A COMPREHENSIVE REVIEW ON CONTENT BASED PULMONARY NODULES RETRIEVAL

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Abstract

Pulmonary cancer is one of the deadliest cancers worldwide. Chain-smoking results in lung cancer. Researches assert that early detection of lung cancer considerably increases the chances of recovery rate. A lung nodule represents a range of abnormalities and irregularities in lung tissue. The low dose spiral or helical CT scan gives an effective and efficient way for early-stage lung cancer diagnosis. Currently, the computer tomography research-based analysis includes nodule detection or localization and classification of nodules. This is a crucial task in the initial stages of pulmonary cancer diagnosis and treatment. The low-dose spiral CT scan gives three-dimensional X-rays of the lungs and a detailed analysis of the lung abnormalities. The deep-learning model for detecting and classifying lung nodules with clinical factors reduces the early-stage lung cancer's misdiagnosis and false-positive (FP) test results. Most pulmonary nodule deep learning detection techniques use the standard LIDC-IDRI dataset for testing and give better detection results than the existing methods.

Keywords: Deep neural networks, pulmonary nodules detection, cancer, neural networks, CT Scan, CNN.

I. INTRODUCTION

Pulmonary cancer is one of the prime reasons for death due to cancer in both men and women worldwide. Chest computed tomography(CT) scans of the human lungs are used to identify harmful and malignant pulmonary nodules early on, improving lung cancer patients' survival rates. Many studies and research have used neural networks and machine learning algorithms to assist radiologists in detecting nodule candidates. However, neural networks and deep learning algorithms can improve both the sensitivity and the specificity of a test. Some algorithms can suffer from a few challenges because the detection networks fail to detect some lung nodules available in the training dataset. The several factors that affect the detection algorithms are the vague definition of nodules, the imbalanced level of expertise among radiologists or the insufficient information provided by CT scan images, etc.

Neural networks are susceptible to unexpected image distortions that can occur in real-world CT imaging[1]. Most nodule detection frameworks generate candidates using an image-processing pipeline or convolutional neural networks (CNNs) [1]. A separate classifier is trained to decrease false-positivity counts[1]. Recently, studies propose generative networks to discover the nodules in a lung,. These networks will enhance the performance of diverse lung-nodule detection applications.

A lung nodule may suspect as cancerous if it proliferates or has ridged edges. In benign or non-cancerous nodules, the patient has to take chest scan follow-ups to monitor the nodule characteristics such as size, shape, appearance etc. The doctor orders additional tests such as a CT scan, positron emission tomography, a needle biopsy or a bronchoscopy to determine the cause of the nodule.

Low-dose computed tomography (LDCT) is an effective screening technique for higher risk of pulmonary cancer and will reduce lung cancer mortality[2]. Many patients also had other kinds of pulmonary abnormalities, which may increase

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the false-positive rates of manual readers and network-based algorithms. The pulmonary nodule detection CAD system generally contains two phases: nodule-candidate detection and false-positives reduction[2]. Traditional computer-aided-design (CAD) systems give simple assumptions and low-level descriptors that may give inferior detection results. However, deep neural network algorithms which use 3D CT images, play a crucial role in recognizing nodules quickly. It will give a promising performance in false reduction also.

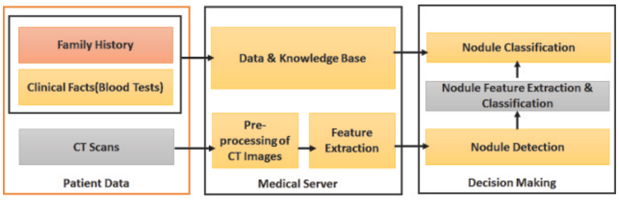

Fig. 1. General Diagram of Nodule Detection

Most of the algorithms incorporate two main phases for lung nodule detection. They are

a) Candidate detection.

Candidate detection is the primary step in lung nodule detection, which detects the total number of nodule candidates which are highly sensitive. In this step, an object recognition model is used for finding the candidate nodules from the CT scan images. This model gives the dimensions and other details of candidate nodules.

b) False-positive reduction

In the initial phases, the very close resemblance of benign and malignant nodules makes it challenging to categorize them. The false-positive rate is the possibility of incorrectly rejecting the null hypothesis for a partic $\frac{FP}{N}$ ar experiment [3].

The false-positive rate is $\frac{FP}{FP+TN}$

False-Positives Rate (FPR)={QUOTE }

= {QUOTE } (1)

Here, FP defines the number of false positives and TN defines the number of true negatives. Here, N defines the sum of false positives (FP) and true negatives (TN).

