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AN EXAMINATION OF THE USE OF MORPHOLOGICAL PROCESSING IN IMAGE PROCESSING FOR THE PRECISE AND EARLY STAGE IDENTIFICATION OF LUNG CANCER

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ABSTRACT

One of the most deadly and pervasive diseases, cancer causes a significant number of fatalities each year. Lung cancer is the most common and has the greatest fatality rate of all the major forms of cancer. Computed tomography scans are employed to detect lung cancer because they give a clear image of the tumor inside the body and monitor its development. Despite the fact that CT is favored over other imaging modalities, visual interpretation of these CT scan pictures may be a laborious process that increases the chance of mistake and delays the discovery of lung cancer. As a result, several medical professions utilize image processing algorithms for lung tumor early detection. This paper presents an automated approach for detection of lung cancer in CT scan images. The algorithm for lung cancer detection is proposed using methods such as median filtering for image pre- processing followed by segmentation of lung region of interest using mathematical morphological operations. Geometrical features are computed from the extracted region of interest and used to classify CT scan images into normal and abnormal by using support vector machine.

INTRODUCTION

Cancer death rates are rising daily, making it a notable global public health concern. The most frequent and lethal kind of cancer that affects both men and women is lung cancer. Lung cancer, also known as carcinoma, is the development of malignant lung tumors (cancerous nodules) as a result of unchecked cell proliferation in the lung tissues. The two main risk factors for developing malignant lung nodules are smoking and tobacco use. In all, just 14% of lung cancer patients survive the disease after all stages, during a period of 5–6 years. The primary issue with lung cancer is that it is typically discovered when it is well advanced, making treatment more difficult and drastically decreasing survival rates. Hence detection of lung cancer in its earlier stages can increase the survival chances up to 60-70% by providing the patients necessary fast treatment and thusit curbs the mortality rate. Small cell lungcancer and non-small cell lung cancer are two main types of lung cancer classifications based on cell characteristics. The mostcommonly occurring is non-small cell lungcancer that makes up about 80-85% of all cases, whereas 15-20% of cancer cases are represented by small cell lung cancer. Lung cancer staging depends on spread of cancer in the lungs and tumor size. Lung cancer ismainly classified into 4 stages in order ofseriousness: Stage I-Cancer is confined tothe lung, Stage II and III-Cancer is confinedwithin the chest and Stage IV-Lung cancerhas spread from the chest to other parts of thebody. Lung cancer diagnosis can be done byusing various imaging modalities such Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and Chest X-rays. CT scan images are mostly preferred over other modalities because they are more reliable, have better clarity and less distortion. Visual interpretation of database is a tedious procedure that is time consumingand highly dependent on given individual. This introduces high possibility of human errors and can lead to misclassification of cancer. Hence an automated system is ofutmost importance to guide the radiologist inproper diagnosis of lung cancer. The methodology developed for this systemincludes dataset collection, pre-processing, lung segmentation, feature extraction andclassification.

LITERATURE SURVEY

Lung cancer has become one of the most significant diseases in human history. The World Health Organization estimates the worldwide death toll from lung cancer will be 10,000,000 by 2030. The 5-year survival rate for advanced Non-Small Cell Lung Cancer (NSCLC) [1] remains disappointingly low. It has been hypothesized that quantitative image feature analysis can improve diagnostic/prognostic or predictive accuracy, and there- fore will have an impact on a significant number of patients [2]. In the current study, standard-of-care clinical computed tomography (CT) scans were used for image feature extraction. In order to reduce variability for feature extraction, the first and essential step is to accurately delineate the lung tumors. Accurate delineation of lung tumors is also crucial for optimal radiation oncology. A common approach to delineate tumor from CT scans involves radiologists or radiation oncologists manually drawing the boundary of the tumor. In the majority of cases, manual segmentation overestimates the lesion volume to ensure the entire lesion is identified [3] and the process is highly variable [4,5]. A stable accurate segmentation is critical; as image features (such as texture and shape related features) are sensitive to small tumor boundary changes. Therefore, a highly automatic, accurate and reproducible lung tumor delineation algorithm would represent a significant advance.

Accurate extraction of soft tissue lesions from a given modality such as CT, PETor MRI is a topic of great interest for computer-aided diagnosis (CAD), computer-aided surgery, radiation treatment planning and medical research. However, segmentation of a lesion is typically a difficult task due to the large heterogeneity of cancer lesions, noise that results from the image acquisition process and the characteristics of lesions often being very similar to those of the surrounding normal tissues. Traditional medical image segmentation techniques include intensity- based or morphological methods [6–9], yet these methods sometimes fail to provideaccurate tumor segmentation. A lung tumoranalysis (LuTA) tool [10] within the DefiniensCognition Network Technology [11] wasdeveloped by Definiens AG [12] and Merck &Co., Inc. . . It is a prototype application that demonstrates the ability to automatically and semi-automatically identify and recognize organs and tumors in CT images. With the motivation of overcoming the above drawbacks of the ‘‘Click & Grow’’ algorithm, we propose a new delineation algorithm basedon using multiple seed points with region growing [13]. The new algorithm makes use of the original algorithm by using an original seedpoint to define an area, within which multiple seed points are automatically generated. Ensemble segmentation can be obtained from the multiple regions that were grown. Ensemble segmentation has played an important role in many medical image applications recently [14–15] and refers to a set of different input segmentations (multiple runs using the same segmentation technique with different initializations) that are combined in order to generate consensus segmentation. In this paper, we demonstrate that such an approach reduces inter observer variability with significantly fewer operator interactions when compared to the original algorithm.

