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Lung Cancer Detection Using the Quasi Newton Optimization Algorithm Using Deep Learning

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Abstract— This research work is to find out the early stage of lung cancer and explore the accuracy levels of various machine learning algorithms. After a systematic literature study, we found out that some classifiers have low accuracy and some are higher accuracy but difficult to reached nearer of 100%. Low accuracy and high implementation cost due to improper dealing with DICOM images. For medical image processing many different types of images are used but Computer Tomography (CT) scans are generally preferred because of less noise. The performances of the proposed approaches are evaluated based on their accuracy, sensitivity, specificity and classification time. Machine learning based lung cancer prediction models have been proposed to assist clinicians in managing incidental or screen detected indeterminate pulmonary nodules. Such systems may be able to reduce variability in nodule classification, improve decision making and ultimately reduce the number of benign nodules that are needlessly followed or worked-up. In this article, we provide an overview of the main lung cancer prediction approaches proposed to date and highlight some of their relative strengths and weaknesses. We discuss some of the challenges in the development and validation of such techniques and outline the path to clinical adoption.

Keywords — Pulmonary Nodules, Lung Neoplasms, Lung; Machine Learning, Decision Making, Structural Co-Occurrence Matrix (SCM), Classifier, Data Set, ROC Curve and Malignant Nodule.

I. INTRODUCTION

Image processing is a key topic in bio-medical applications due to the necessity to refine and identify pixels from diverse image sources including Computed Tomography (CT) scans, X-rays, Magnetic Resonance (MR) Imaging, etc. The term "exception" is used to describe data that deviates from the norm for a limited set of reasons (such unusual process conditions). Therefore, image processing is either the first step in the care process or the last model for spotting aberrant events like cancer. According to the research, medical image processing decides how cancer is treated and how practises need to change so that cancer may be readily identified.

However, recent research has shown that cancer is localised to certain body parts. The existing methods of detection aren't without their flaws, such as the fact that they don't work well with other types of cancer investigations. Such improvements, together with increased sensitivity in cancer diagnosis, are urgently needed. Several new efforts have been launched in recent years to enhance detection techniques as a result of the shortcomings of old approaches. The failure of tried and proven approaches on certain datasets has recently shifted research attention to exception location.

Lung cancer detection was a primary focus throughout the study's data collection, preparation, extraction, segmentation, and classification processes. Misleading image results, for instance, might seriously impede the clustering process. Error analysis and accurate detection are both crucial, thus new, effective discovery processes that may be used in a wide range of contexts should be proposed.

Numerous scientists are working on methods for detecting lung cancer. The most generalizable techniques are unsupervised computations since they may be used with any dataset without the requirement for specific training data. As a result of the algorithms' efficient implementation, researchers were able to easily compare their methods, and non-experts, investigators, and professionals could apply the calculations on the fly to handle complex data.

B. Lung Cancer

The term "lung disease" is often used to refer to cancers of the respiratory epithelium (the lining of the trachea,

bronchi, bronchioles, and alveoli). Lung cancer is defined by the uncontrolled expansion of lung cells. As a malignant tumour, it is among the most frequent and potentially deadly types. Malignant growth from it accounts for more annual fatalities than do breast, colon, and prostate cancers put together. Multiple carcinogens and tumour cells are found in cigarette smoke and contribute significantly to lung cancer.

