Classification of Lung Nodules using Improved Residual Convolutional Neural Network

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Abstract: The most common cancer of the lung cannot be ignored and can cause late-health death. Now CT can be used to help clinicians diagnose early-stage lung cancer. In certain cases the diagnosis of lung cancer detection is based on doctors' intuition, which can neglect other patients and cause complications. Deep learning in most other areas of medical diagnosis has proven to be a common and powerful tool. This research is planned for improving the residual evolutionary neural network (IRCNN). These networks apply with some changes to the benign and malignant lung nodule to the CT image classification task. The segmenting of the nodule is performed here by clustering k-means. The LIDC-IDRI database analysed those networks. Experimental findings show that the IRCNN network archived the best performance of lung nodule classification, which findings best among established methods.

Keywords: Deep learning, Improved Residual Convolutional Neural Network, k-means clustering and lung segmentation.

I. INTRODUCTION

Lung cancer is one of the world's most common cancers and causes deaths associated with cancer. It constitutes 13% of all current cancer cases and 19% of worldwide cancer-related deaths. In 2012, it has been estimated that there were 1,8 million new cases of lung cancer [1]. The most common cancer-related and cancer-related mortality in men in India with the largest populations of both male and female Mizoram (age 28.3 and 28.7 per 100 000 population in males and females) [2] is lung cancer that accounts for 6.7 percent of new cases and 9.3 percent of cancer-related deaths in both sexes.

In recent years, conventional AIs have been defeated by neural networks, which are called 'deep learning,' in every crucial task: speaking recognition; images characterisation; and normal, readable sentences producing. In addition to accelerating essential tasks, deep learning enhances device accuracy and CT image recognition and classification efficiency [3]. In this paper, the issue of the classification of benign and malignant is considered and can be solved with k-medium nodule segmentation via the Improved Residual Convolutional Neural Network (IRCNN). The work can be used

directly as an input to the complex recovery of data during the extraction and classification of features.

The remaining paper is structured like this. The corresponding works are discussed in section 2. Section 3 outlines the methods suggested for classifying lung nodules. Section 4 addresses the experimental findings obtained. Section 5 contains the conclusion and future work.

II. RELATED WORK

Various approaches for the classification of lung nodules using CT scans have been proposed in the literature. The proposal is made for a new CADe system based on a hierarchical vector (VQ) system [4]. The high-level VQ results in an accurate segmentation of the lungs from the chest volume in comparison with the commonly used simple threshold approach. Based on the Gestalt visual cognition theory, a new lung nodule detection scheme is proposed in [5].

The proposed scheme includes two parts that simulate cognitions of human eyes, for example simple, complete and classified. The nodules were characterized by a gray level co-currency

(GLCM) texture features in the wavelet domain computed by [6] and classified with a radial basis function SVM to classify CT images into two categories: with cancerous lung nodules and without lung nodules.

In [7] classification was focused primarily on the use of supporting vector machines for benign and malignants. The current methods cannot, however, reach great sensitivity and specificities. A method, based on traditional features to compose the contour and texture properties with low frequency curvelet coefficients, is suggested in [8]. Furthermore, the LDA methodology is used for classification labeling. The new intelligent bat algorithm is used to optimize SVM parameters, making it easy and fast. In 9 a new automatic segmentation of the Watershed method lung nodules, multi-size gradient vector flow snakes

and the detection method for small lung nodules was introduced using the extracted features and classification. In [10] the effectiveness of DCNNs in the classification of lung nodule malignancy at expert level was assessed.

III. PROPOSED METHODOLOGY

The proposed approach from the Lung Image Database Consortium on the LIDC-IDRI [13] dataset is evaluated in this section. The latter detects lung nodule segmentation from CT images using k-means. For conventional medicine, the complex steps of image extraction function can be minimized by inputting the original image directly into IRCNN. IRCNN based lung nodule classification architecture diagram is illustrated in Figure 1.

3.1. Input LIDC-IDRI

The data set was acquired as a free resource from Lung Image Database Consortium and Image Database Resource Initiative (LIDC / IDRI) that consisted of CT scans of annotated lesions to assess the performance of the proposed nodular-deep system. This database is open to the public, in addition to is used in several studies. An experienced radiologist was asked to mark two types of the lung nodules, such as benign and malignant nodules. Figure 2 represents[10] an example in HRCT scan images of benign and malignant lung nodules collected from the LIDC-IDRI dataset and its boundaries marked by an experienced radiologe. In this study, the 1200 slices were selected from the LIDC-IDRI dataset which contained 2600 equal number of benign and malignant lung nodules.

3.2. Lung Nodule segmentation Using K-means clustering

This section used clustering of K-means to detect lung nodule similar to the approach proposed in [11]. Nucleus subspaces are categorized using K-means clustering to use mahalanobis distance metric to cluster the objects into separate clusters. K-means algorithmic rule clustering is projected to find the traditional and anomalous nucleus in the CT picture. In short, the clustering procedure in Kmeans has the following phases:

Step 1: Randomly evaluate the initial centroid point K of the cluster.

