AGGREGATED MODEL FOR TUMOR IDENTIFICATION AND 3D RECONSTRUCTION OF LUNG USING CT-SCAN

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ABSTRACT

This paper facilitates radiologists in diagnosis of lung tumor and provides with a probability to differentiate between the types of tumor through automated analysis and increase in accuracy. The system is aggregated model for tumor identification and 3D reconstruction of lung using (computed Tomography) CT-scan images in Digital Imaging and Communications in Medicine (DICOM) format to identify the lung tumor (Benign or Malignant) using learning algorithm. The proposed system is capable to reconstruct the 3D model of lung tumor using CT-scan medical images and identify tumor (Benign or Malignant) including location of tumor (Attached to wall or parenchyma) with significant accuracy. The proposed diagnostic software provides significant results with bright CT scans to identify lungs tissue with different orientations by rotating it and reduces the enormous false positive rate by increasing the efficiency and accuracy of the diagnostic procedure. Whereas, CT-scan image is below required brightness or if CT-scan is done in a dark room than the module does not shows considerable results of segmentation. The proposed computer aided diagnosis can help the radiologists to detect tumor at early stage, decrease the enormous false positive rate, and the overall cost of the diagnostic procedure; thus, bringing windfall benefits in the field of medical imaging.

KEYWORDS

Medical Imaging, Image Processing, Lung Tumor, Machine learning.

1. INTRODUCTION AND RELATED WORK

Health of an individual is a worldwide issue that implies lots of problems especially where health service may be deficient and unsupervised. Lungs tumor is one of the leading causes of death in both males and females. Smoking is one of risk factors of lung tumor. However, the duration of smoking and number of cigarettes consumed also contribute a lot in the risk of lung tumor. The chances of expanding lung tumor can be lowered if the habit of smoking is dropped to a certain extent. Majorly, both smokers and people are exposed to second-hand smoke. Individuals who were never passive smoker and never exposed to second-hand smoke can have tumor. There might be no apparent cause of lungs tumor in these cases. Doctors believed that lungs tumor damage the cells; when an individual inhales smoke of the cigarette, which is full of substances (carcinogens) that can cause tumor, immediately bring changes in lungs tissue.

Firstly, the body may be able to adjust these changes, but with the continuous exposure, the normal cells that link lungs are damaged increasingly. Afterwards, the damaged cells act abnormally and develop tumor eventually. The occurrence of small lungs tumor is exclusively found in heavy smokers. Small lungs tumor is least common as compared to non-small lungs tumor. Adenocarcinoma, large cell carcinoma, and squamous cell carcinoma are included within on-small cell lung tumors. Scientists currently developing a diagnostic system based on sputum color images. Many algorithms for medical imaging have been suggested. In lung tumor detection method, a robust method of abstraction was proposed in which all the features are transferred through an artificial neural network (ANN) accompanied by training the framework for classification purposes (Miah & Yousuf, 2015).

Previously, an edge system was used to recreate volumes of emphysema in the lungs (McCollough *et al.*, 2006). A limit method was appropriate for dividing each picture. However, a 3D reproduction was not endeavored. The normality or abnormality of the lung is determined by image processing-based identification of lung tumor on CT scanning images. Lung tumor has been optimized through support vector machine (SVM) algorithms and techniques (Abdillah, Bustamam, & Sarwinda, 2017). In this optimization, the function used is relied on gradient-oriented histogram, color moments, texture, and; therefore, is

graded for identifying its medicinal value (Venkataraman & Mangayarkarasi, 2017). A vector-dependent support method was used based on the gray level rivalry matrix and the eight texture characteristics histogram to describe and differentiate objects either without or with nodules (Madero *et al.*, 2015).

No thought was given during the stage of process segmentation. Similarly, lung CT images testing were performed and indicated effective use of predictive computer-aided design (CAD) for lung tumor diagnosis (Tiwari, 2016; Ritika et al., 2011). An enhanced SVM classifier was used for diagnosing leukemia tumor using a fast-correlation-based filter to choose the most influential and non-correlated genes. The picture was transformed to the processing period and provided more accurate results. Lung tumor detection phases in CT scanning pictures use different image processing techniques (Kavitha, Gopinath, & Gopi, 2017).

