

A Fully Convolutional Deep Neural Network for Lung Tumor Identification

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Abstract

Delineation and identification of lung tumor from neighbouring tissues from a sequence of magnetic resonance images (MRI) causes many difficulties because of the resemblance of the volume of interest and the surrounding region along with the influence of respiration. However, exact segmentation of the tumor region is very important for the radiation therapy on the patient. An off target radiation therapy may affect the healthy tissues due to excessive radiation. The manual delineation and identification of the entire MRI series is tedious, time consuming and expensive. This paper proposes a fully automatic technique for identification of lung tumors using convolutional neural networks. We proposed to use a convolutional neural network architecture with modified Dice metric as the cost function. The proposed approach evaluates a total of 600 images with resemblance to a medical expert. The proposed method yielded an average Dice score of 0.91 ± 0.03 and Hausdorff distance of 2.88 ± 0.86 mm. The proposed approach provides an accuracy of 90-95% outperforming the recent methods that are being used in terms of accuracy in delineation of lung tumors.

Keywords: Lung Tumor Identification, convolutional neural networks, magnetic resonance images (MRI)

1. INTRODUCTION

Lung cancer is the most frequently occurring cancer standing second in the list of most common cancer. Lung cancer is one of the leading cause of cancer death among both men and women, constituting 25% to all the cancer deaths[1]. The survival rate of a lung cancer patient depends on the early detection of cancer and successive follow up. Lung tumors are detected using MRI images of the affected patient. The screening trials also include low dose thoracic computer tomography (CT) scans. According to *National Lung Screening Trial*, a patient who undergoes thoracic CT scans have 15-20% increase survival rate compared to the patients who undergo primitive X-ray scans[2]. There are many softwares developed to improve the efficiency of the workflow and early detection of lung tumor in thoracic MRI images. The huge datasets from the former softwares along

with the emerging high performance computing techniques have enabled the development of a field named radiomics. Radiomics helps in extracting high importance features from the MRI images which are known as radiomics signatures. These radiomics signatures are integrated with different machine learning and deep learning techniques which help in predicting lung cancer associated results. Radiomics helps in detecting volume of interest (VOI) around the lung tumors and the possible sub-regions. The development of these automated computerized techniques pose a real asset to the medical applications. It helps in eliminating the variation in the comprehension of the MRI images among different expert individuals. Moreover, the manual detection of lung tumor is a very tedious job and requires a high amount of investment of time and money. Thus, these automated techniques constitute a very big role in medical field, effectively reducing human labour involved and playing a pivotal role in the growing standard of early lung cancer detection and diagnosis.

2. OVERVIEW OF PROPOSED SYSTEM

This paper proposes the identification of lung tumor with the help of fully deep convolutional neural network. The input to the systems will be given as a set of MRI images. The images first undergo pre-processing, then feature extraction and a neural network is generated. The pre-processing helps in reducing the noise in the image and increasing the contrast by Dual-Tree Complex Wavelet Transform (DT-CWT). Then texture features are extracted from the input image using GLCM. Feature extraction helps in calculating the gray level co-occurrence matrix for various pixels and their neighbours. The selected feature is then compared with the sample images already present in the database. The comparing is done with the help of generating a convolutional neural network. The processed image is fed as an input to the neural network. Neural network are used to classify an image into a list of form pre-established types. In a simple way, it is used to deduce if something is identified or not. In our case, the result of identification can be a YES/NO (YES if there is a tumor and NO if there is not). The neural network is trained using image classification. Image classification is the process in which a list of sample images are fed into the network and the outcome is compared with the expected outcome.

3. SYSTEM ARCHITECTURE

3.1 Pre-processing

In the pre-processing stage, smoothening of the image is the first step. For the smoothening of image, median filters are used. These filters are applied on the input image. Median filters are helpful in reducing noise in the image. It removes all the high frequency elements from the input image. It is a low pass filter[3]. It provides a smoothened image as an output along with more accurate intensity surface. Then DT-CWT algorithm is applied in the image thus obtained. The dual-tree complex wavelet transform (DTCWT) is used to solve problems related to shift variance and low directional selectivity in two dimensions pictures or for higher dimensions. It is used commonly with discrete wavelet transform (DWT). This algorithm is deployed for applications like texture classification and image retrieval based on content. The algorithm calculates the mean of the energies of the real and imaginary part of the complex wavelet coefficients which are taken separately. These mean energies are then used to identify the effective features of the image in preprocessing for defect detection. DTCWT incorporates shift invariance and selective orientation of dual-tree for surveying

the 2D and 3D wavelets. DTCWT helps in image and volume denoising[4].

