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A Review on Computer Aided Detection of Nodule from Computed Tomography Images Of Lung

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ABSTRACT: The early detection and diagnosis of lung nodules can be done with the help of medical imaging systems. Computer aided diagnosis system reduces the complexity of nodule detection significantly. The main aim of this paper is to inspect various methodologies used in the process of nodule detection and diagnosis. The first part provides an overview of the computer aided diagnosis system, from the process of data acquisition to the final nodule classification stage. The paper discusses various trends and techniques adopted by different works carried out in the area of nodule detection and diagnosis. Favorite data sources, techniques of nodule-segmentation, modes of feature extraction, selection and different classification methods used in different works are discussed in a systematic manner. The final part discusses about the short comings of available databases and techniques. It also put forth some system modifications and suggestions for better results and efficient detection and classification of nodules.

I. INTRODUCTION

Lung cancer is one of the most common causes of cancer deaths in the world. It is because of the lack of efficient systems to identify the disease at its preliminary stages. Lack of symptoms and the inability in detecting the disease at an early stage lead to the missing of timely treatments. Identification of the diseases at a later stage will result in decreased survival rate of the patient. Appropriate and effective treatment can be done only if the presence of the disease is identified at early stages.

Computer-aided detection system

During the process of medical image interpretation radiologists seek the help of Computer Aided Detection (CAD) systems. It reduces the misinterpretation and provides supportive hints to the radiologists regarding the status of the analyzed image. Basic stages are shown in the figure 1, through which a CAD system processes an image. The acquired images are segmented and from that, various features are extracted and selected. The nodules are classified by analyzing the features.

Data acquisition

Data for the CAD system can be obtained from various imaging modalities. The popular medical imaging modality used in lung cancer detection is low dose CT. But the data from different private sources or CAD systems for the study will not be persuasive. So we have to rely on various public databases for the purpose. LIDC - Lung Image Database Consortium, ELCAP - Early Lung Cancer Action Program, LIDC IRDI - Image Database Resource Initiative and LUNA16 - LUng Nodule Analysis 2016 (LUNA16) are providing database resources for recent research works.

Nodule segmentation

Segmentation of the nodule aims to remove unimportant information and focus on significant information to deal with. This is an important part of the system and it needs sufficient attention. Different methods are employed for the segmentation process in various works. Small nodule patches obtained from raw lung scans are used in the network to learn deep features.

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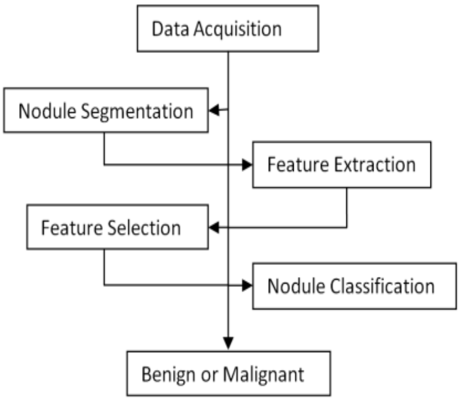

Figure 1: CAD system basic process steps

Feature extraction and selection

Features from 2D and 3D images are obtained from various images. From that, features with good diagnostic results are selected as an ultimate classification. There will be deep nodule features and traditional nodule features within this classification. CNN based networks are used in extracting deep features. Feature descriptors are used to calculate various traditional features like size, shape, texture, intensity etc. The process of feature selection plays an important role in obtaining maximum efficiency in classification. Dimensionality reduction and reduction of the chances of over fitting is accomplished by the feature extraction and selection processes.

Nodule classification

As of now we have detected lung nodules in the CT images and are segmented accordingly. The process of classification is the next important step. That is to classify them as malignant nodules and benign nodules. The accurate classification of samples is a mandate before the training the model. According to the malignancy level of the nodules as indicated in the data base most of the works classify the images as malignant (average malignancy level >3), benign (average malignancy level < 3) and rejected uncertain sample (average malignancy level = 3). Two works [1], [2] ignored the nodules with levels between 2.5 and 3.5 and proceeded with the remaining nodules. Liu et al. [1] and Nishio et al. [3] proposed two different levels for malignancy.

Classifiers that use traditional and deep learning methodologies are widely used in different works. The features extracted from the nodules are used for training the classifier. Commonly used traditional classifier is support vector machine classifier and most of the deep learning classifiers are convolutional neural network based. Deep learning classifiers are most frequently used method in classifying the pulmonary nodules. But in deep learning, the amount of data needed for training is very large and the process of training consumes a huge amount of time. The classification methodologies used in various works are listed in the Table 1(traditional) and Table 2(deep learning)

Table 1

Auther		**Traditional methodology employed**
Chen et al. [4]	2018	Support Vector Machine (SVM)
Farag et al. [5]	2017	
Dhara et al. [6]	2016	
Akram et al. [7]	2016	
Costa et al. [8]	2018	GA and SVM
Gong et al. [9]	2018	SVM, naïve Bayes classifier and linear discriminant analysis
Kaya et al. [10]	2018	Cascaded classifiers and stacking methods
Naqi et al.[11]	2018	Geometric texture features descriptor (GTFD) and SVM
Filho et al. [12]	2017	GA and SVM
Sweetlin et al. [13]	2017	Antcolony optimization (ACO), Rough dependency measure (RDM) and SVM
Firmino et al. [14]	2016	Rule-based classifier and SVM
Xiabi et al. [15]	2015	Fisher criterion and GA
Tartar et al. [16]	2013	Random Forest (RF), Logistic Model Tree(LMT) and J48 decision tree classifier