Step 2: Find the K-Means clustering objective $C(x)$ to minimize the sum of square distances between all points and the cluster center $C(x) = \sum_{j=1}^k \sum_{i=1}^n \|x_i^j - c_j\|^2$, where k denotes the number of clusters, n is the number of CT images, x is the particular image and c is the cluster centroid and $x_i^j - c_j$ is the mahalanobis distance function.

Step 3: Compute the distance of each pixel against the centroid, and group them.

Step 4: Based on each centroid member, measure the New centroid value.

Step 5: Repeat steps 2 and 3 until the current centroid value has not changed from the previous centroid value.

3.3. Improved Residual Convolutional Neural Network for lung nodule classification

In this section, the Improved Residual convolution neural network (IRCNN), which utilizes the strength of the Residual convolutional Neural Network (RCNN), the Inception Network, and the Residual Network, is a new Deep learning model. This method increases the precision of Inception-residual network identification with the same number of network parameters. However, this proposed architecture generalizes the Inception Network, the RCNN, and the Residual Network with a significantly improved training precision.

The RCNN block that includes Recurrent Convolution Layers (RCLs), Inception Units, and Residual Units is the most significant part of this proposed architecture. Initially, the inputs are fed into the input layer, at that moment passed through the starting units where RCLs are applied, then finally the outputs of the starting units are added to the RCNN-block inputs. Here, consider the x input sample in the l th layer of the IRCNN-block and a pixel located at (i, j) in an input lung images on the k th feature map (f) in the RCL. Furthermore, assume the output of the network $Y_{ijk}^l(time)$ is at

the time step T . The output can be expressed as in equation (1):

$$Y_{ijk}^l(T) = (w_k^f)^{time} * x_l^{f(i,j)}(time) + (w_k^{rcl})^{time} * x_l^{rcl(i,j)}(time - 1) + b_k \quad (1)$$

Where $x_l^{f(i,j)}(time)$ and $x_l^{rcl(i,j)}(time - 1)$ stand the inputs for the standard convolution layers in addition to for the l th RCL correspondingly. The w_k^f and w_k^{rcl} values are the weights on behalf of the standard convolutional layer then the RCL of the k th feature map respectively, and b_k is the bias. The outputs o of the starting units for the various size kernels and average pooling layer are determined using equation (2)

$$o = af(Y_{ijk}^l(time)) = \max(0, Y_{ijk}^l(time)) \quad (2)$$

Here af is the activation function of standard Rectified Linear Unit (ReLU) of IRCNN. At this time, likewise reconnoitred the performance of this model with the Exponential Linear Unit (ELU) activation function. The outputs o of the inception units for the diverse size kernels at that moment average pooling layer are well-defined as $o_{1 \times 1}(x)$, $o_{3 \times 3}(x)$, and $o_{5 \times 5}(x)$ respectively. The

ultimate outputs of IRCNN unit are defined as $\mathbb{Y}(x_l, w_l)$ which can be expressed as

$$\mathbb{Y}(x_l, w_l) = o_{1 \times 1}(x) \odot o_{3 \times 3}(x) \odot o_{1 \times 1}^p(x) \quad (3)$$

Where $\odot$ represents the concatenation procedure with reference to the channel or feature map axis of input lung image. The IRCNN-component outputs are then inserted accompanied by the IRCNN-block inputs. The IRCNN-block residual activity can be expressed by equation (4).

$$x_{l+1} = x_l + \mathbb{Y}(x_l, w_l) \quad (4)$$

Where x_{l+1} references to the inputs for the instant subsequent transition block, x_l represents the input image samples of the IRCNN-block, w_l signifies the kernel weights of the l th IRCNN-block, besides $\mathbb{Y}(x_l, w_l)$ characterises the outputs from of l th layer of the IRCNN-unit. Nevertheless the number of feature maps and the elements of the residual unit feature maps are the same as in the IRCNN block. The batch normalization refers to the RCNN-block outputs [12]. The outputs of this IRCNN-block are finally fed to the inputs of the next immediate transition block.

Not the same operations are performed in the transition block, including convolution, pooling, and dropout, depending on where the transition block is located in the network. In the intervening time the size of the input and output features in the IRCNN blocks does not change, it is unbiased a linear projection on the same dimension and the RELU and ELU activation functions add non-linearity. Consequently each convolution layer in the transition block a 0.5 dropout was used here. Eventually, at the end of the architecture, used a Softmax, or normalized exponential function area.

For input lung sample x , weight vector w , and k distinct linear functions, the Softmax operation can be well-defined for the i th class as in equation (5):

$$P(o = i|x) = \frac{e^{x^T w_i}}{\sum_{k=1}^K e^{x^T w_k}} \quad (5)$$

This proposed IRCNN model was studied and compared across different models by means of a set of experiments on different benchmark datasets. Figure 3 gives a systematic flow diagram for the proposed IRCNN.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the proposed IRCNN is evaluated in this section, and the performance results are compared with existing SVM [7], SVM-LDA [9] and DCNN [10] image compression schemes. The Lung Image Database Consortium image database (LIDC-IDRI) in real time consists of diagnostic and lung cancer screening thoracic computed tomography (CT) scans of annotated marked-up lesions. Seven academic centers and

eight medical imaging companies partnered to create this collection of data that contains 1018 cases. That subject contains images from a clinical thoracic CT scan and an accompanying XML file that documents the findings of four experienced thoracic radiologists conducting a two-phase image annotation procedure. The figures given below show that the device proposed has achieved better performance in terms of precision, f-measurement, recall and accuracy.