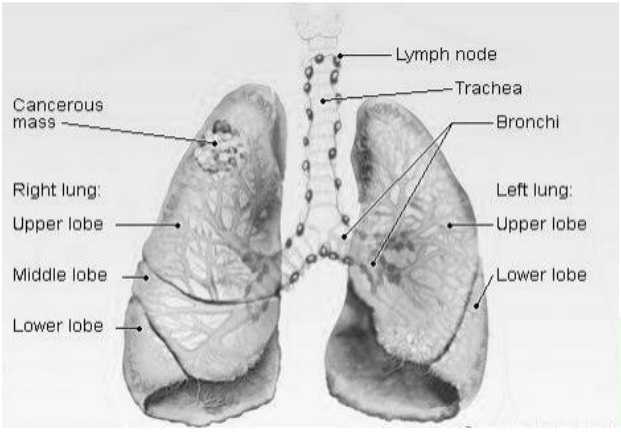

Fig. 1: Lung cancer

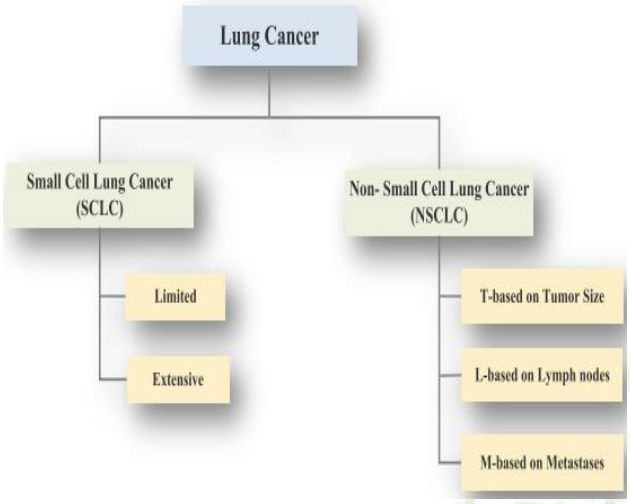

Fig.2: Types of Lung Cancer

In 2011, the National Lung Screening Trial Research Team successfully reduced lung-cancer death rates by using computed topography screening. Similarly, chronic obstructive pulmonary disease (COPD) is one of the smoking-related disorders that may raise the chance of getting lung cancer. Cigarette smoking is simply one of several risk factors for developing lung cancer. Pollutants in the water, soil, and soil are mentioned. When compared to men, women are more likely to have negative health effects from smoking. There is potential for a wide range of dietary cultural changes to minimise cancer risk.

Lung cancer is shown in Figure 1.3 to be divided into two classifications, limited and extensive, where "limited" refers to the cancer's growth staying on one side of the lung and "extensive" to its spread to the other. Staging of NSCLC is performed using the TNM system, which takes into consideration the location of the primary tumour, the presence or absence of lymph nodes, and the presence or absence of distant metastases. The rate at which cancer spreads to other organs is measured in metastases (M).

C. Motivation

Consider the ethical and legal ramifications of introducing a medical image processing system. Ensure the safety of patient information and get any necessary permissions before putting the technology to use in a clinical setting:

- **Early Detection:** Lung cancer may be hard to detect with standard procedures because of the absence of early signs. However, early detection significantly increases the chances of successful treatment and long-term survival. Using a high-tech CT image processing technology, doctors may see minute abnormalities in lung scans that could otherwise go unnoticed.
- **Improved Accuracy:** Medical images such as CT scans might be misinterpreted if left up to the judgments of people. Improved diagnosis accuracy and reduced false positives are two outcomes of the widespread use of algorithms for automated image processing.
- **Reduced Radiologist Workload:** Providing the individualized care each patient need might be challenging when radiologists are overworked. Possible areas of concern might be flagged by an automated lung cancer detection system, allowing radiologists to focus on those who really need treatment.
- **Faster Diagnosis:** Manually analyzing CT images might take a long time. Automating certain parts of the process may cut down on the time spent analyzing data, which might lead to a quicker diagnosis and, if required, the initiation of therapy sooner.
- **Quantitative Analysis:** CT image processing allows for the quantitative assessment of lung nodule or lesion size, shape, and characteristics. This data might be useful for keeping tabs on progress and determining future moves.

II. LITERATURE REVIEW

In this section discussion the literature survey of proposed research work that is presented by different researchers in the last decade in the aera of lung cancer detection.

Karthick Prasad Gunasekaran et.al. (2023) -It is impossible to stress the importance of early diagnosis in enhancing patient outcomes from lung cancer, a significant international public health problem. Applying recent breakthroughs in deep learning algorithms to the analysis of medical images has shown promising outcomes. The focus of this study is to investigate the feasibility of using object detection, and more especially the state-of-the-art YOLOv5 object identification system, in medical imaging for the detection of lung cancer. Kaggle data, including chest X-rays and their associated annotations, were used for the program's training and testing. A YOLOv5 model-trained technique for detecting lung cancer lesions. Training the model saw improvements in performance

