LUNGSCREEN: DETECTION AND CLASSIFICATION OF LUNG CANCER NODULES USING R-CNN

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Abstract:

Lung cancer nodules are a major cause of cancer-related deaths globally. It is essential for the prompt diagnosis of lung cancer that these nodules are found early on chest CT images. However, the heterogeneity and morphological complexity of 2-D nodule features often lead to low detection sensitivity and high false-positive rates, making accurate detection challenging. To tackle these concerns, a detection system aided by CT image has been created to enhance the sensitivity of detection and accuracy of classification of nodules in the lungs. The present plan suggests an efficient algorithm for predicting lung cancer nodules, which is based on an enhanced RCNN. The objective is to address the shortcomings of the existing detection techniques that include inadequate precision and sluggish pace. The suggested approach entails pre-processing the initial CT copy and subsequently forwarding it to the RCNN for the identification of pulmonary nodules The identification outcomes are subsequently employed to finalize the categorization of harmless and cancerous lung growths via the Region-centric Convolutional Neural Network. The findings acquired from the LUNA16 dataset experiment indicate that the enhanced network architecture can achieve a mAP score of 96.71% and a detection rate of 41.99 FPS. These findings imply that the suggested network has the potential to offer an efficient diagnostic instrument for possible nodules of lung cancer and could hold encouraging prospects in the field of clinical practice.

Keywords: Deep Learning, R-CNN, Nodules, Histogram, Computed Tomography.

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1. Introduction

To create predictive models for lung nodule diagnosis, artificial intelligence (AI) and machine learning methods, particularly deep learning, are being applied. One of the most prevalent cancers, lung cancer accounts for more than 25% of all cancer-related fatalities globally. According to statistics, patients do have 63% chance of living for 5 years if a tumour is discovered and cured at an initial stages. Early identification is crucial for enhancing patient outcomes. Massive amounts of data of CT scans can be used to train algorithms using deep learning, such as convolutional network neural networks (CNNs), to properly identify lung nodules, assisting in the early identification of lung cancer. This innovation may enhance patient outcomes and lower the mortality rate related to lung cancer.

Lung nodules, if not detected and diagnosed early stage, may become cancerous, grow and spread to other parts of the body. As a result, the issue of Lung Cancer Tumor Detection is crucial to the early identification of malignancy and to improving patient survival. Lung Cancer nodules are small, round or oval-shaped growths in the lungs that can be detected on a chest CT scan. While many nodules are benign, meaning they are not cancerous, some of these may be precursors to lung cancer.

Lung nodules, if not detected and diagnosed early, may become cancerous, grow and spread to other parts of the body. Thus, the topic of lung nodules detection is crucial for early lung cancer diagnosis and for improving patient survival.

A. Related Work:

Deep learning algorithms for medical picture segmentation have made considerable strides recently and are increasingly in demand as diagnostic equipment due to their capacity to detect crucial features. Deep learning algorithms have a remarkable capacity to learn relevant feature representations from data, and some have demonstrated excellence compared to traditional methods in analyzing lung CT scans, producing more reliable results.

According to latest global latest data, cancer is a very common type of cancer and is to blame for the greatest number of cancer-related fatalities globally. These algorithms must accurately segment and classify nodules on ultrasound imaging (CT) images, as well as assess intra-nodular heterogeneity, in order to eliminate bias in later radiological analysis and increase radiologist productivity. Currently, radiologists perform manual delineation of lung cancer nodules in CT images, which involves segmenting each slice individually. While this method may guarantee accuracy to some extent, it has several drawbacks.

Automatic segmentation and computer tomography (CT) picture categorization of lung nodules, is becoming increasingly necessary due to several shortcomings of the manual segmentation method. Manual delineation of the boundary among lung tumour on each CT slice by a radiologist is a tedious procedure and relies on subjective experience. Also, the rise in lung nodule patients over the past few years makes detection and segmentation and classification less practical. In addition, for the current big data-driven medical imaging workflow, manual delineation of the ROI contradicts the objective of using artificial intelligence. In order to optimise the workflow of medical imaging, there is an increasing need for final algorithms which can automatically segment and categorise biomarker on CT images. Automatic methods for lung nodule segmentation and classification, as well as intra-nodular heterogeneity image generation, are crucial in current radiological practice. In conclusion, the requirement for additional user intervention and the challenge of precisely fragmenting nodules that are adherent to other structures limit the effectiveness of standard approaches for tumor segmentation division. Deep learning models, on the other hand, have demonstrated potential in overcoming these constraints through meticulous picture well before as well as the application of pre-selected nodule patches.