Precision: It reflects the proportion of positive samples correctly classified as expected in equation (6):

$$Precision = \frac{TP}{FP+TP} \quad (6)$$

Recall: The recall of a classifier reflects the positive samples properly assigned to the total number of positive samples and is calculated as in equation (7):

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

F-measure: this is also referred to as F 1-score, and as in equation (8) is the harmonic mean of precision and recall:

(8):

$$F - measure = \frac{2 * (Recall * Precision)}{(Recall + Precision)} \quad (8)$$

Accuracy: This is one of the most frequently used performance classification measures and is defined as a ratio between the correctly classified samples and the total number of samples as in equation (9):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

Where true positive (TP) samples are properly classified as natural, false positive (FP) samples are incorrectly classified as irregular, True negative (TN) samples are properly classified as irregular, and false negatives (FN) are incorrectly classified as natural.

4.1. Precision Rate comparison

Figure 4. Representation of Precision Comparison

From the above Figure 4, the graph shows how accurate the number of images in the specified datasets is compared. These methods are implemented as SVM, SVM-LDA, DCNN, and IRCNN. When the number of records increases according to the precision value. From this graph, it is learned that the proposed IRCNN offers 94% higher precision than previous methods that yield better results in the classification of lung nodules due to prior segmentation of the lung nodules using k-means technique. The numerical results of Precision Comparison is shown in Table 1.

Table 1. The numerical results of Precision Comparison

No.of images	SVM	SVM - LDA	DCNN	IRCNN
50	80	82	85	87
100	82	85	86	90
150	83	87	89	92
200	87	89	90	93
250	90	91	92	94

4.2. Recall comparison

Figure 5. Representation of Recall Comparison

From the above Figure 5 the graph illustrates the recall relation for the number of images in the listed datasets. These methods are implemented as SVM, SVM-LDA, DCNN, and IRCNN. Increasing the number of photographs often increases the correct value for the recall. Through this graph, it is discovered that the current IRCNN offers recall 94% higher than previous methods. The explanation for this is that the IRCNN extracts the features directly which will enhance the lung nodule classification tests. The numerical results of Recall Comparison is shown in Table 2.

Table 2. The numerical results of Recall Comparison

No.of images	SVM	SVM - LDA	DCNN	IRCNN
50	83	85	87	89
100	84	87	89	90
150	85	88	90	91
200	86	90	91	92
250	89	91	93	94

4.3. F-measure Rate comparison

Figure 6. Representation of F-measure Comparison

From the above Figure 6, the graph explains the f-measure relation for the number of images in the given datasets. These methods are implemented as SVM, SVM-LDA, DCNN, and IRCNN. When the number of data is increased, and the f-measure value is increased accordingly. From this graph it is learned that the proposed IRCNN offers 95% higher f-measurement than previous methods. Therefore the proposed IRCNN algorithm is stronger than the current algorithms in terms of better performance of classifying lung nodules. The numerical results of F-measure Comparison is shown in Table 3.

Table 3. The numerical results of F-measure Comparison

No.of images	SVM	SVM - LDA	DCNN	IRCNN
50	75	85	89	90
100	77	87	90	91
150	79	88	91	93
200	80	89	92	94
250	85	90	93	95

4.4. Accuracy comparison

From the above Figure 7 the diagram illustrates the processing time relation for the number of images in the specified datasets. These methods are implemented as SVM, SVM-LDA, DCNN, and IRCNN. From this graph it is known that the proposed IRCNN algorithm is higher than the existing algorithms with a high precision rate of 97% in terms of better template matching results. This is due to the automatic extraction of the function in the IRCNN classification algorithm, which increases the classification precision resulting in lung nodules. The numerical results of Accuracy Comparison is shown in Table 4.

Table 4. The numerical results of Accuracy Comparison

No.of images	SVM	SVM-LDA	DCNN	IRCNN
50	90	91	91	92
100	91	92	92	93
150	92	93	94	94
200	93	94	95	95
250	94	95	96	97

V. Conclusion and future work

A classification of the lung nodule is proposed in this work, based on deep learning. This detection scheme can avoid the extraction of candidates and can be less scale based. The k-means algorithm is used for segmentation of the lung nodule, too. Since IRCNN does not recognize anatomical features, several regions of the lung nodule occur in the results of the detection. Experimental results show that most nodules with a high accuracy rate of 97% can be detected by the designed IRCNN. There are

other problems that still need attention with this, such as increasing algorithm sensitivity, reducing the number of false positives, enhancing and optimizing the detection of algorithms of different types of nodules with various sizes and shapes. Based on this analysis, further research is needed to develop current techniques, and new algorithms are needed with machine learning methods to overcome the identified drawbacks.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

No animals/humans were used for studies that are basis of this research.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The authors confirm that the data supporting the findings of this research are available within the article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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