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Deep Learning Multi-Feature streams for Lung Tumor/Cancer segmentation from CT Images

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ABSTRACT:Volumetric Lung cancer is one of the serious disease which leads to death. Every year Lung Cancer patients severely suffer for there survival. Early prediction of lung cancer becomes mandatory. In the existing research work,two neural networks to segment lung tumors from CT images by adding multiple residual streams of varying resolutions. Our results clearly demonstrate the improvement in segmentation accuracy across multiple datasets. Our approach is applicable to longitudinal tracking of tumor volumes for cancers subjected to treatment with immunotherapy, which alters both the size and appearance of tumors on CT. In the proposed system, To increase the accuracy, Multi-Modal Feature based Deep Learning Neural Networks is used to determine the infected area of the Lung cancer. The infected area and spreading of disease also being determined by the system. The multi-Modal feature study can be analyzed by applying various feature extraction techniques together. The deep learning algorithm accurately predict the process by training the samples in the Neural model.

KEYWORDS: Longitudinal Tracking, Multi-Modal Feature, Neural Networks.

I.INTRODUCTION

Lung cancer is the most common cancer diagnosed worldwide. It is a disease of abnormal cells multiplying and growing into a tumour. Cancer cells can be carried away from the lungs in blood, or lymph fluid that surrounds lung tissue. Lung cancer often spreads toward the centre of the chest because the natural flow of lymph out of the lungs is toward the centre of the chest. Metastasis occurs when a cancer cell leaves the site where it began and moves into a lymph node or to another part of the body through the blood stream [1]. Cancer that starts in the lung is called primary lung cancer. There are several different types of lung cancer, and these are divided into two main groups: Small cell lung cancer and non-small cell lung cancer which has three subtypes: Carcinoma, Adenocarcinoma and Squamous cell carcinomas.

Lung cancer is also the foremost contributor to cancer-related mortality, resulting in 1.38 million cancer deaths per year worldwide.[2] Lung cancer accounts for more deaths than any other type of cancer. Several epidemiological observations performed across varied demographic cohorts in India confirm the significant burden of lung cancer and contributing towards the cancer morbidity and mortality.[3]

According to the GLOBOCAN 2012 report, the estimated incidence of lung cancer in India was 70,275 in all ages and both sexes; the crude incidence rate per 100,000 was 5.6, the age-standardized rate per 100,000 (world), i.e. ASR (W) was 6.9, and the cumulative risk was 0.85. In terms of incidence rates, lung cancer ranked fourth overall among the various types of cancer. The overall estimated lung cancer mortality in India in 2012 was 63,759, making it the third most common cause of cancer-related mortality in India after breast and cervical cancer. Among Indian males, lung cancer was the most common cause of cancer mortality at 48,697; the estimated lung cancer mortality among Indian females was 15,062 (ranking seventh in terms of cancer-related mortality in Indian women behind breast, cervix, colorectal, ovary, stomach, and lip/oral cavity cancer).[3]

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II.SYSTEM MODEL AND ASSUMPTIONS

1. Image Enhancement stage: to make the image better and enhance it from noising, corruption or interference. The following three methods are used for this purpose: Gabor filter (has the best results), Auto enhancement algorithm, and FFT Fast Fourier Transform (shows the worst results for image segmentation).
2. Image Segmentation stage: to divide and segment the enhanced images, the used algorithms on the ROI of the image just two lungs, the methods used are: Thresholding approach and Marker-Controlled Watershed Segmentation approach (this approach has better results than thresholding).
3. Features Extraction stage: to obtain the general features of the enhanced segmented image using Binarization and Masking Approach. The features are brisk feature, fast feature, surf, and MSER feature.
4. Neural Network: are an interconnected collection of nodes called neurons. Every neuron takes one piece of the input data, typically one pixel of the image, and applies a simple computation, called an activation function to generate a result. Each neuron has a numerical weight that affects it result.

The tyoe of cancer depends on area. where we have different ranges as 10,000 to 20,000 which is considered as Adenocarcinoma, from 220 to 10,000 is considered as Carcinoma, 220 to 210 is taken as Squamous and less than 210 is considered as tumor cells.

III. DESIGN METHODOLOGY

1 PREPROCESSING

This module is used to extract the basic info from the image under test. RGB to gray conversion, binary conversion, Image resizing can be done.

2 DESIGN OF MULTI-MODAL FEATURE EXTRACTION

Multi modal feature extraction is nothing but the extraction of multiple feature of the input image such as MSER feature, SURF Feature, BINARY feature and combining all to form a multi vector for analysis.

3 DATABASE TRAINING

Active contour segmentation is used here to segment the cancer from the input image. This method is used to train the datasets and extract the statistical regional study of the input image. Statistical study is used to get the segmented area and its perimeter.

