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Review on Lung Cancer Detection Techniques

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Abstract - *Cancer is the root cause for a large number of deaths, out of which lung cancer is the cause of the highest mortality rates. After heart attack lung cancer is the most prevalent one which increases the mortality rate in our country. It is reported that lung cancer is due to alcohol and tobacco consumption. We can save the lives of many through early detection of cancer. Computer-aided diagnosis systems were brought to assist doctors through medical images. CAD system find out the abnormal growth in the image called nodules. CAD system includes nodule detection, image segmentation, false nodule reduction and nodule classification. Current models initially perform image segmentation and then classify it as malicious or benign which segments both normal as well as abnormal nodules results in false classification of images.*

Key Words: CAD, Segmentation, Nodule Extraction, Deep Neural Network, Benign, Malignant.

1. INTRODUCTION

Early detection of cancer can save people from malicious attacks. Typically, visual examination and manual interpretation of medical images demands high time consumption and is highly prone to mistakes. For this reason, computer-aided diagnosis (CAD) systems were brought to assist doctors through medical images and find the abnormal growth in the image called nodules which might be the first sign of cancer detection. It is always efficient to perform nodule classification before segmentation rather than segmenting the image and then predicting whether it is cancerous. In the latter due to erroneous lung segmentation, findings might be missed or findings outside the lungs might be included in the analysis which will result in improper prediction of cancer whether benign or malignant.

2. LITERATURE SURVEY

For the diagnosis of lung cancer CT (Computed Tomography) is one of the best methods for examining pulmonary nodules [1]. Quality of image depends on the radiation dose [2] but it affects our body since most of the x-rays are being absorbed by the lungs. In order to reduce the risk physicians are advised to reduce the radiation dose which affects in the quality of the image with noise. For lung cancer detection different methods are involved mainly (i) Preprocessing (ii)Segmentation (iii)Nodule extraction (iv)Classification

2.1 Preprocessing

Image preprocessing is the initial step for the automatic detection of diseases. It simplifies identification and classification in the upcoming steps. Generally, in biomedical applications object and contour preservation is important so Farag et al. introduced technique for such detailed structures. Certain noises and distortions can be eliminated using applying median filtering[3],wiener filtering[6],Gaussian filtering [6][7],bilateral filtering[8] and high pass filtering technique[9].Combining two filters can also enhance the nodule in the images just like combination of median filters with Laplacian filter .Basically for medical images bilateral filter provides better result in preprocessing. In pathological images morphological information plays a vital role in feature extraction. By using morphological filters like spherical enhancement filter will enhance the image region [10] thereby enhance the nodule structure for classifying it as benign and malignant. Internal factors like poor lightning technique cause poor contrast so for removing such distortions adaptive median filtering can be used. Generally, in CT scan images CLAHE equalization technique can be used to improve the contrast. In 3-D images, 3D multi-scale structure enhancement filters are applied based on eigen values of the Hessian matrix for separating nodule structures from vessels and bronchi.