thanks to hyper parameter tuning and augmentation techniques. The trained YOLOv5 model was very effective in detecting lung cancer tumours, both in terms of accuracy and recall. A new series of tests verified its superiority over previous techniques for finding cancer spots in chest x-rays [01]. ***Yahia Said et.al. (2023)-*** Lung cancer ranks high on the list of global fatalities. Lung cancer screenings rely primarily on image processing and segmentation for early detection. Segmenting medical pictures by hand is a time-consuming process that radiation oncologists must endure. In this research, we propose developing a thorough approach to early lung cancer detection in CT scan imaging. The suggested lung cancer diagnostic system is composed of two primary parts: a segmentation component based on the UNETR network, and a classification component based on the self-supervised network, which is utilised to categorise the segmentation output as benign or malignant. Extensive testing has led to enhanced segmentation and classification outcomes. There have been several initiatives that have utilised the Decathlon dataset for testing and training purposes. Experiments have resulted in new best-in-class segmentation (97.83%) and classification (98.77%) results [**02].** ***Iftikhar Naseer et.al. (2023)*** **-** Lung nodules are a warning sign of lung cancer, the most lethal and debilitating disease there is. Unchecked cell growth in the lungs is a crucial factor. Screening and early diagnosis of lung cancer rely heavily on the detection of lung nodules in Computed Tomography (CT) scan images. Detecting lung cancer at an early stage considerably improves survival chances and the range of available treatments. In addition, pulmonary nodule classification strategies based on convolutional neural networks may be used for accurate early lung cancer detection. Automated nodule detection in CT images is made possible using Lung Net-SVM, which is based on a hybrid of the modified Alex-Net architecture and the Support vector machine (SVM) algorithm. The proposed model uses 7 convolutional layers, 3 pooling layers, and 2 fully connected layers to perform feature extraction. A support vector machine classifier is used to identify whether a nodule is malignant or not. The experimental research makes use of the publicly available LUNA16 dataset as a benchmark. The proposed model achieved a high degree of accuracy (97.64%), sensitivity (96.37%), and specificity (98.08%). The proposed Lung Net-SVM model for classifying lung cancer was compared to existing state-of-the-art approaches. The experimental results on the LUNA16 dataset demonstrate the superior accuracy of the proposed Lung Net-SVM model compared to the state-of-the-art approaches [03]. ***Ashwini Pawar et.al. (2023)*** **-** Lung cancer is one of the most devastating illnesses conceivable. Different methods of data management and analysis have led to breakthroughs in the detection and diagnosis of lung cancer. In this research, we use a support vector machine and image processing to build a lung cancer detection system for aggregating evidence of the disease in CT scan images and blood tests [04]. ***Dr. P. Nancy et.al. (2022)*** **-** Lung cancer is caused in large part by the uncontrolled multiplication of lung cells. Cigarette smoking and/or heavy use of tobacco products are the leading causes of lung cancer. The great majority of lung cancer cases are caused by two main kinds. Lung cancer may be broadly classified into two categories: small-cell and non-small-cell. The results of a computed tomography (CT) scan may be very useful in diagnosing cancer and tracking its progression in a patient. Additional diagnostic tools include biopsy and pathology examination. Researchers in the field of machine learning work to perfect algorithms that will allow machines to pick up skills and knowledge from their environments. In this study, we explore the potential of machine learning for lung cancer diagnosis via the application of improved feature selection and image processing. Image quality might be improved with the use of the CLAHE algorithm. The K Means technique is used to segment a picture into its individual pixels. The PSO technique is used to identify useful traits. After that, we utilise SVM, ANN, and KNN to categorise the images. Imaging is performed using a CT scan. The results of PSO SVM for diagnosing lung cancer are more trustworthy [05]. ***Imran Shaf et.al. (2022)*** **-** In addition to the high expense and repeated radiation exposure associated with computed tomography (CT), the absence of symptoms in early-stage lung cancer may make diagnosis challenging. Even for a trained eye, sifting through CT images of the lungs to look for pulmonary nodules, which are commonly produced by cell lung cancer tumours, is a time-consuming and error-prone process. In this study, we propose a deep learning-enabled support vector machine (SVM) for cancer detection. The proposed CAD model can differentiate between normal and pathological cross-sectional variations in lung cancer lesions involving soft tissue. In order to train the algorithm to recognise lung cancer, CT images of patients with the illness and healthy controls are compared to selected profile parameters. After training, the model is put through its paces by using CT scans of both patients and controls for validation and testing. From the LIDC/IDRI database, the study team analysed 888 CT scans with annotations. The proposed deep learning-assisted SVM-based model achieves 94% accuracy for identifying pulmonary nodules, which reflect early-stage lung cancer. It surpasses state-of-the-art techniques for identifying nodules in lung CT images, which include intricate deep learning, simple machine learning, and hybrid algorithms[06].

III.PROPOSED METHOD

ANN initial divides training information into many subsets, exploitation ambiguous clustering techniques. After this, it trains different ANNs by exploitation different subsets. Then it determines the membership grade of those subsets and connects them through a replacement ANN to induce the ultimate result. The whole structure of ANN is shown in figure 5.3. Within the kind of a selected machine learning framework, feed forward ANN covers each the coaching part and therefore the testing part.

Step I: Featured Selected data training

Step II: Training for training by specific teaching algorithms for training (i = 1, 2, k), ANN model, ANN, (i =

1,2, ... k) for every training set numerous Base ANN model

Step III: to scale back the error for every ANN, we tend to simulate the ANN exploitation the complete training set TR and find the results. Then we tend to use the membership grade, which were generated by the ambiguous cluster module to combine the results.

After this, tend to train another new ANN exploitation combined results. Within the testing part, we tend to input directly the take a look at set information into numerous ANN and receive the output. Supported these outputs, final results is achieved by ultimate ambiguous aggregation module

There are three necessary lawsuits in three phases of the ANN structure-

- Produce totally different training subsets from the initial training dataset TR;
- Produce different base models ANN with different coaching subsets;
- A way to collect numerous results made by numerous base models ANN.