Picture quality appraisal changes where low pre-preparing strategies were utilized considering Gabor channel inside Gaussian guidelines. Depending on general highlights, a typical correlation was made. In this exploration, the primary identified highlights for exact pictures correlation were pixels rate and mask-labeling (Altarawneh, 2012). Lung tumor detected using the ANN has also low accuracy. It was comparatively easier for abstract or complex issues such as image identification but increase precision to strengthen the scale by several extents (Agarwal, Shankhadhar, & Sagar, 2015; AlZubaidi *et al.*, 2017).

The noteworthy change was noted in previous study conversely of masses alongside the concealment of foundation tissues, which were acquired by tuning the parameters of the proposed change work in a predefined extent (Patil & Kuchanur, 2012). A study was on lung tumor detection using a deep learning approach. A pipeline of pre-processing techniques has been proposed for emphasizing lung regions susceptible for tumor and extracted features through ResNet and UNet models. The element set was assigned into different classifiers through Random Forest and XGBoost. Methods for detecting lung tumor nodule were evaluated, including principal component analysis, support vector machines, Naïve Bayes, decision trees, and artificial neural networks, and K-Nearest neighbors. The study has compared all strategies for pre-processing and without pre-processing. According to the results, the best outcome was obtained from the ANN with approximately 82%

accuracy after image processing. CT images of lungs were examined on a computer-aided classification (Dev et al., 2019).

MATLAB software has been applied to implement all the procedures in the proposed system. Different stages entailed image pre-processing, segmentation, SVM classification, feature extraction, and image acquisition. Firstly, a threshold value was computed, and image was segmented into right and left lung. Secondly, the DICOM format lung CT image was surpassed as input, which undergone pre-processing. Lungs were extracted and passed as input to the SVM after those 33 features of each segmented lungs. Lastly, the CT image was categorized as tumorous or non-tumorous based on the training data. This strategy allows more satisfactory outcomes when compared to other current systems (Dev et al., 2019). Different computer-aided techniques were assessed for investigating the existing technique and for examining their drawbacks and restrictions. In addition, the study has proposed the new model with enhancements in the effective model. Lung tumor detection techniques were listed and sorted based on their detection accuracy.

The techniques were investigated on each step and overall restriction, whereas limitations were pointed out. Some techniques might have higher accuracy and low accuracy, but not closer to 100%. The need of 3D rotatable model was to view lungs from different orientations and other functionalities for detecting lungs tumor including feature extraction nodule detection by learning classifier, active contour-based nodule contour extraction, and nodule connectivity recognition by tissue classification. Detection of tumor using learning algorithm support vector machine (SVM) helps radiologist to diagnose the nature of tumor by performing biopsy. The proposed diagnostic tool detects and classifies lungs tumor as benign or malignant.

Detection was based on extracted features, in comparison with benign and malignant sizes. The objective was to see lungs tissue with different orientations by rotating it and reducing the enormous false positive rate by increasing the efficiency and accuracy of the diagnostic procedure. It not only reduces the overall cost but also creates a better environment for the screening of lung tumor; lessens the duration of diagnosis, and prognosis of the disease.

The significance of this paper is of twofold. Firstly, this study aims to mitigate the variability in order to assess and report the lung tumor risk between interpreting physicians. In fact,

computer assisted approaches have been observed for enhancing consistency between physicians in different clinical contexts such as mammography screening and nodule detection. Secondly, learning classifier can enhance classification performance by stimulating the less experienced or non-experienced clinicians in order to evaluate the risk of a specific nodule being malignant.

2. DESIGN PHASES

This paper has divided its objective in three different phases.

Firstly, this study extracted or selected different features for the 3D construction. Secondly, this study has developed learning classifier. Lastly, the study has designed a tool for integrated solution. In the first phase, personnel from two different areas of expertise took part. Firstly, radiologists help to understand the relative information of the anatomy, physiology of the lung functionality and the symptoms of the tumors, and their types derived from the available CT scans.

Secondly, researchers from engineering discipline analyzed the transformation of the parameters related to lung tumors (disease and their types) in computer understandable parameters, which were used to drive the further stages for developing the tool. The second phase of this paper processed the related information that was transformed from physical results of patients to computer based learning algorithms.