EXISTING SYSTEM

The existing methodology for lung cancer detection in CT images is done by visual interpretation of doctors. Visual interpretation of database is a tedious procedure that is time consuming and highly dependent on given individual. This introduces high possibility of human errors and can lead to misclassificationof cancer.

The previous techniques comprise of study of Mammography, Computerized Tomography Scan, Magnetic ResonanceImaging images. The professional physicians identify the disease and determine the stages ofcancer by professionalism. The treatmentincludes some surgical procedures, chemical treatment

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to kill or halt the replication and stopof cancerous cell, radiotherapy and targeted therapy. This analysis is very long, expensive and part of the body affected with pain.

PROPOSED SYSTEM

In proposed system of the lung cancer detection in CT images median filters are used for better enhancement. Support Vector Machine (SVM) is used for accurate classification of lung cancer. The proposed system for lung cancer detection in CT imagesis shown in figure.

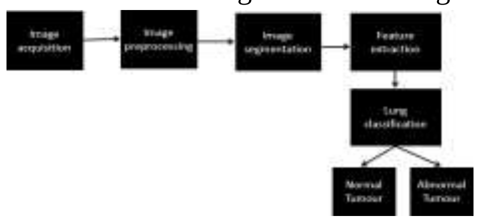

Fig 1: Block diagram of the proposed system

SOFTWARE

For developing this project, we mainly used software is MATLAB. The MATLAB software stands for MATRIX LABORATORY. MATLAB is a high performance language for technical computing. MATLAB is a data analysis and visualization tool which has been designed with powerful support for matrices and matrixoperations. As well as this, MATLAB has excellent graphics capabilities, and its own powerful programming language. One of the reasons that MATLAB has become such an important tool is through the use of sets of MATLAB programs designed to support a particular task. These sets of programs are called toolboxes, and the particular toolbox of interest to us is the image processing toolbox.

METHODOLOGY

Data Collection

The first step is to obtain lung CT images of cancer patients. For research work, the images have been downloaded from the Cancer Imaging Archive database. The images are stored in DICOM format. The image database contains ComputedTomography images of patients with and without lung cancer.

Image Pre-Processing

The objective of image preprocessing stage is to suppress unwanted distortions present in the image and to enhance some features useful for further processing. It includes two main steps such as image smoothing and image enhancement. Image smoothing is done to remove unwanted noise present in the image. CT scan images are prone to salt and pepper noise, hence median filtering is found to be quite effectivetechnique in eliminating this impulse noise while preserving the edges. Median filtering gives the best results for image smoothing asit removes noise without blurring the image.

Image enhancement technique improves the quality of digital images to produce better output for further processing. Contrast adjustment is done to enhance the image since image quality is affected by artifacts caused due contrast variations in the image. Contrast adjustment enhances the contrast of an image by transforming input pixel values to new values such that by default 1% data gets saturated at low and high intensity of input image data.

Image Segmentation

The process of separating out required region of interest from the image is known as segmentation. Mathematical morphologicaloperations are powerful tools in acquiringlung region from binary images. In our methodology, first the preprocessed gray scale images were converted to binary images.

Morphological opening operation was performed to the binary image with disk structuring element for removal of unwanted components from the image. The opened image was then complemented and clear border operation was performed to it. The lung masks were obtained by filling the holesand gaps present in the lungs. Finallyexclusive OR operation was performed tolung mask output and clear border output to give us the segmented tumor region.

Feature Extraction

Feature extraction is the most essential step that transforms input data into required features. This stage extracts out significant features of segmented region of interest and these features serve as input for classification of CT scan images. The size and shape of tumor present in the lungs is estimated by extracting three geometrical features. The features are area, perimeter and eccentricity of cancerous lung nodule.

Area: This is a scalar quantity which gives total number of pixels acquired by cancerous lung nodule. The area isevaluated from the binary image by taking summation of pixel areas in theimage that are registered with value 1.

Perimeter: This is a scalarquantity that gives the total pixelspresent at the border of the lung tumor. The perimeter is evaluated from the binary image by summing the pixels registered with value 1, at the outline of lung nodule.

Eccentricity: This metric value is also referred to irregularity index (I) or circularity or roundness. For a circular shape eccentricity value isequal 1 and the value is less than 1 forany other shape.

Eccentricity =length of major axis/length of minor axis

Classification

The Classification stage involves labelingthe CT scan images as normal and abnormal.In our method SVM algorithm will be used for detection of lung cancer in CT images. SVM classifiers are supervised learning models that analyze input data and classify them according to pattern. The SVM classifier builds a model by using training dataset and categorizes it into two classes. The SVM algorithm then assigns new examples of testing dataset to one of the two classes. SVM classifier thus finds the best hyper plane that separates the two groups and thus classifies the lung CT images.