3.2 Feature Extraction

There are various techniques to implement feature extraction from an image. In our proposed approach we use GLCM (Gray Level Co-occurrence Matrix) for the feature extraction from the MRI images of the lungs. Feature extraction is a process of dimensionality reduction. It transforms the data into a set of features. A Gray Level Co-Occurrence Matrix (GLCM) contains information about position of the pixels in the image having similar gray level values. In this paper, the GLCM feature used is entropy. Entropy is used to measure the loss in information or message in the process of transmission. It also measures the image information.

$$Entropy = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij}$$

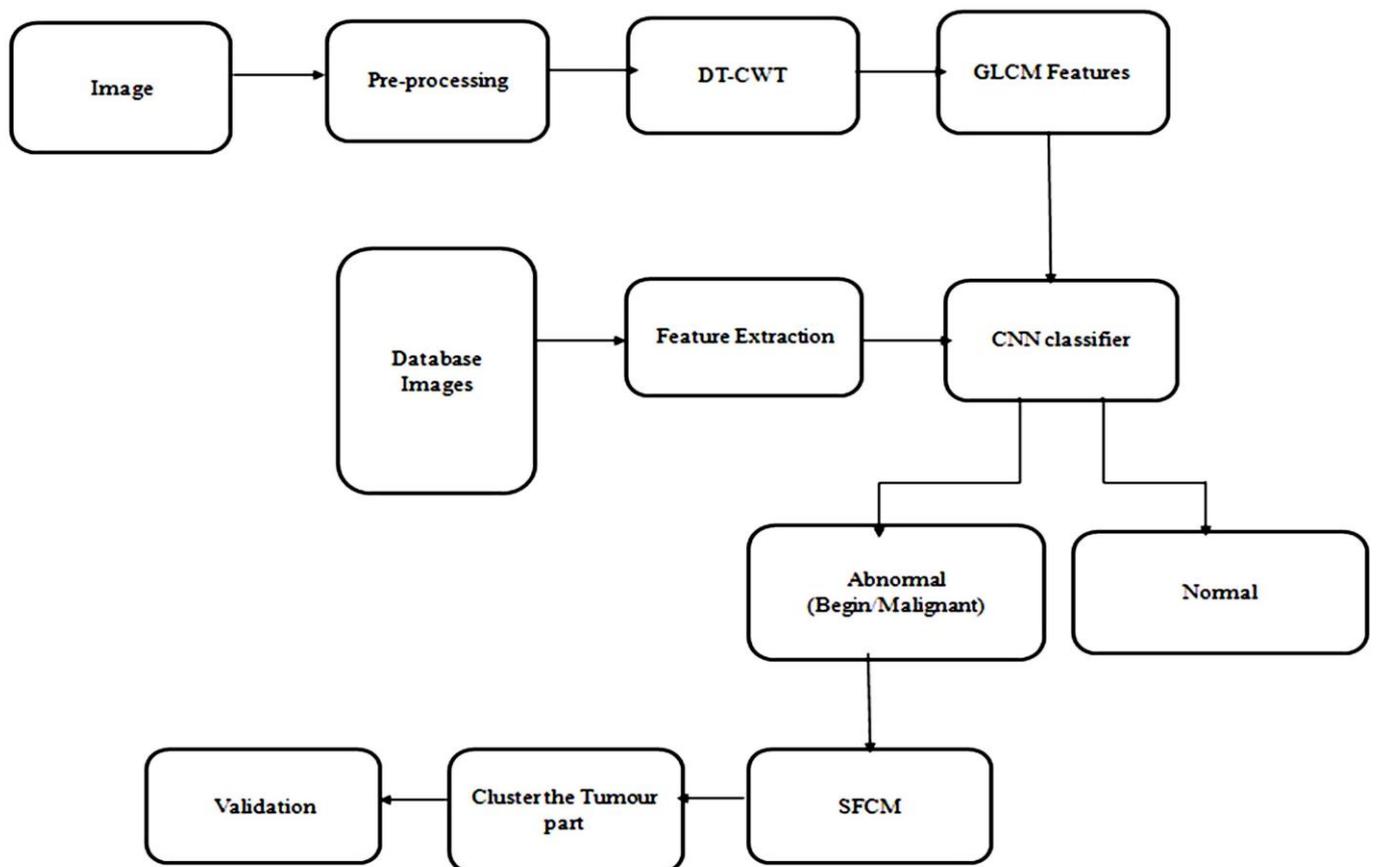


Fig 1. System architecture of the proposed system.

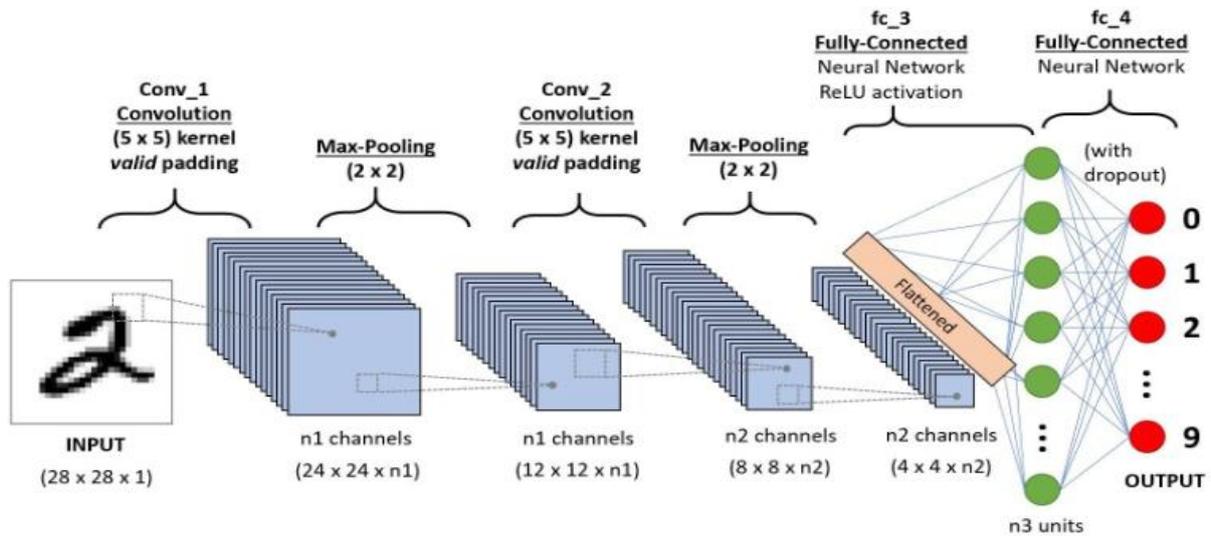


Fig 2. An example of Convolutional Neural Network(CNN)

3.3 CNN Classifier

A Convolutional Neural Network(CNN) is a deep learning algorithm which takes an input image, in this case an MRI image, assigns separate weights and biases to numerous elements of the image and infers conclusions by comparing it with other images.[6] The pre-processed and feature extracted image is given as input to form a neural network. A CNN contains several convolutional and subsampling layers. These layers can be optionally followed by fully connected layers. The input image provided to a convolutional layer is of dimension $m \times m \times r$ where m is the height and width of the input image and r is the number of channels. An RGB image will have $r=3$.[7]

3.4 SFCM Segmentation

Fuzzy c-means (FCM) is an unsupervised clustering technique that is used in feature analysis, clustering and classification. An image can be depicted in several feature spaces. The FCM algorithm classifies and groups the images on the basis of the similar data points in the feature space into separate clusters. The process of clustering includes the repeated minimization of cost function that depends on the distance of the pixels in the image from the cluster centers. One of the important property of an image is that the adjacent pixels are extremely associated. These adjacent pixels have close feature values and there is a very high possibility that they belong to the same cluster. FCM algorithm does not incorporate this spatial relationship between the clusters. To incorporate the spatial information, a spatial function is defined,

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik}$$

$NB(x_j)$ stands for a square window concentrated on pixel x_j . SFCM is a combination of fuzzy theory and k-means clustering algorithm.[8]