In this paper, one of the significant research oriented tasks was to identify the best or fairly relative feature to transform the actual information of the CT scan result into computer based outcome. Machine learning was used to achieve this goal and the selection of the feature was done from available feature stream and some were derived as new features using in-depth understanding of the physiology of the lung with and without disease. In the next step, the machine learning tool used the derived features from the previous step to select the most appropriate or accurate classifier based on recognition percentage value. These results were used to develop the combination of different classifiers with derived features to select the most accurate classifiers in particular situation. The result of the classifier identified lung tumor with appropriate features and learning classifiers.

In this phase, the CT scan images were segmented to get the mask of images by applying multiple functions of image processing. The masks of these images were combined to get the 3D image, which can be seen over different orientations using Matlab viewer. The lung tissue was used fully for radiologists to identify the tumor by just looking at the 3D reconstructed images. In the third phase of this paper, an integrated application for lung tumor detection was developed.

The results derived were used along with significant features, classifiers, and their combinations. The developed software tool for lung tumor detection was capable of addressing the following aspects:

- Improve the false positive rate of results.
- Software based CT scan Diagnosis.

2.1. FEATURE SELECTION

The following parameters for lung tumor classification, symptoms and nodule classification were Apex, Base, Lobes, surfaces and borders:

Lobes: Lobular structure of both the lungs varies from each other. The left lung comprises of inferior and superior lobes, which were divided by an oblique slit. The right lung was comprised of middle, inferior, and superior lobes. In addition, the lobes were divided from each other by two different fissures.

- Oblique fissure starting from the inferior border, it grows in the super posterior direction, till it sees the posterior lung border.
- Horizontal fissure: It increases horizontally at the 4th rib level for meeting the oblique fissure from the sternum.

Lung tumor may be caused due to the irregular and uncontrollable growth of cells in lung tissue. Lung nodules were the abnormalities in the lung tissue. They were generally small and approximately spherical masses of tissue, having a size of about 5 millimeters to 30 millimeters. Non-small cell lung tumor and small cell lung tumor were two broad categories of lung tumor.

Hemoptysis, weight loss, shortness or wheezing of breath, fatigue, fever, and coughing were the signs and symptoms of lung tumor. Due to a tumor mass, the symptoms stress on adjacent structures such as superior vena cava obstruction, difficulty swallowing, chest pain, and bone pain. The presence of metastatic disease was recommended within the symptoms, including weight loss, neurological symptoms, and bone pain. The kidney, bone, brain, adrenal glands, liver, pericardium, and opposite lung were included as common sites of spread. There were two major classifications of a tumor. It can either be a benign or a malignant tumor with the following characteristics as shown in Figure 1 and Figure 2.

2.1.1. BENIGN CHARACTERISTICS

- It was not tumorous.
- It was localized in a region and does not invade in other tissues.
- The size was less than 2 cm and does not changes for 2 years.
- It was rounded in shape with smooth edges.
- It has calcium deposits in it and the HU value was near to bone.

2.1.2. MALIGNANT CHARACTERISTICS

- It was tumorous
- It invades in surrounding tissues and may spread in the body.
- Size was more than 2.5cm.
- It has irregular and speculated edges.
- It has no calcium deposits and HU values corresponds to that of fluids and soft tissue

2.2. SELECTED FEATURES

The following features were selected for classification of tumor area, perimeter, diameter, centroid, robustness, smoothness, indentation, and calcification along with pixel value for tumor classification.

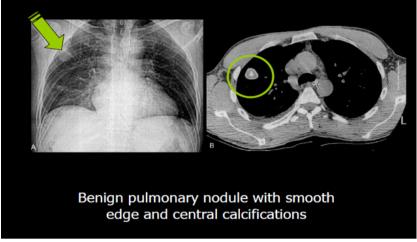


Figure 1. Benign Pulmonary Nodule with smooth edge and central calcification.

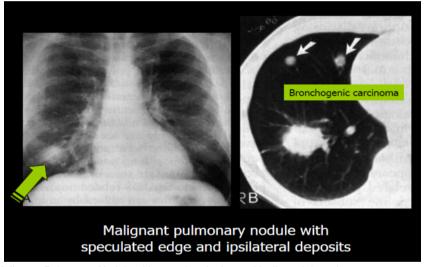


Figure 2. Malignant Pulmonary Nodule with speculated edge and ipsilateral deposits.