B. Contributions:

R-CNN (Region-based Convolutional Neural Network) is a transfer learning model commonly for object recognition and localization. Its applications extend to various image recognition tasks, including the recognition of lung tumor nodules in CT scans. Studies have employed various machine learning models for the detection of lung cancer nodules, among which is R-CNN. For example, a research detect an R-CNN model for lung nodule detection, which combines a region proposal network with a convolutional neural network to improve accuracy. Another study introduced an R-CNN-based method for finding lung disease on low-dose CT scans, using three-dimensional deep learning for end-to-end screening.

Although R-CNN has shown promise in lung nodule detection and has the potential to improve the accuracy of lung cancer screening and early detection, it is important to conduct further research to validate its effectiveness in clinical settings. Additionally, efforts must be made to enhance its performance on various types of CT scans and lung nodules.

II. Proposed

A technique for automatically identifying and classifying nodules that uses deep learning-based algorithms can greatly improve the accuracy and efficiency of lung cancer treatment. The work aims to decrease False effective finding by implementing multiple strategies, which can help reduce unnecessary interventions and ensure patients receive appropriate care. To achieve its detection and accuracy goals, the system employs a two-phase process of node recognition and categorization.

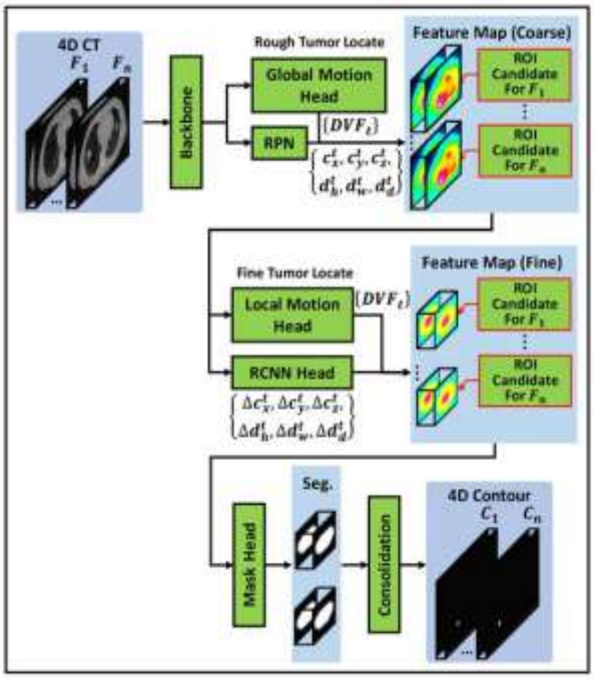


Fig 1.1

R-CNNs (Region-based Convolutional Neural Networks) are a type of model based on deep learning models that has developes for object detection. Unlike traditional neural networks, R-CNNs are designed to identify objects within an input image. When an image is fed into an R-CNN, the model leverages a process called selective search to extract information about regions of interest within the image. These regions of interest are typically represented as rectangular boundaries, and there can be hundreds or even thousands of them in a single image. After the focus areas have been determined, a CNN (Convolutional Neural Network) is used to produce the output features. The SVM (Support Vector Machine) classifier is utilized to categorize the items present in each region of interest when these features are supplied into it.

III. System Implementation- Module Description:

1. Training Phase: Dataset Annotation:

A portion of the publicly accessible LIDC-IDRI dataset, which has 2610 lung nodes overall, was used in this investigation. To create our subset, we screened 888 CT scans, each of which was labeled by at least four radiologists who classified linked lesions into one of three categories: non-nodular (background), nodes larger than 3mm in periphery, and nodes smaller than 3mm in periphery. To establish our gold standard for the dataset, we only included nodes larger than 3mm in periphery that were marked by at least three radiologists. Nodes smaller than 3mm in periphery, as well as those marked by only one or two radiologists, were excluded from the final dataset. Overall, our final dataset consisted of 1186 lung nodes and included information on the periphery and position of each node. In our research, a machine attempting to learn system for the identification and categorization of lung nodules was developed and evaluated using this dataset.

