtained and compared.

Table-9: Result comparison summary structure

No	Lung Cancer stage	Proposed methodology Survival rate improvement counter	Actual count
1	**NSCLC Stage-0**	6	6
2	**NSCLC Stage-1**	4	4
3	**NSCLC Stage-2**	2	2
4	**NSCLC Stage-3**	1	1
5	**NSCLC Stage-4**	1	1
6	**SCLC Limited Stage**	2	2
7	**SCLC Extensive Stage**	1	0

The final result shows that 16 out of 17 patient survival rate improvement achievement comparisons holds good with the proposed methodology and actual implementation handled earlier.

The proposed methodology produces 94.12% success rate. The following graph as in fig-5 shows the proposed methodology result achievement process based on the values in table-9.

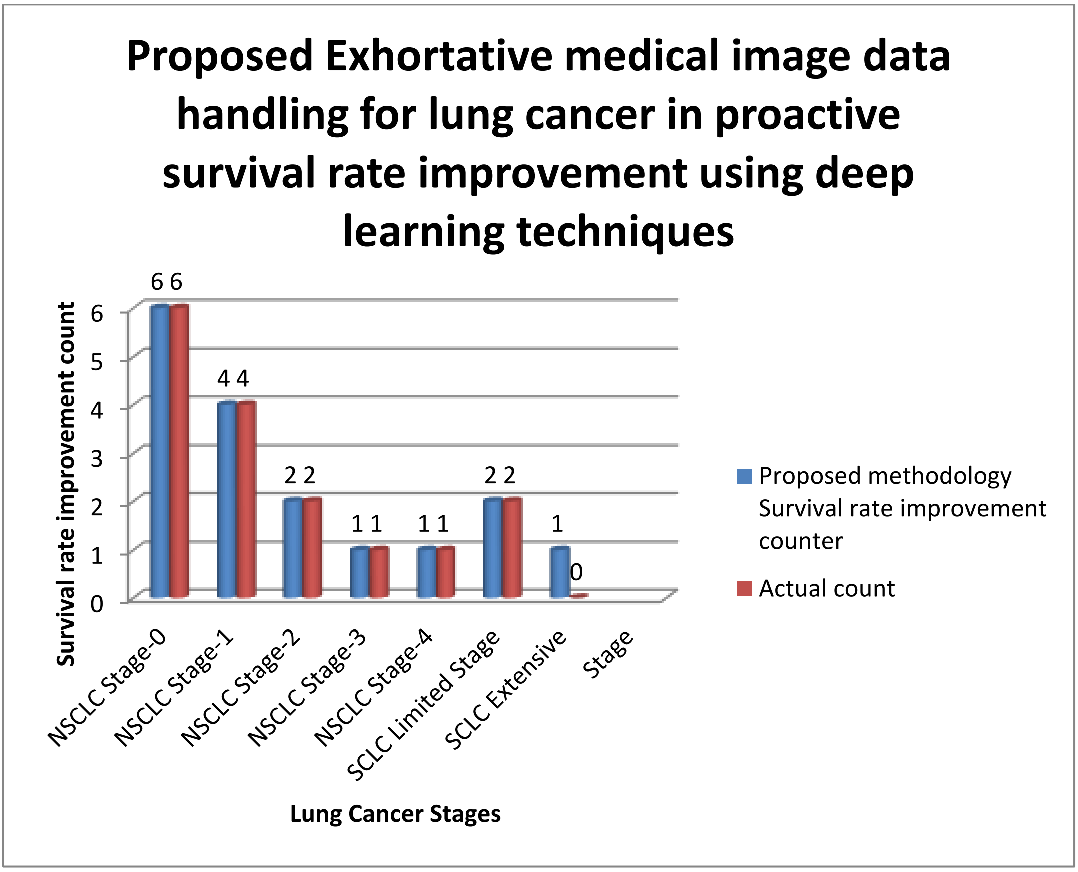

Fig-5: Proposed methodology for survival rate improvement

While comparing the proposed methodology results with existing medical image mining approaches which produces only 8 out of 17 lung cancer survival rate improvement which achieves only 47% of success rate whereas the proposed methodology produces 94% results of 16 out of 17.