2.3. FEATURE EXTRACTION

Feature extraction was used to extract the lung mask from CT-scan images. Dataset was generated using 16 slice machine currently being used in many hospitals in Pakistan. It included many variations in cases. Some were squamous cell carcinoma, adenocarcinoma, and large cell carcinoma. The study has used DICOM image format using 3D Viewers to extract DICOM image features. Segmentation module was used after preprocessing to extract lung mask from CT-scan images in Figure 3. There were different set of tools used to develop the software for 3D reconstruction and identification of lungs tumor. MALAB

tool was used for Graphical User Interface (GUI), image segmentation for getting 3D functionalities, and identification of wall tumor. Figure 4 shows the basic flow of system. In 3D image viewer, function can be used to view 3D image volumes like CT scans. It has maximum Volume Rendering (VR), Slice render or intensity projections (MIP) (Figure 5). Image Segmentation for getting 3D mask functionalities comprises on following steps as shown in Figure 6.

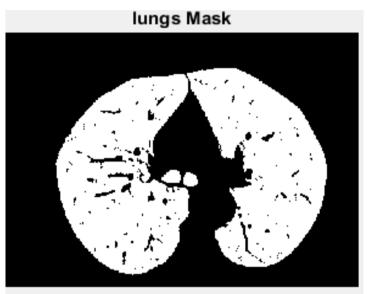


Figure 3. Lung Mask.

2.4. LEARNING CLASSIFIERS

Machine learning offers systems the competence for getting more appropriate outcome to predict result regardless being comprehensively programmed. Data mining and predictive modeling was the process involved in machine learning. Support Vector machine was an attractive approach for defining decision boundaries, as the idea related about decision planes. Simple technique for finding decision planes that a set of objects separates out between different memberships of class. SVM was used for classifying data analysis and regression analysis. For example, there was a n-dimensional space; the study has plotted each data item in each point that each feature value being the particular coordinate value. By finding the best hyper-plane, the study has performed the classification that differentiates the two classes very well.

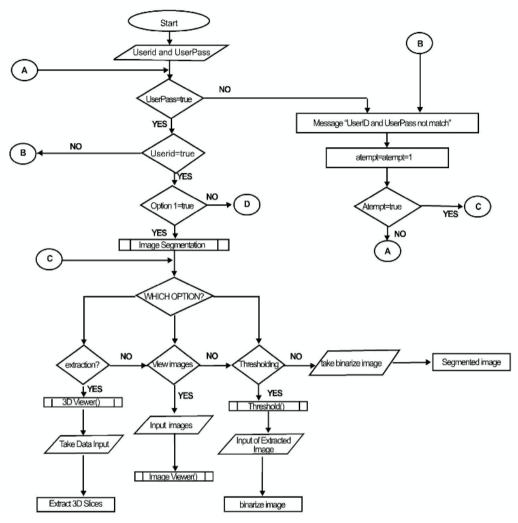


Figure 4. Design Flow Diagram.

3. EXTRACTION OF SLICES AND 3D RECONSTRUCTION

In this module, the tumor was extracted from lungs mask and converted them into object form (Array). The array obtained consists of different ranges of pixels. The number of pixels varies with the CT scan. Some CT scans may have 250 pixels; some may have more than 400 pixels. Different set of tools were used to develop the proposed software for 3D reconstruction and identification of lungs tumor.

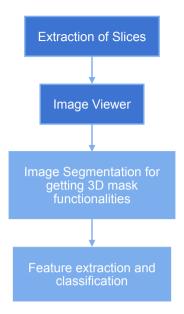


Figure 5. System Flow.

Extraction of slices were performed using 3D viewer. This function was used to view 3D image volumes like CT scans. It has a maximum Volume Rendering (VR), Slice render or intensity projections (MIP). In this window, 'File' has an option for loading medical data, 'Render' has an option viewing 3D slices, 'Volume1' indicates that data was loaded and 'save picture' was used for saving slices coronal (XY), sagittal (YZ) and axial (XZ) (Figure 6).



Figure 6. Basic flow of 3D Viewer for extraction of slices.