ADVANTAGES

1. Increase in accuracy of cancer noduledetection than the best current model.

2. Classifies the detected lung cancer asmalignant and benign.

3. Removes salt and pepper noises from imageswhich causes false detection of cancer.

APPLICATIONS

The main application of the detection oflung cancer in CT images using image processing is medical field. Although CT is preferred over other imaging modalities, visualinterpretation of these CT scan images may beerror prone task. Therefore, image processing techniques are widely used in medical fields forearly stage detection of lung tumor.

EXPERIMENTAL RESULTS

The implementation of proposed system was done using MATLAB software.Database for this study was obtained from the Cancer imaging Archive (TCIA). Fig 2 shows the CT scan image of patient affectedby lung cancer and its corresponding histogram. Histogram of an image is a graphical representation of an image which gives pixel distribution amongst its various gray levels.

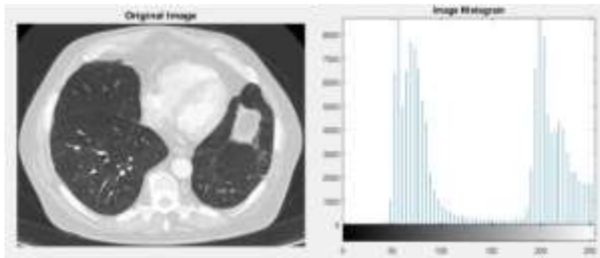

Fig. 2. Cancerous lung CT image and histogram of image

Next, a 3*3 median filter was applied to the lung CT images to eliminate salt and pepper noise from the image while preserving the edges.

Fig.3.Median filtering method forimage smoothing

Further in the preprocessing stage image enhancement was done using contrast adjustment.

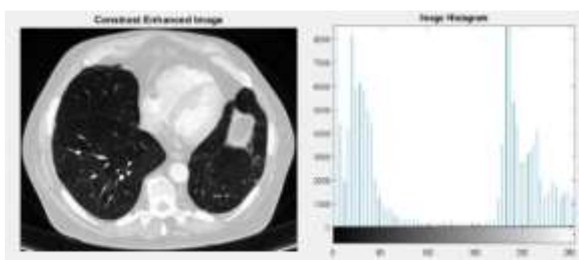

Fig. 4. Contrast enhanced image and histogram of image

The lung masks and tumor region were obtained from CT image as shown in Fig 5.

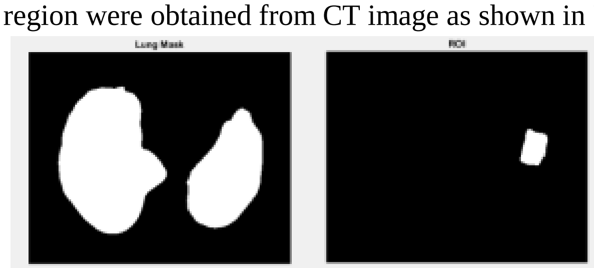

Fig. 5. Lung mask and extracted tumor region

Next three geometrical features namely area, perimeter and eccentricity were extracted from segmented tumor region.

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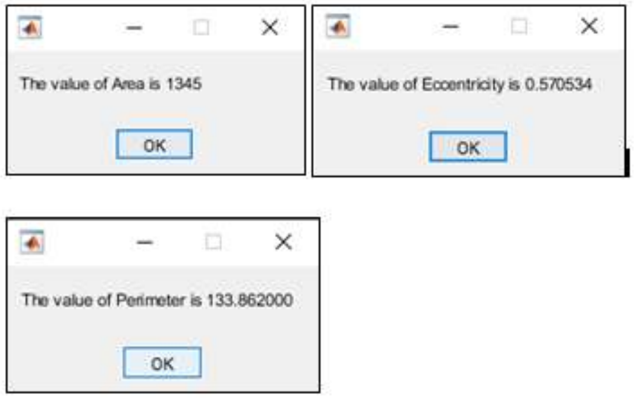

Fig. 6. Message boxes with features

In the final stage, SVM classifier is used to determine whether the CT scan imagesare cancerous or non cancerous.

Fig.7.Message boxes with final result

CONCLUSION

In this study, an image processing approach was effectively used to create a system for the automated identification of lung cancer in CT scans. When it comes to improving, segmenting, and extracting characteristics from CT images, the selected technique works effectively. The median filtering method worked well to remove impulsive noise from the photos without distorting them. Accurate segmentation of the lung and tumor regions is made possible by mathematical morphological processes. Area, perimeter, and eccentricity, three geometrical parameters, were taken from the segmented tumor region and supplied into the classifier's input for the categorization of lung CT scans into normal and abnormal. Hence this proposed methodology helps in accurate and early stage detection of lung cancer.

FUTURE SCOPE

Future enhancements will focus on part-solid tumor types, which result in unstabletumor boundaries when given different start seed points. The problem of incomplete tumorsegmentation with big tumors is also a remaining challenge.

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