2.2 2-D and 3-D Segmentation

Partitioning the pre-processed CT image into multiple regions to identify the pixel values from the surrounding anatomy is done in the segmentation phase. Generally, 2D and 3D approaches are involved in the segmentation phase. Segmentation is based on certain factors namely: threshold, stochastic, region-based, contour based and learning based. Binary image reduces and simplifies complexity as well as process of recognition and classification by applying thresholding from grey scale images. If Pixel values of the component and background are consistent in their respective values over the entire image, global thresholding is applied. Three types of thresholding algorithms mainly Global, Local, Adaptive thresholding. Different global thresholding techniques are Otsu, optimal thresholding, histogram analysis, and iterative thresholding, maximum correlation, clustering, multispectral and multi-thresholding. Threshold based clustering results in effective storage and fast retrieval. Fuzzy c means, K-means are different clustering methods. Otsu algorithm is good for evaluating since it simplifies the calculation of threshold. But too much noise in the background will occur. Region based technique are better than edge-based technique in noisy images where edges are difficult to detect mainly for lung tissue segmentation which has described by Aggarwal et al. [12], Lee at al. [13]. In region growing textual features [14] local binary patterns are used as ROI. SURF and LBP descriptors are used for generating the features for describing the texture. Certain morphological operations like closing and opening is done for combining the region growing. Stochastic approach described by Guo et al. [15] used lung segmentation method using expectation-maximization (EM) algorithm with morphological operations. Segmentation technique also involves isolation of lung region from the surrounding structure using Gibbs Markov Random Field (GMRF) and abnormalities in the lungs are detected using adaptive template matching and genetic algorithm. Contour based methods include deformable and gradient based methods. Bellotti et al. [16] described region growing with contour to isolate juxta-pleural nodules. Sobel based edge detection is used to detect the cancer nodules and for extracting the nodule boundaries snake algorithm is used. For extracting lung background Tariq et al. [17] used gradient mean and variance methods. Rule based technique is applied to use fuzzy map to improve contrast between nodules and background. Genetic algorithm can be applied along with thinning algorithm to detect lungs edges. There are different approaches in volumetric lung nodule segmentation. They are as follows: thresholding, mathematical morphology, region growing, deformable model, and dynamic programming. After applying k- means clustering or gradient magnitude algorithm appropriate values can be deducted based on threshold values adopted by Zhao et al. [18]. For detection of lung nodules in 3D CT images Mathematical Morphology was used. By using binary morphological filtering Kostis et al. [19] and Kuhnigk et al. [20] have proposed iterative approaches with various combinations of these basic operators. Okada et al. [21] discribed a data-driven method for finding the ellipsoidal structuring element by using anisotropic Gaussian fitting. To discriminate the volumetric lung nodules from other dense structures Fetita et al. [23] proposed a gray-level mathematical morphology operator. In, Goodman et al. [24] introduced segmentation of the lung nodules using watershed algorithm followed by a model- based analysis. More recently, studies used the region growing approach for overall segmentation algorithms. From a prior segmented image with geodesic distances Diciotti et al. [21] proposed a modified region growing algorithm. The existing concept with Euclidean distance map is also introduced later. A 3D region growing algorithm is used by Gong et al. for segmenting the lung lobes and used Otsu threshold algorithm for extracting the regions of interest. Graph-Cuts is one of the techniques for region-based segmentation. By using coupled segmentation-registration method with B-spline registration, Zheng et al. [22] applied graph- cuts to find the initial 2D nodule segmentation. Deformable models introduced by Kawata et al. [25] are used mostly for 3D segmentation purposes by adopting the geodesic active contours approach. Active contours is used in image segmentation research community. By taking 3D gradient, curvature, and penalized contours Way et al.[26] proposed an active contour method which minimized energy. Dynamic Programming is another technique for detecting optimal contours in images. Several methods extend this technique to a 3D surface detection process. Before applying the standard 2D dynamic programming algorithm transformation of 3D spherical lung volume to the 2D polar coordinate system is done for detecting 3D lesion boundary. According to Diciotti et al. [27] segmentation algorithms is evaluated with well-defined labels for verification on large databases. Generally, a nodule will appear in several slices of image in a CT scan. In 2D method, benign and malignancy are found out by the slice with the greatest sized nodule. Compared with 2D method, the addition of extra dimension dramatically increases the complexity in operations and computational cost for processing the entire 3D nodule volume.

2.3 Nodule Extraction and Classification

Lung nodule detection identifies the location of the nodules. Detection by classification and clustering is the most widely approach. This comprises four categories: Fuzzy and neural network, K- nearest neighbor, Support vector machines and linear discriminate analysis. A knowledge-based, fully automated method uses Fuzzy rules designed by Brown et al. [28] developed for segmenting volumetric chest CT images. Anatomical model, image processing routines, and an inference engine are utilized in the modular architecture. Later, an automated rule-based classifier was developed by Li et al. [29] for classifying nodules and non-nodules. For segmentation lung Computed Tomography (CT) image to identify the lung nodules detection Bong et al. [30] applied state-of-the-art fuzzy hybrid scatter search by utilizing fuzzy clustering method. Later for the lung nodule CAD application employed two fuzzy methods: The Mamdani model and the Sugeno model of the fuzzy logic system. Through ROC curve analysis and root mean squared error methods these method's results were compared and evaluated. Artificial neural networks for lung nodule detection were employed by Arimura et al. [31]. By Directional-gradient concentration (DGC) and morphological opening, identification of the pleural region is proposed by Reticoet al. [32] here after features extraction candidate nodules are classified using Feed-forward Neural Network. Combining fuzzy logic and neural networks a two-level convolution neural network was proposed by Lin et al. [33] Lin and Yan and Lin et al [34]. Here, lung nodule detection and combination were superior to rule-base, convolution neural network, and genetic algorithm template matching approaches. Automatic detection of pulmonary nodules in low-dose CT images was done by adopting a decision fusion technique to develop a computer-aided detection (CAD) system which was proposed by Antonelli et al. [35]. In the classification stage, multi-classifier systems were introduced by aggregating the decisions of a feed forward four-layer neural network and a decision tree. Recently, Akram et al. [36] implemented Artificial Neural Networks based on hybrid features consist of 2D and 3D Geometric and Intensity based statistical features. A nearest cluster method was used by Ezoe et al. [37]and Tanino et al. [38] for classification and the detection of nodules candidate. Estimation of probability density function of intensity value of the trained opacity nodules was proposed by Zhao et al. [39] by boosting KNN classifier. With k-nearest-neighbor (KNN) classifier Kockelkorn et al. [40] designed a user-interactive framework for lung segmentation. After that, Mabrouk et al. [41] selected a total of 22 image features from the enhanced CT image. Then, a fisher score ranking method was used for feature selection to select the top ten features and classification was done by K-Nearest Neighborhood classifier. To classify the nodule feature vectors Support vector machines (SVM) were performed by Ginneken [42]. Based on the concept of machine learning, Lu et al. [43] also used this method for classifying the volumetric lung cancer.