4. IMAGE SEGMENTATION AND THRESHOLDING

Image segmentation divides the data into adjoining regions elected by individual anatomical objects. The process of image thresholding was to divide an image into a background and a foreground. Objects were isolated from image segmentation and gray scale images to binary images. One of the most influential aspects in images was image thresholding with high

contrast levels. 'Load' option was used for load slices image that applies thresholding, moves the 'Threshold slider' to adjust the segmentation until the lungs appear well-delineated, and simply sets the 'minimum' and 'maximum' properties. The 'save' option was used for saving thresholding slices images individually as shown in Figure 7.

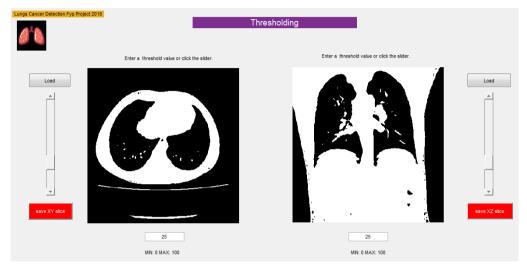


Figure 7. Image Threshold Window.

Image viewer window was used for viewing each slice individually. The following steps were developed to 3D reconstruction of lungs using mask shown in Figure 8.

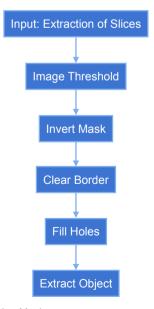


Figure 8. 3D Reconstruction of Lungs Using Mask.

4.1. INVERT MASK

On the segmentation tab, click 'Invert mask' to make the segmented lungs the foreground. 'Imcomplement()' unction was the complement of binary image; black become white and white become black; zeros and ones were reversed.

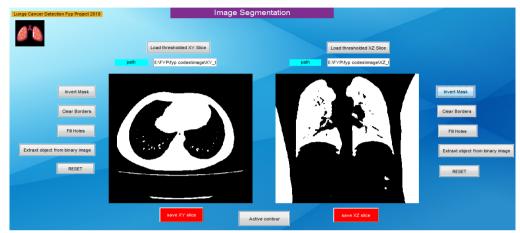


Figure 9. Invert Mask on Image Segmentation Window.

4.2. CLEAR BORDER

On the segmentation tab, click 'Clear border' removed all the segmented parts that were not the lungs. Since these all touch the edges, use the 'imclearborder()' function to remove them.

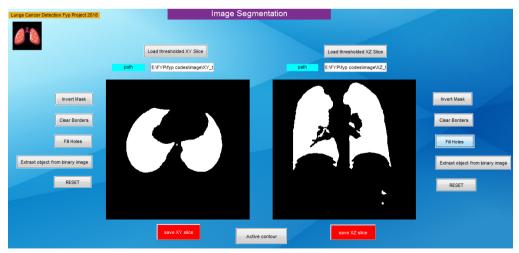


Figure 10. Clear Border on Image Segmentation Window.

4.3. FILL HOLES

On the segmentation tab, click 'Fill holes' means fill the small holes that appear in the lung areas. Use 'imfill(t,'holes')' function means input binary image filled with holes.

4.4. EXTRACT OBJECT

On the segmentation tab, click 'Extract objects' mean extract objects from binary image by size. Use 'bwareafilt(t1,n,keep)' function means it keeps the 'n' largest/smallest objects. If you want to keep n largest object, specify the 'keep' parameter with the value 'largest'.



Figure 11. Extract Objects on Image Segmentation Window.

4.5. JPEG, TIFF IMAGE SEGMENTATION

In this module, a JPEG or tiff image was loaded and checked whether it was a grey scale image or not. If not than it was converted into a grey image. Afterwards, the grey image was used as input to draw the histogram of the pixels value in the image. The image was then binaries and fill holes and clear border function was applied to filter the image. A function to extract two lobes of lungs was called and extracted the lungs from the CT scan. Finally the lungs mask was obtained by inverting the lungs using binary image.

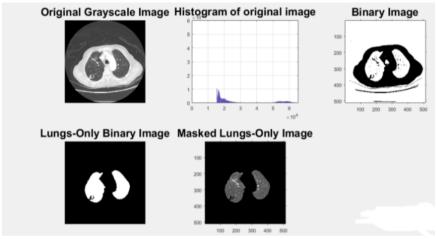


Figure 12. Tiff Image Segmentation.