4 ACTIVE CONTOUR SEGMENTATION

Image segmentation still plays an important role in image understanding and computer vision. Active contour models (ACMs) have been widely applied to image segmentation since their introduction [1]. ACMs can obtain closed object contours as segmentation results, which can be conveniently used for shape analysis and recognition. The active contours can utilize various types of prior knowledge, such as image intensity distribution information, boundary shape information, and texture information [4–6], to obtain accurate results for object boundaries in image analysis.

ACMs can be categorized as edge-based models [7–10] or region-based models [11–16]. . Region-based models use image statistical information to attract the active contours to the object boundaries. They outperform edge-based models in many cases, such as computer tomography (CT) and magnetic resonance (MR) images.

According to Li et al. [29] considered the bias field in the local region to segment an image with intensity inhomogeneity and estimate the bias field. Based on the retinex theory [31], the considered bias field model can be written as follows:I=b.j+n where *I* is an image to be measured, *b* is the bias field, *J* is the true image and *n* is the additive noise.

OUR MODEL

The segmentation result may affect the bias field correction, and using only the local region intensity means and bias field in Li's model is not sufficient to approximate the measured image well. Thus, motivated by the contributions and methods of [27–30], we present a new ACM to segment images with intensity inhomogeneity and estimate the bias field, and this model incorporates the local difference information between the measured image and Li's estimate. In Li's model, the segmentation result is essential for the estimation of the true image *J* and the bias field; an accurate segmentation result can accurately estimate the bias field, whereas a bad segmentation result cannot do so. In our model, we introduce the difference in the local region of the image domain to improve the accuracy of the segmentation result and bias field estimation. For an input image *I*, the model can be described as follows:I=b.j+d+n where *d* is the difference between the measured image *I* and approximated model *b·J* in the local region.

Segmentation by region growing:

The active contour segmentation is applied by usingregiongrowing techniques.
Region growing approach is the opposite of split and merges.
1. An initial set of small area are iteratively merged based on similarity of constraints.
2. Start by choosing an arbitrary pixel and compared with the neighboring pixel.
3. Region is grown from the seed pixel by adding in neighboring pixels that are similar, increasing the size of the region.
4. When the growth of one region stops we simply choose another seed pixel which does not yet belong to any region and start again.
5. This whole process is continued until all pixels belong to some region.
6. A bottom up method.

Statistical Analysis

Statistical analysis is performed using the statistical software MedCalc [40]. To assess the performance evaluations of segmentation quality (JS, DSC, RFP, RFN) presented in (21), the tests of statistical significance are performed using 120 simulated MR images. First, we perform the F-test [41]. If the associated (two-sided) P-value is less than the conventional 0.05, the null hypothesis is rejected and the conclusion is that the two variances do indeed differ significantly. If the P-value is low ($P<0.05$), the variances of the two samples cannot be assumed to be equal and it should be considered to use the t-test with a correction for unequal variances (Welch t test, [42]). The variables are expressed as Mean ± SD (standard deviations). For Welch t test, when the P-value is less than the conventional 0.05, the null hypothesis is rejected and the conclusion is that the two means do indeed differ significantly.

IV.SOFTWARE DESIGN

MATLAB
MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment and proprietary programming language developed by MathWorks. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, C#, Java, Fortran and Python.

MATLAB was first adopted by researchers and practitioners in control engineering, Little's specialty, but quickly spread to many other domains. It is now also used in education, in particular the teaching of linear algebra and numerical analysis, and is popular amongst scientists involved in image processing.[8]

NEURAL NETWORK
A neural network is a computing model whose layered structure resembles the networked structure of neurons in the brain, with layers of connected nodes. A neural network can learn from data—so it can be trained to recognize patterns, classify data, and forecast future events.

A neural network breaks down your input into layers of abstraction. It can be trained over many examples to recognize patterns in speech or images, for example, just as the human brain does.Neural networks are especially well suited to perform pattern recognition to identify and classify objects or signals in speech, vision, and control systems. They can also be used for performing time-series prediction and modeling.

Deep Learning
Neural networks that operate on two or three layers of connected neuron layers are known as shallow neural networks. Deep learning networks can have many layers, even hundreds. Both are machine learning techniques that learn directly from input data.Deep learningis getting lots of attention, and for good reason. It's achieving results that were not possible before.

Pattern recognition is an important component of neural network applications in computer vision, radar processing, speech recognition, and text classification. It works by classifying input data into objects or classes based on key features, using either supervised or unsupervised classification.

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For example, in computer vision, supervised pattern recognition techniques are used for optical character recognition (OCR), face detection, face recognition, object detection, and object classification. In image processing and computer vision, unsupervised pattern recognition techniques are used for object detection and image segmentation.

V. RESULT AND DISCUSSION

In the fig 1, it shows the graph of Epchosvs Mean Square Error. The graph gives the information on the performance plot and its efficiency.