Forward Neural Network

A directly proportional relationship between input and output occurs in perception, whereas a connection between input and output occurs in FFNNs. The activation function in the hidden layer creates a nonlinear connection. There is a network with a direct connection between the input layer and the output layer that is formed by combining the connection form based on perception with a multilayer network. Cascade Forward Neural Networks (CFNN) are the result of this connection pattern (CFNN). The following are the equations that can be derived from the CFNN model.:

$$y= \sum_{i=1}^{n} f^{i}\omega_{t}^{i}\chi_{i} + f^{0}\left(\sum_{j=1}^{n}\omega_{j}^{0} f_{j}^{h}\left(\sum_{i=1}^{n}\omega_{ji}^{h}\chi_{i}\right)\right) \quad [1]$$

Where $f^{i}$is the activation function from the input layer to the output layer and ω_{ji}^{h} is weight from the input layer to the output layer. If a bias is added to the input layer and the activation function of each neuron in the hidden layer is then equation (2) becomes

$$y = \sum_{i=1}^{n} f^{i}\,\omega_{i}^{i}\chi_{i} + f^{0}\left(\omega^{b} + \sum_{j=1}^{k}\omega_{j}^{0}\left(\omega_{j}^{b} + \sum_{i=1}^{n}\omega_{ji}^{h}\chi_{i}\right)f^{h}\right) \quad [2]$$

In this research, the CFNN model is applied in time series data. Thereby, the neurons in the input layer are the lags of time series data $Xt-1, Xt-2, \ldots, Xt-p$, whereas the output is the current data Xt . The architecture of CFNN model in predicting time series is shown at **fig 3.**

Feed Forward Network

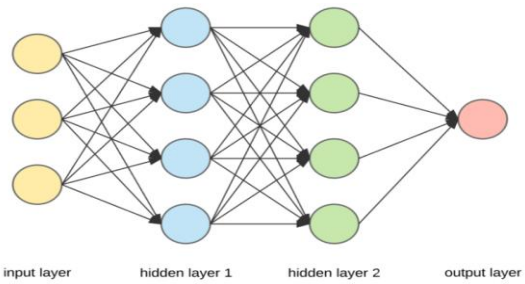

Fig. 3 Different layers of back proportion method

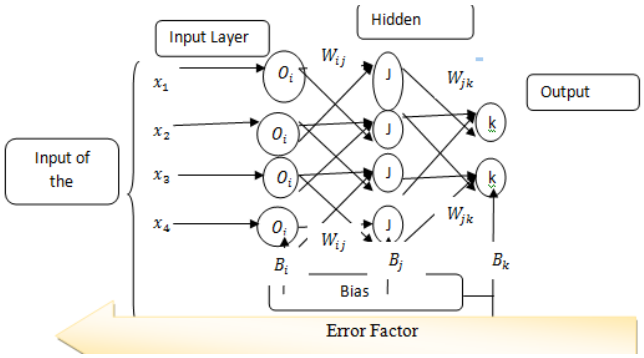

Fig 4.Back proportion method

Algorithm Start

Step 1 – Each neuron has a set of weights that need to be maintained. One weight for each input connection and an additional weight for the bias.We will use a dictionary to represent each neuron and store its properties by name so that we can train it.such as weights of weights.

1. Initially all the weights and bias.

$$W_{ij} = \{0.1.2.3 \ldots\ldots\ldots\ldots N\} \quad [3]$$

$$B_{i} = \{0.1.2.3 \ldots\ldots\ldots\ldots N\} \quad [4]$$

2. Iteration perform till end reach the desired output.

3. If x_i as an input therefor inputs - $x_i = x_1, x_2, \ldots\ldots\ldots\ldots\ldots\ldots x_n$ and outcome of the input x_i therefor the output $O_i = O_1, O_2, \ldots\ldots O_n$.

$$O_i = x_i \quad [5]$$

O_iIs the output of the first stage depend on the input ofx_i,

4. Hidden Layer

$$x_i = \left(\sum W_{i,j} \times O_i\right) + B_j \quad [6]$$

5. Output of hidden layer is depended on

$$O_j = \frac{1}{1+e^{-x_i}} \quad [7]$$

$O_j$is the output of the hidden layer for different values of j calculate the value

$$O_j = O_1, O_2, O_3, O_4 \ldots\ldots\ldots\ldots N \quad [8]$$

6. Output layer outcomes

$$x_K = \left(\sum W_{j,k} \times O_j\right) + B_k \quad [9]$$

7. Output of hidden layer is depended on

$$O_K = \frac{1}{1+e^{-x_k}} \quad [10]$$

$O_K$is the output of the final output layer for different values of k calculate the value

$$O_j = O_1, O_2, O_3, O_4 \ldots\ldots\ldots\ldots N \quad [11]$$

8. that is the initial phase of the back propagation, now calculate the error factor (E_j layer) and error factor of ($E_k$layer).