4. IMPLEMENTATION

This paper was implemented using MATLAB. We used python as the programming language to implement all the algorithms that needed to included in the project. All the images are taken from an MRI machine. First the image is input into the software. After taking the input preprocessing techniques are applied to the image. The preprocessing includes implementation of median filter and the application of DTCWT algorithm for denoising and volume regulation. After that gray level co-occurrence matrix is prepared to convert the image into gray scale image. After the preprocessing stage is completed, feature extraction takes place. I feature extraction stage, the texture features and shape features are calculated and recorded. Now the filtered and feature extracted image is given as input to the neural network to form a fully convolutional neural network. The CNN helps in analyzing the image and comparing it with the test images already present in the database. CNN helps in making a decision if the given MRI image is normal or abnormal. The result are displayed in a dialogue, displaying a message “Normal” or “Abnormal”. After this, the software provides a detailed report on the MRI image displaying the affected area coloured in red.



Fig 3. GUI for the proposed system

4.1 Preprocessed image:



Fig 4. Preprocessed image after filtering

4.5 Segmentation:

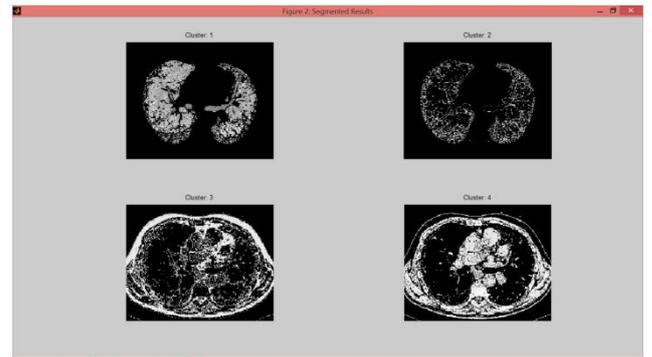


Fig 8. Results of segmentation

4.2 DTCWT stages:

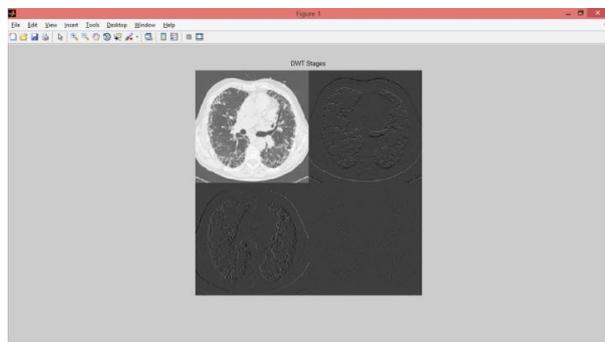


Fig 5. Four stages of DT-CWT

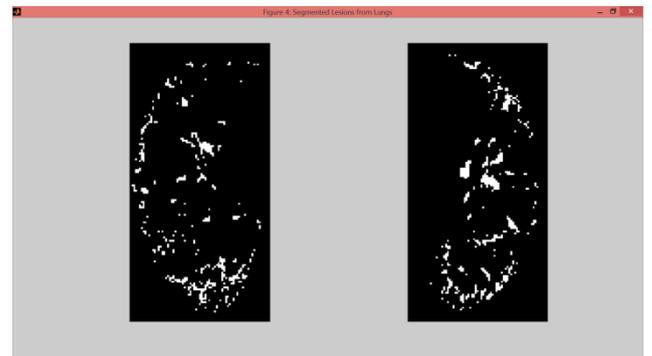


Fig 9. Segmented tumors in the lungs

4.3 Gray Scale Co-occurrence Matrix (GLCM):

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Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.
0.0468 0.0617 -0.0179 0.0322 0.0468 -0.0349 -0.0467 -0.0172 -0.0278 -0.1048
0.2012 0.2018 0.1836 0.2062 0.2012 0.1816 0.1874 0.1944 0.1871 0.1566
0.5902 0.5876 0.5541 0.5770 0.5902 0.5350 0.5161 0.5515 0.5392 0.4887