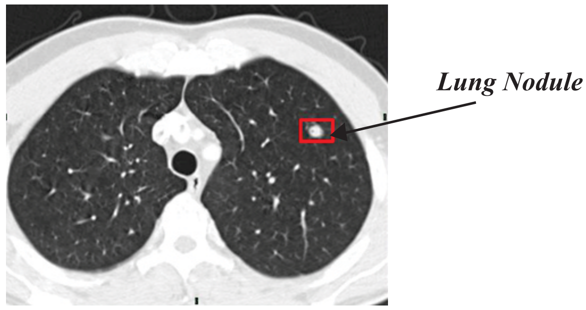

Fig. 2. Lung CT Scan

II. LITERATURE REVIEW

Gurcan et al. proposed a k-means clustering algorithm based multistage CAD system to segment the interested regions from a lung CT scan[4]. In this system, the area's CT values that separate the lungs and the lung walls are higher than the air surrounding the patient. A threshold value separated the region between the surrounding region and the thorax. Here, k-means clustering technique is used to segment the lung regions and are again separated as central and peripheral sub-regions. The CT values of the thoracic cavity and pleura division are higher than the air surrounding the patient. For clustering, the pixel gray level is used. Here a threshold of R=1 is used to segment the lung regions within the thorax [4]. The left and right lungs are detected after the segmentation and is separated into central and peripheral sub regions. A weight-based k-means clustering algorithm was used again to divide the structures of each pulmonary region. This system detects lung nodules by using rule-based classifiers and linear discriminant analysis (LDA). The structures contain real lung nodules and normal blood conduits. The two-dimensional and three-dimensional nodule and standard blood vessel structural features distinguish them separately and are done by a rule-based classifier algorithm. Here, the linear discriminant analysis (LDA) was used to diminish the count of false positive objects [4]. The preliminary investigation was performed using 1454 CT image slices of thirty four patients with sixty-three lung nodules. The proposed system reports a sensitivity of 84% and produces 1.74 false positives per slice on average[4].

Nasrullah et al; recommended a unique multi-strategic approach based on deep learning concepts to correct the malignant-nodules' correct diagnosis [3][5]. In this paper, a deep three-dimensional CMixNet architecture was proposed for pulmonary nodule localization and classification [4][6]. This system uses a faster three-dimensional R-CNN for nodule identification and a GBM-gradient boosting machine to classify nodules[5]. The nodules features were learned by using a U-Net-based CMixNet network[4][7]. These details are used to conduct the diagnosis and analysis of the detected nodules[7]. The identified candidate nodules are transferred to a nodule classification network, where the classification features are extracted by a three-dimensional deep dual path network[7]. The patient is detected as a cancer victim provided that any of the detected nodules are positive otherwise considered as a non-cancer patient [8]. They proposed a classification algorithm based on deep-residual network to alleviate the high false-positive rate and accuracy [9]. A combined version of residual and migration learning was used to create the deep residual network(DRN). This deep-learning model based on clinical elements reduces the wrong diagnosis and falsely positive outcomes in the initial diagnosis of pulmonary cancer. This model obtains an accuracy of 98.23% and 1.65% of false-positive rates. The suggested DRN has superior performance in the classification task. This system requires an optimized network model to eliminate the long training time required to train a large dataset of lung CAT images[8]. This system uses LIDC-IDRI dataset to verify and conducting the experiments on the lung CT Scans, and the evaluation reports a test sensitivity of 94% and test specificity of 91% [10].

Masood et al. designed an Internet of Things(IoT) based neural network for identifying and categorizing pulmonary nodules in a CT image. The sensors that are attached to the patient's body collects all the physiological information about the patient. The symptoms of lung cancer differ depending on its stages and are visible only when the cancer cells spread in the body [10]. Several pre-processing steps were used. In lung nodule identification using the threshold method, a threshold value is used to divide the image pels into objects or backgrounds for taking out the regions of interest. The extracted region of interest (ROI) is used to train the DFCNet[10]. DFCNET uses spatio-temporal statistics around the given voxel to detect the voxel as nodule or not. Primarily, the nodules were classified as either malignant(harmful) or benign. Subsequently, the harmful nodules were categorized into four sub-categories based on CT image details and metastases. Overall accuracy, sensitivity, specificity, and false-positives were calculated for the current CNN approach and the proposed DFCNet method [5]. The CNN detected true-positive (TP) results were 83.0% while true-positives of DFCNet was 89.0%[10]. But, the DFCNet showed better results than the CNN method. Generally, CNN and DFCNet sensitivities were 74.2% and 80.7%, respectively [10]. The overall accuracy was 77.6% and 84.6% respectively [10].