Error factor of kthlayer

$$E_k = O_j\,(1-O_j)(T_j - O_j) \quad [12]$$

T_j is the test attributes which is calculated in the initial stage.

9. Error factor of jth layer (Hidden layer)

$$E_j = O_j(1-O_j)\left(\sum_k E_k \times W_{ij}\right) \quad [13]$$

10. Wight updating of bias

$$(\delta W_{ij}) = \iota \times (E_j \times O_j) \quad [14]$$

ι = isthegivenlearinigrate

11. Wight updating($ƫW_{ij}$)

$$ƫW_{ij} = W_{ij} + \delta W_{ij} \quad [15]$$

12. Bias updates

$$(\delta B_j) = \iota \times (E_j) \quad [16]$$

ι = isthegivenlearinigrate And E_j error of j.

$$ƫB_j = B_j + \delta B_j \quad [17]$$

Now bias and error both are updated.

Continue run this process up to n times iteration perform till got the decide result or depended on the termination condition [28].

Section -2 Apply Neural Network for Training using Back Propagation

A neural network-based network (FNN) is used for the training of the proposed method in this section. Back-propagation can be used to train a feed-forward neural network., which depicts a flow chart outlining these steps, can be found below.

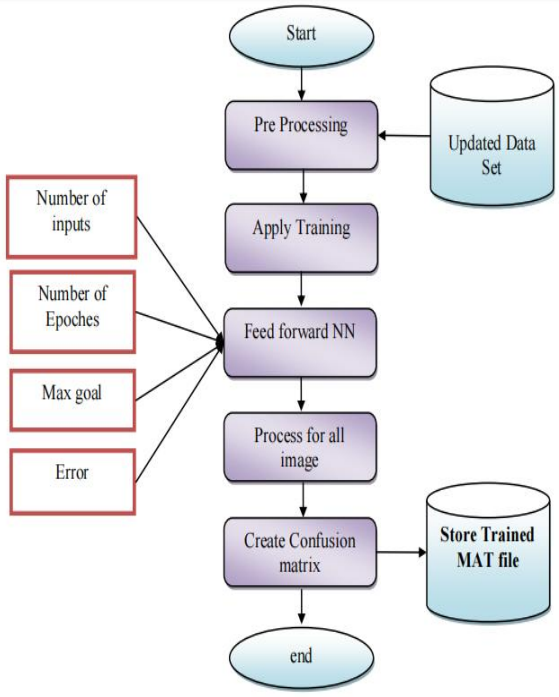

Fig. 5: Training algorithm of Proposed Method

IV. SIMULATION AND RESULTS DISCUSSION

The simulation model and its results will be discussed in this chapter along with the proposed algorithm. Matrix laboratory should be utilized for the process of implementing the proposed algorithm. The Matrix Laboratory is a well-known piece of software that can be used for various calculations related to the imple-mentation of algorithms for data analysis. The number of data analysis tools available in MATLAB is quite extensive. The results of the simulation of the proposed method for developing middleware using machine learning technique for histopathological image-based lung cancer detection are shown in this section, along with the result calculation and the simulation of the proposed method.

A. Data Sets

To train computer models using machine learning algorithms, large datasets are needed. It's not enough to have a collection of images from various medical entities; more are needed from cancer pathology in particular. The availability of ML-ready image datasets is even more limited. An image dataset (LC25000) containing 25,000 colour images divided into five categories was created specifically to meet this demand.

B. Dataset description

A total of 25,000 colour images are included in the dataset, divided into five groups of 5,000 images each. .jpeg files are used to store all of the images, which have a resolution of 768x768 pixels. The 1.85 GB zip file LC25000.zip is included in this data set. After unzipping, you'll find two subfolders called "colon image sets" and "lung image sets" in the lung colon image set main folder. There are 5,000 images of adenocarcinomas, squamous cell carcinomas, and other lung tissues that are not cancerous in the subfolder lung image sets/lung aca/.

C. Discussion

ML requires a large number of images to train computer models successfully. Although there are medical image datasets available, more large image datasets are needed from a variety of lesions. To address this necessity, we created an image data-set (LC25000) with 25,000 images in 5 classes. Anatomical entities in each class include colon and lung cancers, benign colonic tissue; lung adenocarcinomas; and squamous cell carcinoma. AI researchers can download images that have been de-identified, checked for accuracy, and are in compliance with HIPAA at no cost. [10].