tv =
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
1 1 1 1 1 2 2 3 3 4
    
```

Fig 6. GLCM for given image

4.4 Generation of CNN:

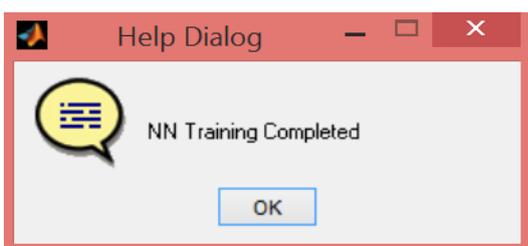


Fig 7. Dialogue box after generation of CNN

4.6 Final decision:

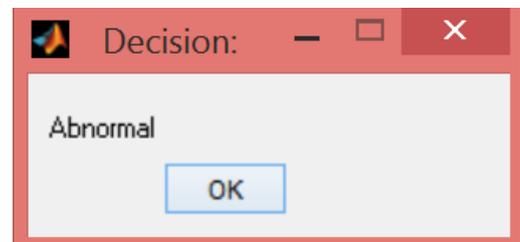


Fig 10. Decision after classification

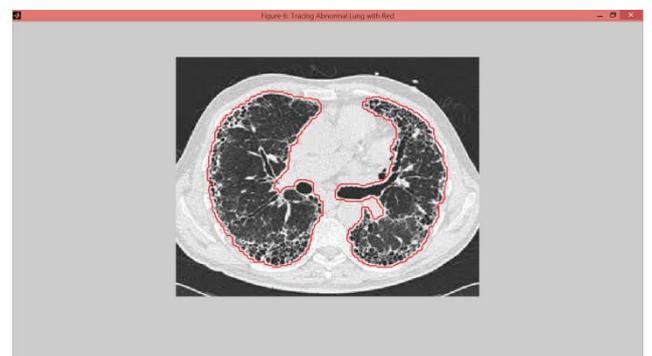


Fig 11. Tracing the affected portion of the lungs

5. RESULTS AND DISCUSSION

The experimental results of this paper are found to be accurate and in accordance to the expected result. The proposed study reduces time and increases accuracy as compared to other approaches. The proposed study provides an accuracy of 90-95% correct. . The results are verified by the medical experts. The proposed study is implemented using convolutional neural network(CNN). As the early detection of lung tumors are really important for the treatment of lung cancer, this approach can prove to be a really trustable method for detection of the same. Because of the accuracy and minimum time consuming factor, it can be used by experts worldwide. However, the accuracy can be further increased by the use of 3D CNN techniques. It provides a broader spectrum for the detection of tumors. Instead of MRI scans, CT scan images can be used as well. In future, with the enhancement of 3D imaging technique, one can use 3D CNNs for detection of tumors.

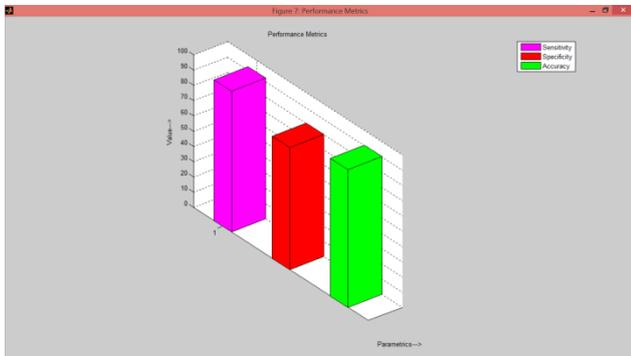


Fig 12. Histogram showing the report of the result

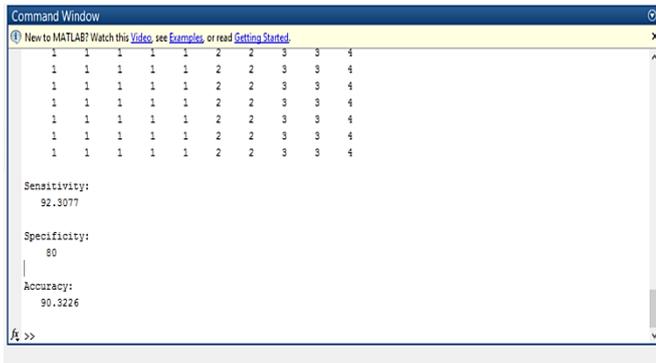


Fig13. Accuracy of the proposed system

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