The parametric comparison between existing and proposed methods with precision, accuracy etc. are represented in the below format as in table-10.

Table-10: Proposed methodology parametric comparisons

No	Approach	Accuracy	Precision	Recall	F1 score value
1	Medical Image mining method	47%	0.48	0.49	0.47
	Proposed comprehensive medical image	94%	0.95	0.96	0.95

	data handling for lung cancer stage creening and proactive sustain using deep learning techniques				

The following fig-6 shows the performance comparison between the proposed and existing methodologies.

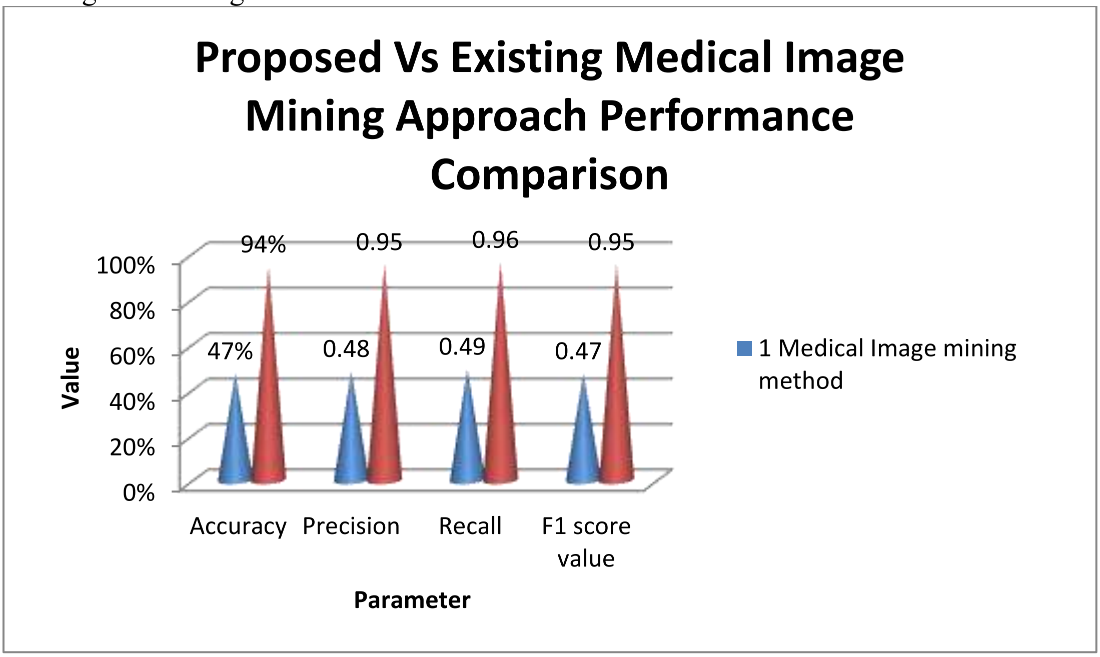

Fig-6: Proposed vs. existing image classification methodology performance comparisons

VI. CONCLUSION

Deep learning in medical data domain is an important factor in collecting, analysing and decision making for the betterment of medical diagnosis and treatments. Lung cancer is a disaster disease which affect the human life time with improper shortage of life span in earlier days, but nowadays the impact of deep learning study in the field of medical image data domain reduces the time consumption in decision making foe providing the effective treatment for improving the survival rate of the lung cancer patients. This paper performs 3 major kind of tasks with initial focus on universal DICOM image conversion process as in classical neural networks format in deep learning, followed by the lung cancer diagnosis based grid based convolution neural networks approach in deep learning, then with the deep learning based association learning approach for gene mutation mapping and finally with the unrestricted

Boltzmann machine learning approach in deep learning for the survival rate improvement of lung cancer patients. The experimental results for the proposed methodology produce 16 out of 17 patient survival rate improvement achievement states. This research will be further enhanced with soft computing based automated survival rate improvement model for lung cancer domain system.

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