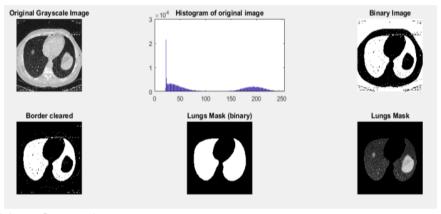


Figure 13. Image Segmentation.

5. RESULTS AND DISCUSSION

To detect the tumor, proposed software methodology was tested on two fronts. Due to the limited amount of data availability, the core focus was on a single image testing. The array obtained from the previous module contains the length of pixel in mm. This data was used to train the SVM algorithm and classified the data into two hyper planes. First, hyper plane was assigned 1 for which the length of the pixel was below 30mm and the other hyper plane consist of the pixels having length more than 30mm and they were assigned as -1. Since the size for malignant tumor was more than 30mm, so basically this algorithm was based on classifying malignant and benign tumor as shown in Figure 14.

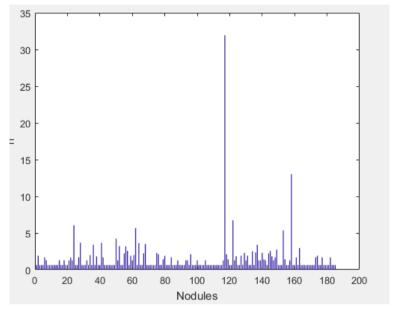


Figure 14. Position of pixel for more than 30mm.

All three modules were tested on single slice data of CT scan. The slice selected for input was on random basis and was manually selected for gaining accurate results. Tumor on selected slice was clearly visible so that the results can be compared, and the accuracy of the module can be found. Two image testing formats were used in this proposed software 1) TIFF format and 2) JPEG format. The input was provided in TIFF format to module and applied segmentation on image, TIFF images having less count than JPEG image. In the output stage, considering JPEG image which were much clear than TIFF image. In the final phase of the system, the extracted tumors were then passed to a machine learning algorithm. The algorithm compares the size of extracted tumor to the learned size and if the size of some pixels exceeds a particular value then malignant tumor was identified. The study has compared the results with the radiologists. If the malignant probability was more for a case of malignant that means that system was working correctly. The study had found no false negative rate in the system.

This study has performed image processing on CT scan image so the quality of image was critical. Experimental output provided significant results with bright CT scans. CT scan image was below required brightness or if CT scan was done in a dark room than the

module cannot do segmentation clearly. Accuracy of machine learning algorithm depends on the data set. The more the data set, the more accurate results will come.

The system's accuracy was currently compromised due to limited data. The accuracy can be improved by training and testing the data on larger amount of data. Furthermore, some other more advanced machine leaning methods can also be used for better performance. Currently, the study was working on supervised learning to switch to unsupervised algorithm, which may prove to be better for the accuracy of the system. The algorithm can be implemented to other imaging techniques like PET scan, MRI, Nuclear Medicine, bioluminescence, mammography, fluorescence etc. so that one can see which technique works well with computer aided diagnosis of lung tumor detection.

6. CONCLUSION

In this study, computer aided diagnosis software was proposed that can detect and classify lungs tumor as benign or malignant. Detection was done based on extracted features, in comparison with benign and malignant sizes. This proposed method incorporated functionalities like segmentation of lungs through threshold and some morphology functions to obtain the mask of lungs and then use these masks to make a 3D model. The need of 3D rotatable model was to view lungs from different orientations and other functionalities for detecting lungs tumor are feature extraction nodule detection by learning classifier (SVM), Active Contour Based Nodule Contour Extraction and Nodule Connectivity Recognition by Tissue Classification. The diagnostic tool was capable for reconstructing the 3D view of lung tumor and classifies the nature of tumor by identifying the location of tumor attached to the wall or parenchyma. Furthermore, diagnostic tool reduces the false positive rate by improving the significant accuracy. Moreover, this application will help in the reduction of the overall cost and create a better environment for the screening of lung tumor using CT scan (Medical Imaging), lessen the duration of diagnosis, and prognosis of the disease using learning algorithm.

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