D. Simulation Outcomes and Results

In the above discuss the GUI design for simulation of proposed method shows discuss the simulation outcomes of proposed method. The proposed method simulation divided into three parts. In the first part discuss the simulation outcomes on 70% training data and remaining 30% data for testing as well as validation. Similar that apply training with 80% data for testing use remaining 20% data. Last in the training with 90% data for testing use only 10% data. In the below discuss the simulation outcomes on different percentage of training data.

Training testing outcomes on 70% data

In the training of proposed method use GUI interface with modified feed forward neural network, number of epochs, 15 and other training parameters as an input. For initialization of training process follow these steps,

1. Using browse button to select the target input folder data.
2. After that in the next enter training ratio in the editable text window. Give the file name in the for

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training data.

Fig. 6: GUI of training data with 70%

3. Now click on train button.
4. Start training, after completion of training, the outcomes of proposed method in 70% training accuracy is **98.5556%** .
5. The confusion matrix of proposed method also shown in the GUI.

In the above fig. 6 shows the training outcome of proposed method.

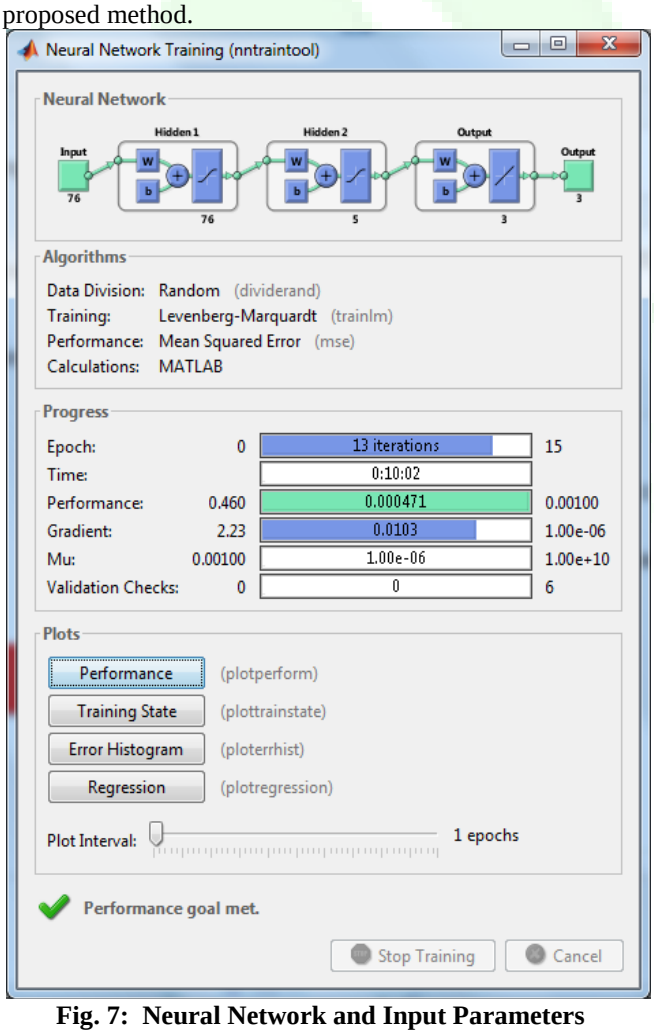

Fig. 7: Neural Network and Input Parameters

In the above fig. 7, shows the neural network input parameters. The proposed method is based on feed forward neural network.

- There are 76 input parameter are selected as an input parameters.
- There are two input hidden layers are apply.
- Data division is in random process.
- For training process use levenberg marquardt (LBM).

These are major input parameters which are apply in the input of the proposed method. Now discuss the testing outcome plots. There are three major plot for the performance analysis of proposed method. First is performance validation, second one is training state, third one is error histogram and last one is regression plot.

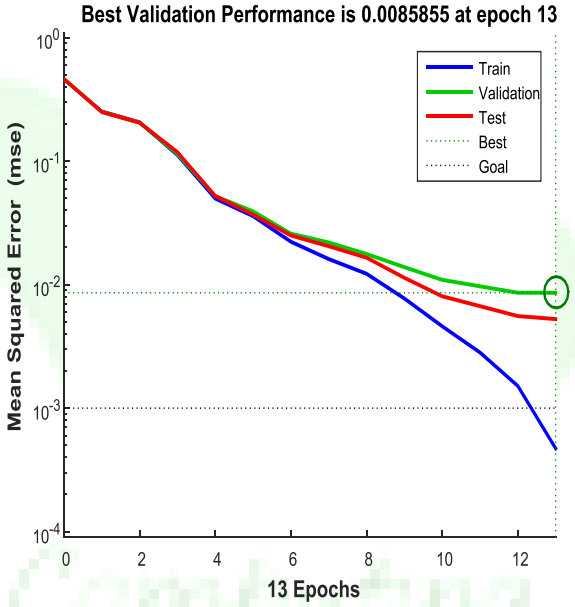

Fig. 8: Neural Network performance input train, validation , test, best and goal

In the above Fig. 8 error histogram of proposed method. Whenever a feed forward neural network is trained, the error histogram shows the histogram of errors between the target values and the predicted values. It is possible that these error values are negative because they show how the predicted values differ from the target values. On a graph, bins represent the number of vertical bars you can see at a glance. In this case, the total error range is broken down into 30 smaller bins for easier visualization. The number of samples in a given bin on the Y-axis represents the size of your data set.