2.4 DCNN based Approach

A novel contour- based minimum model for nuclei segmentation using minimal a prior information is developed by Antoine Veillard et al [44]. With respect to shape features this framework avoids a segmentation bias. In general, deeper neural networks are more difficult to train and the learning was done using unreferenced functions. By increasing the depths, complexity will be high. So, Kaiming He et al. [45] reformulated the layers as learning with residual functions with reference to the layer inputs and provides comprehensive empirical evidence by increasing depth which shows these residual networks are easier to optimize, and can gain accuracy. Weakness of deep segmentation models results in implausible segmentations which results in the limited ability to encode smoothness and preservation of complex interactions between object regions. In the work of AïchaBenTaieb et al [46], formulated and optimized a new loss, by introducing the first deep network trained to encode geometric and topological priors of containment and detachment. Previously, gland segmentation and contour prediction were treated as a single and independent problem. When the glandular structures are seriously deformed, they may fail to achieve satisfying performance in malignant subjects. So here, Hao Chen et al. [47] formulated a multi-task learning framework by using the complementary information, which results in both object detection and contour detection. Segmentation techniques have not demonstrated to work on multiple organs or disease states right out of the box (without re-training). Neeraj Kumar et al. [48] found out inter-nuclear boundaries using a third class of pixels to separate crowded nuclei. The newly technique trained to work on multiple organs as well. Two classes are introduced including third class of pixels (nuclear boundary), in addition to the two usual class background (outside all nuclei) and foreground (inside any nucleus). Only few features have been extracted for cancer nodules. No preprocessing like noise removal, image smoothing which can probably assists in increasing the detection of nodules accurately has been implemented and no classification as benign or malignant of extracted cancer has been performed. So, a new technique by Suren Makajua et al [49]. removes salt-pepper noises and speckle noise that creates false detection of cancer. Classification as benign or malignant of extracted cancer has been performed. All existing methods of semantic segmentation still suffer from two aspects of challenges: intra-class inconsistency and inter-class in distinction. A Discriminative Feature Network (DFN), which contains Smooth Network and Border Network was introduced by Chang qian Yu et al. [50]. ASmooth Network with Channel Attention Block and global average pooling were introduced to select the more discriminative features along with a Border Network to make the bilateral features of boundary distinguishable with deep semantic boundary supervision. To handle the intra-class in- consistency problem. Smaller strides or patching with a lot of overlapping is both, computationally intensive and results in redundant information. Secondly, in the field of biomedical image, analysis is constrained by the lack of huge annotated samples. Small patches and large patches result in loss of contextual information and tamper with the localization results respectively. Lastly, non-overlapping patches results in a loss of context information. An architecture called U-Net convolutional implemented by Humera Shaziya et al. [51] exclusively for the segmentation of biomedical images. Primarily U-Net employs data augmentation technique to increase the size of the data which does not create limitation in number of data. Due to the diversity in staining procedure, cell morphology, and cell arrangement between different histopathology images, especially with different color contrasts are yet remains to be a challenging task. Zitao Zeng et al. [52] not only extract the semantic information of the former layer, this do pay much attention to the shallower layers' semantic information too by introducing RIC-UNET for image segmentation and classification. Residual block to extract more representative features for segmentation. Inception module for its computational efficiency while incorporating multiscale features with different kernel sizes. Channel attention mechanism can focus the parameter training on the region of interest and alleviate the over fitting problem. End to end trained deep multi-instance networks for mass classification based on the whole mammogram image was done and not on the basis of region of interest (ROI). So, Dina A. Ragab et al. [53] introduced CAD system to classify benign and malignant mass lesions from mammogram samples. Using a threshold and region-based techniques for segmentation DCNN is connected to SVM to obtain better classification results.

3. CONCLUSION

The performance of lung segmentation is highly dependent on disease prediction task. Challenges for predicting and segmentation raise the need of using multiple learning techniques. Current models initially perform image segmentation and then classify it as malicious or benign. This consumes more time since it segments both normal and abnormal nodes. Due to improper segmentation of images the region of interest will be inaccurate and results in false classification of images.

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