Hongyang Jiang et al. developed a group-based approach for the detection of pulmonary nodules using multi patches. Deep learning network with Frangi filter was used to increase the performance. A 3D CNN with four channels was proposed to study the marked features. In the CT images, the entire vessel and nodule image elements emerged in the form of bright tissues among the adjacent darker pixels [10]. The vessels anatomy and structure were distinct from lung nodules. The pulmonary nodules appeared in the form of ellipses or irregular spheres while vessels resembled tubular structures. Here, a multi-scale Frangi filter was used to eliminate vascular structures or other tiny noises. Four different size of sampling patches were used to divide the nodules into different range of sizes. The CNN model's input is a cropped pair of images of the original image and this model extracts more details of the object nodules. In this system, the diagnostic information provided by the radiologist is also used to predict the pathology of nodules[10]. The multigroup-patch learning system gives a sensitivity of 94% with false-positives rate of 15.1 and its efficiency is better to enhance the performance of lung nodule detection [10].

Setio et al. suggested a three-dimensional convolutional neural network-based web framework to eliminate the false positives rate in pulmonary nodule detection and classification. It was used to inspect three-dimensional CAT scans to minimize incorrect analysis and wrong diagnosis. A weight-based sampling was used to increase the outcomes. A combination of classical candidate detection algorithms were used for candidate nodule detection and these candidates were analysed with convolutional neural networks to yield excellent results. It attained a detection sensitivity in a range of 79.3- 98.3% at 1 and 8 false-positives/scan [1].

Panpan Wu et al. introduced a deep-residual network method to classify the lung nodules. A 50-layer deep-residual network was created by joining the residual learning and migration learning methods [9]. The lung nodule image is directly inputted to the network to avoid complicated feature extraction and selection [9]. This system has achieved an accuracy of 98.2% with the greatest efficiency[9]. The sensitivity and specificity are 97.7% and 98.4%, respectively [9].

III. LUNG IMAGE DATABASE CONSORTIUM (LIDC-IDRI) DATASET

Most of the research techniques use the LIDC-IDRI image collection to develop a system that detects and localizes lung nodules. This publicly available dataset contains 1018 characterized and annotated lesions of lung cancer thoracic CT scans. It also contains CT scan images of high risk patients with independent annotations of four experienced radiologists. Each CT scan contains several cross-sectional slices of the chest and meta data: HU values, slice thickness, number of slices, the spacing between the voxels and the origin. By using a two-stage annotation process, the thoracic radiologists were inspected every CT scan. In the first stage, each radiologist independently marked lesions category based on their size. The second stage is reviewed with the marks of other anonymized marks by the other three radiologists. A final annotation is marked based on the radiologist's consent.

IV. EVALUATION METHODS

Computer-based pulmonary nodule identification and categorization techniques have large detection abilities than traditional systems. But, the identification capability of clinical biomarkers is very low whereas the specificity is high. The collective decision based on identification and classification techniques with clinical evidence reduces the false-positive results [6]. This will increase the chances of malignancy.

The various systems performance is calculated based on false-positives rate and various statistical measures. The values of AUC curve vary from 0.5 to 1.0. Higher AUC values indicate significant performance of the system. The statistical measures are used to measure the system performance are true-positives (TP), true-negatives (TN), false-negatives (FN) and false-positives (FP) respectively. Sensitivity gives the rate of true-positives (TP), whereas specificity gives true-negatives(TN).

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Positive predictive value} = \frac{TP}{TP + FP}$$

$$\text{Negative predictive value} = \frac{TN}{TN + FN}$$

V. PERFORMANCE COMPARISON

The sensitivity results of the various techniques in LIDC-IDRI dataset are shown in the following table.

Method	Sensitivity (%)
3D fully CNN	98.3
Deep ResNet	97.7
3D CMixNet	94.0
3D CNN & franki	94.0
DFCNet	89.0
LDA	84.0
CNN& DFCNet	80.6

Table 1: Sensitivity Results

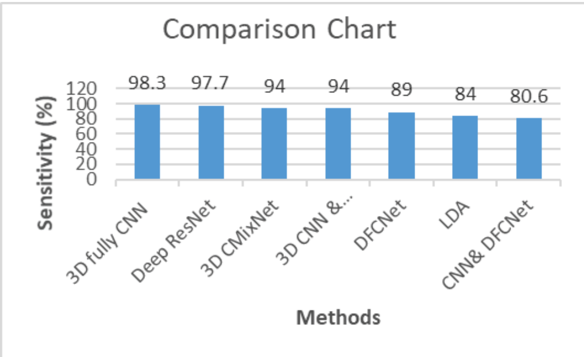

Fig. 3. Comparison Chart

VI. CONCLUSION

The 3D Convolutional Network-based deep learning algorithms identify pulmonary nodules from low-dose 3D CT scans automatically. It is capable of predicting the malignancy of the pulmonary nodule using its temporal evolution. Several deep learning techniques are used to resolve the issues of lung nodule classification. Reviews shows that the results of deep learning techniques are superior and the performance is promising one. We require more training time to deal with a large number of lung CT images. Deep learning methods give better performance in comparison with the previous approaches. We can include clinical diagnosis as a parameter to these algorithms to improve the performance of the system.

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