In the below figure 8. shows the regression plot of proposed method. In this plot there are four subplots. Four plots are divided into four parts, training, test, validation and all. In the x axis denote the target value and Y axis denote the outputs.

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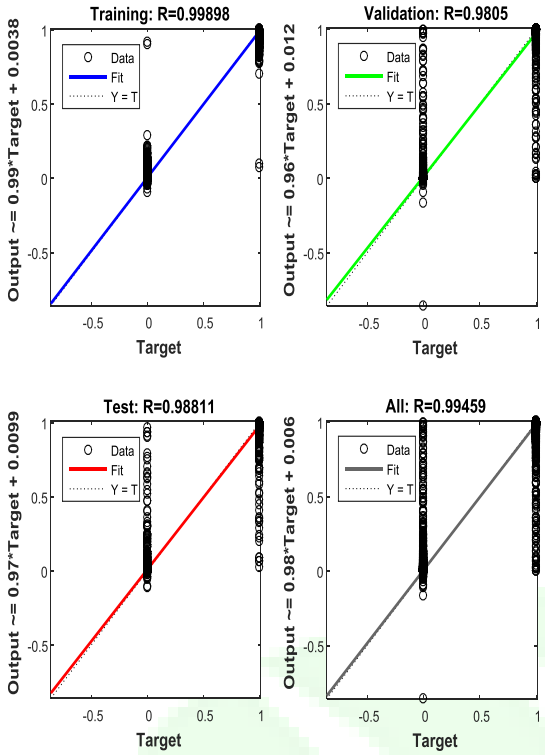

Fig. 9: Shows The Regression Plot of Proposed Method

In the above Fig. 9 to 8 shows the validation performance of proposed method. Now discuss the different quantitative result parameters confusion matrix (CM), true positive (TP) , true negative (TN), false positive (FP) ,false negative (FN) , accuracy (Acc), precision (Pr) , Selectivity (Sel), Sensitivity (Sen) and Specificity (Spc).

Training Outcomes

A. True positive (TP)

T.P. = 4954 5000 4939

Avg, (TP) = 14893

A. **False Negative (FN)**

F.N. = 46 0 61

Avg (FN) = 107

B. **False Positive (FP)**

F.P.= 61 2 44

Avg. (FP) = 107

C. **True Negative (TN)**,

TN = 9939 9998 9956

Avg. (TN) = 29893

D. **Accuracy** = 99.5244

E. **precision** = 99.2869

F. **Selectivity** = 99.2869

G. **Sensitivity** = 99.2867

H. **Specificity** = 66.7465

I. **Confusion Matrix (CM)** mat =

	4954	2	44
	0	5000	0
	61	0	4939

Training testing outcomes on 80% data

In the training of proposed method use GUI interface with modified feed forward neural network, number of epochs 15 and other training parameters as an input. For initialization of training process follow these steps, Using browse button to select the target input folder data. After that in the next enter training ratio in the editable text window. Give the file name in the for training data.

Result at 70% Training Data Set

In the data set classified in the three different category. For the testing of proposed method. First select the input image, after that select the 70% input data set.

1st Category

Fig. 10. Shows the result Cancer tissue detection first category detection

In the above **Fig. 10.** clearly detect the cancer tissue by the proposed method. The outcomes of proposed also loc =1 that is denoted that 1st category.

1st Category

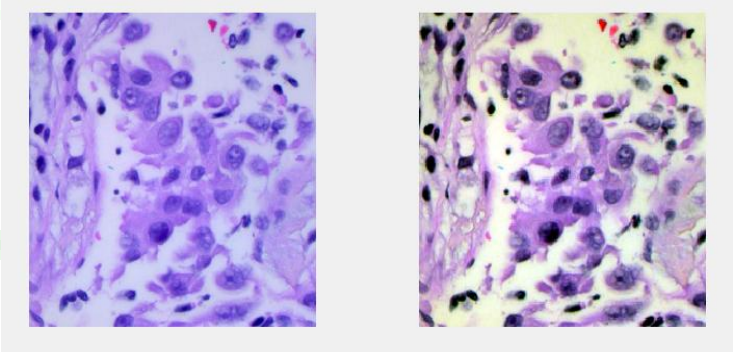

Fig. 11: Shows the result Cancer tissue detection first category

Code for <Variation in Phase Symmetry> Starts

Taking Median for scale 1/4

Taking Median for scale 2/4

Taking Median for scale 3/4

Taking Median for scale 4/4

Code End for <Variation in Phase Symetry>

val = 1.0013

loc = 1

In the above **Fig. 11.** clearly detect the cancer tissue by the proposed method at 80% training. The outcomes of proposed also loc =1 that is denoted that 1st category.