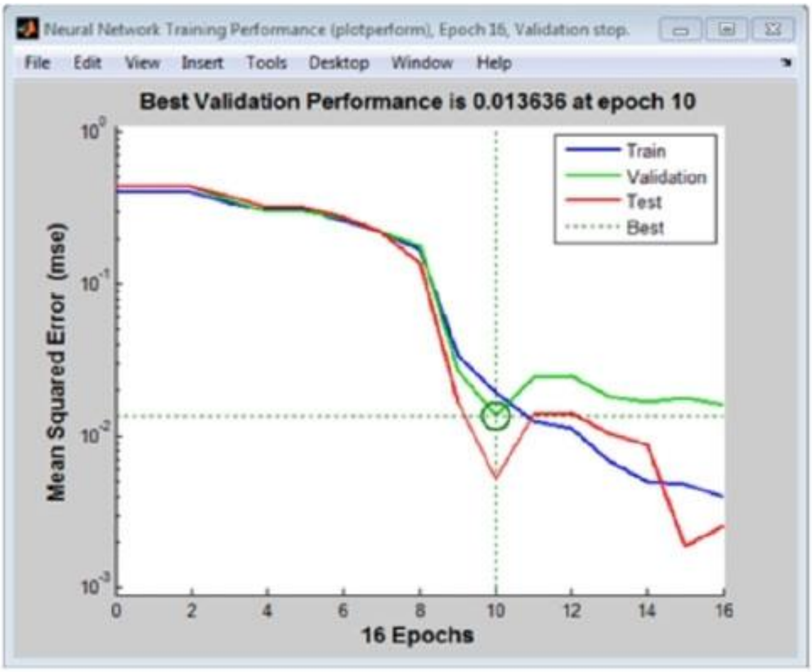

Fig. 1 Epchosvs Mean Square Error

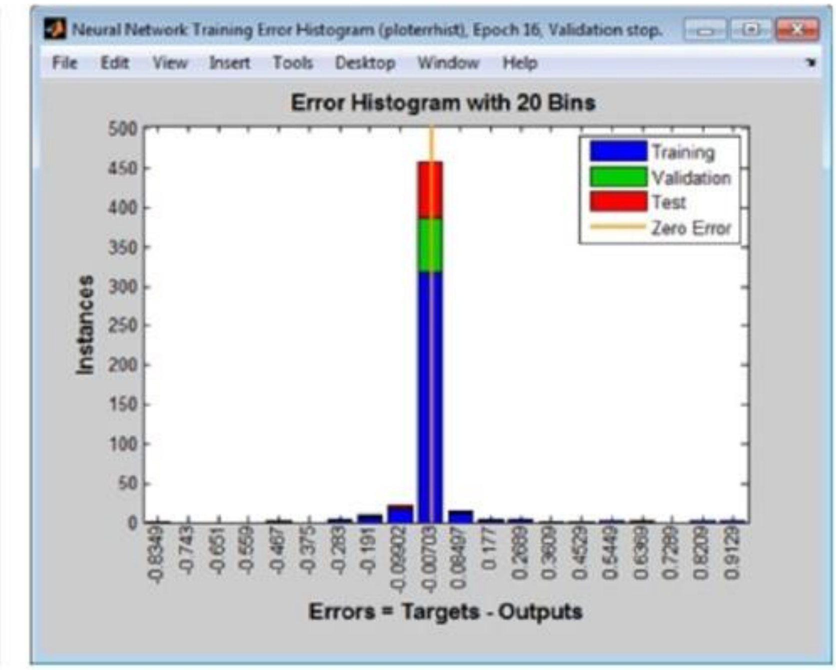

Fig. 2 Errors vsInstances

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In the fig 2, it shows the graph of Errors vs Instances. This gives the information on histogram errors.

Fig .3 Target classVsOutput class

In Fig 3, Target class Vs Output class. In this we have the pixel range variation with respect to the type of matix used. They are Training confusion matrix, validation confusion matrix, test confusion matrix and All confusion matrix.

Deep Learning Toolbox provides a set of blocks for building shallow neural networks in Simulink. All blocks are compatible with Simulink Coder™. These blocks are divided into four libraries:

- **Transfer function blocks**, which take a net input vector and generate a corresponding output vector
- **Net input function blocks**, which take any number of weighted input vectors, weight-layer output vectors, and bias vectors, and return a net input vector
- **Weight function blocks**, which apply a neuron's weight vector to an input vector (or a layer output vector) to get a weighted input value for a neuron
- **Data preprocessing blocks**, which map input and output data into the ranges best suited for the neural network to handle directly

Alternatively, you can create and train your networks in the MATLAB environment and automatically generate network simulation blocks for use with Simulink. This approach also enables you to view your networks graphically.

VI. CONCLUSION

By this work we conclude thatthe multi feature streams of a Computed Tomography(CT) images gives us a more accurate output as it increases the efficiency. The multi-feature streams gives the volume of affect areaby using active contour segmentation. It takes less time when compared to convolution technique. In neural networks it compares the effected image with the data iages with all possible set of values.

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