Table 2

Author	**Year**	**Deep learning methodology employed**

Filho et al. [17]	2018	Convolutional Neural Network (CNN)
Wang et al. [18]	2018	
Nishio et al. [3]	2018	
Tu et al. [19]	2017	
Liu et al. [20]	2018	Dense convolutional binary-tree network (DenseBTNet)
Wang et al. [18]	2018	Semi-supervised extreme learning machine (SS-ELM)
Zhang et al. [21]	2018	Spatial pyramid dilated network
Zhu et al. [22]	2018	Dual path networks (DPN) and gradient boosting machines (GBM)
Zhao et al. [1]	2018	Hybrid CNN based on LeNet and AlexNet
Jung et al. [23]	2018	CNN and ensemble models
Shen et al. [21]	2017	Multi-crop convolutional neural networks (MC-CNN)
Silva et al. [24]	2017	CNN and GA
Sun et al. [25]	2017	CNN, deep belief networks (DBN) and stacked denoising autoencoder (SDAE)

Study on selected works

This paper surveys on various works that are done in the field of pulmonary nodule diagnosis. Papers are selected from recent popular databases. Different approaches in lung nodule diagnosis are selected and compared the methodology employed. The common parameters used for the assessment of the work include no of nodules, size of the nodule, AUC, ACC, sensitivity and specificity. Costa et al. [8] presented a lung nodule classification scheme using the texture descriptors phylogenic distance (MPD) and taxonomy diversity index. LIDC-IDRI data base used for the nodule classification provided impressive results. Filho et al. [17] classified the nodules using CNN. The proposal used image-processing technique and pattern recognition on CT images from LID CIDRI for the diagnosis. Gong et al. [9] proposed a method for nodule classification using the NSCLC database. The performance of computer aided diagnostic scheme studied with the dataset under investigation.

Zhu et al. [22] proposed a fully automatic nodule detection method with GBM and 3D DPN. Two 3D DPNs designed for the purpose. Kaya et al. [10] used various deep and modified features to identify the nodules. Deep features are taken from nodule region and the nodule boundary region. Liu et al. [1] used DenseBTNet learning for diagnosing nodules. 2001 samples were used from LIDC-IDRI database for cross validation. The proposed scheme produced one of the best performance results. Wang et al. [18] proposed a SS ELM based classification of nodules. Reduced training time is achieved by using genetic GA for feature selection. Cross validation is performed using 353 nodules from LIDC database. Filho et al. [12] proposed a pattern classification on CT images of pulmonary nodules. Phylo-genetic diversity was utilized for better feature extraction. Most significant feature selection was done with GA and used SVM for pulmonary nodule classification.

Sweetlin et al. [13] proposed a system extracted features from nodules after the segmentation of the nodule. The sytem trained the learning model, using SVM and NB classifiers. The result produced by the SVM classifier was one of the best in the category, Shen et al. [21] proposed a CNN based system used 2618 nodules from LID-IRDI database for the performance evaluation. Silva et al. [24] proposed methods that don’t compute traditional features. A combination of deep learning with GA used to classify the nodules. Tu et al. [19] presented an automatic categorization system according to the variation in solid nature of the nodule. The system worked with LIDC data base using CNN. 570 nodules with 3 mm diameter or greater are taken in to consideration. Proposed method showed good performance.

Sun et al. [25] compared the performance of three multichannel deep learning algorithms for automatic lung cancer diagnosis in CT images. For better comparison purposes, a traditional CAD system was also used. Wang et al. [26] mainly proposed a hybrid learning model by integrating the traditional features and deep CNN-based features to improve the risk differentiation of benign and malignant pulmonary nodules in CT images. Zhao et al. [1] proposed a CNN based distinguishing system, which composed of framework settings of LeNet and AlexNet. The evaluation is done on 743 nodules from LIDC-IDRI database.

Firmino et al. [14] proposed a SVM based classifier which classified 5 categories of malignancy presence. The evaluation is done on

1109 nodules from LIDC-IDRI database. Nodule features are extracted using histogram oriented gradients. Dhara et al. [6] presented a method of classification, which is a combination of nodule shape, nodule margin and texture features based on CT images. Features are extracted from the segmented pulmonary nodules. In the classification scheme 49 features are selected out of 57 extracted.

II. DISCUSSION AND FUTURE WORK

The review reports the recent advancements in pulmonary nodule diagnosis with CT images. Data collected from various authentic database sources are used for research work. Data obtained from private data bases was not reliable and result in reduction in system efficiency.

Majority of the investigated papers employed the LIDA-IDRI data base for the work. The traditional and deep features produced satisfactory performance in nodule characterization. As a traditional classifier SVM was the most popular one. Many CNN based methods showed satisfactory performance. Efficient CAD systems have great significance in delivering timely, effective and advanced treatment at an early stage. The review came across some efficient and promising works in nodule diagnosis. However, many limitations exist in various result parameters.

Some improvements that can be considered for the future development of the CAD system include, the development of highly efficient networks to excerpt deep features, enhancement of the ability of the existing systems by optimizing the current techniques, increasing the ability to detect small and irregular nodules, developing high quality database etc.

III. CONCLUSION

The aim of this paper is to investigate on the computer aided diagnosis for lung cancer with tomography images. Various stages in a CAD system are introduced in this review. A well organized report of the existing works and a detailed comparative analysis is done. Through this analysis, the review point out the better techniques that can be adopted for future research works. Hence the review is an asset for future research and will be helpful for researchers to learn about the advancements in the area of diagnosis of pulmonary nodules.

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