2nd Category Detection

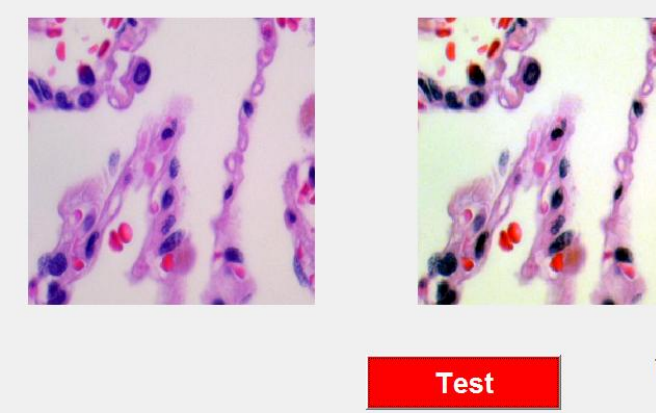

Fig. 12: The result Cancer tissue detection second category detection

Code for <Variation in Phase Symetry> Starts
Taking Median for scale 1/4
Taking Median for scale 2/4
Taking Median for scale 3/4
Taking Median for scale 4/4
Code End for <Variation in Phase Symetry>
val = 0.9610
loc = 2.

3rd Category

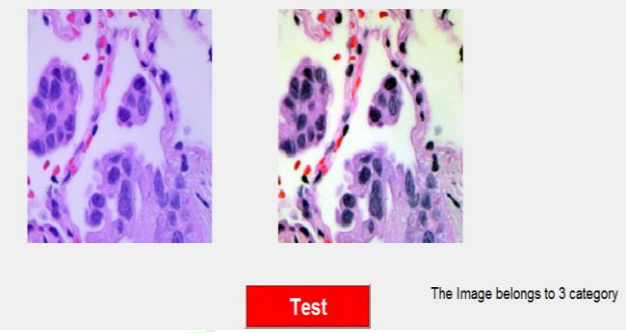

Fig. 13: Shows the result Cancer tissue detection second category detection

Code for Starts
Taking Median for scale 1/4
Taking Median for scale 2/4
Taking Median for scale 3/4
Taking Median for scale 4/4
Code End for <Variation in Phase Symetry>
val = 1.0033
loc = 3

In the above **figure 13.** clearly detect the cancer tissue by the proposed method. The outcomes of proposed also loc =3 that is denoted that **3rd** category.

In the above part of the this chapter discus the result of proposed method. Now discuss the result comparison of proposed method each other at different level of testing 70%, 80% and 90%. After that also compare the proposed method with different previous method. Now discuss the comparison of proposed method with different previous method. The proposed method shows better result as compare to other previous method. The proposed method shows **99.5244%** accuracy at 70% training rate and 99.6933% accuracy at 80% training rate. In 90% training rate results are not better as compare to 80% due to over fit model.

Table II. Result Compare of Proposed Method With Different Previous Methods

Ref./year	Method	Result Accuracy
Proposed/ 2023	**Proposed Modified NN based**	**99.5244 (70%) 99.6933 (80%)**
[02]/2022	Deep Learning with RGB color model	98.78%
[03]/2021	SVM based KNN Machine Learning Methods	95.56%,
[04]/2020	Improved Deep Neural Network (IDNN) method	94.58%
[05]/2020	Convolution neural networks(CNN)	94.56%

In the next chapter discuss the conclusion, future work, application and scope of the presented work.

VI. CONCLUSION

Cancer is a disease that is becoming increasingly prevalent around the world. Numerous researchers have conducted a variety of studies in an effort to determine the areas of the human body that are most commonly affected by cancer. The results of one study like this one motivated us to carry out this research in the field of detecting lung cancer. The most common cause of death attributable to cancer in both men and women is lung cancer. The likelihood of a favorable prognosis for lung cancer patients who undergo early detection is increased. The utilization of image processing systems makes it possible to detect and diagnose abnormalities earlier and more quickly than is possible with the use of other screening tests. When developing a method for the early diagnosis and treatment of disease, taking into account the passage of time is one of the considerations that goes into the process.

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