1.1 Preprocessing

- The CT images are generated by analyzing the intensity distribution of X-ray beams that pass through the body. These beams penetrate through different structures and tissues, such as bones, muscles, and clothing. To prevent interference from other tissues, the lung tissue must be separated from the CT scans in order to detect lung nodules. This reduces the likelihood of erroneous positives and enhances the process of segmentation's accuracy. As a result of dividing the lung, the finding and categorization system's overall efficacy can be improved by concentrating on the precise regions where lung nodules are most prone to develop.
- Segmentation of the lungs tissue in CT images is essential for detecting lung nodules. The lungs tissue is identifiable in CT images as a connected sphere with low Hounsfield scale values surrounded by high Hounsfield scale chest muscles. In our study, we performed the segmentation of the lung parenchyma by binarizing the CT images, removing any regions

similar to air or bed frames, filling any holes created by high-viscosity tissues in the lung parenchyma, and ultimately refining the lung parenchyma mask through the use of morphological algorithms.

1.2 Lung Segmentation

Clinical data are not typically stored in basic image type like PNG or JPEG. This is due to the fact that they are acquired under particular circumstances that may have an impact on the visual acuity To solve this problem, a standard for storing and transferring medical images was created. Its name is Digital Imaging and Communications in Medicine (DICOM).

Diverse medical imaging equipment, including scanning, server, workstation, and prints, can be integrated thanks to DICOM. Yet, additional information in DICOM pictures could exist that is unimportant for some tasks, such lung splitting. DICOM pictures can be transformed into the lossless PNG format to simplify image processing chores. During the conversion of a DICOM image to the PNG format, any specific information about the case and markers that were available in the DICOM format are typically removed. This is done to protect the privacy of the user and maintain confidentiality. The conversion process only retains the necessary information needed for the visual CT processing task, in order to process and maintain the strong security and privacy of the patient's data.

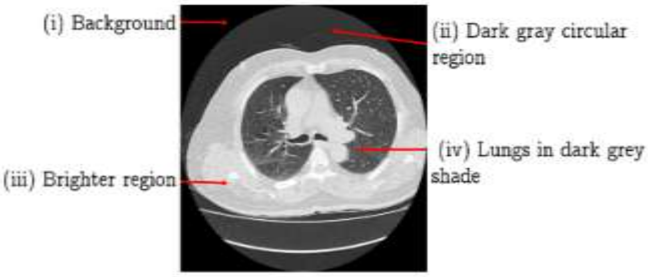


Fig. 1.2

Segmentation of the lung is a critical step in computer-aided diagnosis (CAD) systems, as the clarity of the subsequent analysis stages is heavily reliant based on how well the segments are made. Therefore in section, we provide a lung segmentation approach that makes use of statistical and structural methods for image processing. The PNG image resulting from the conversion of DICOM format usually comprises four distinct components: (i)DICOM conversion is a black background. (ii) dark grey peripheral region. (iii) a more visible region; (iv) dark grey shade.

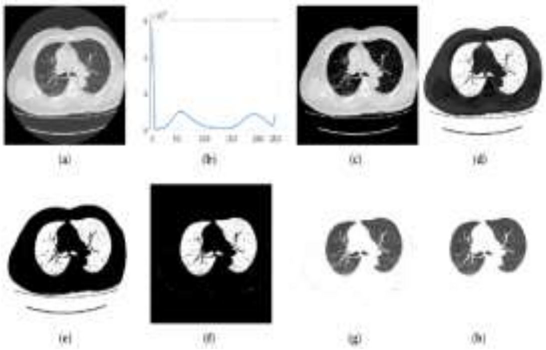


Fig 1.3

An automatic histogram-based approach is employed for initial segmentation: (a) A CT slice serves as the input for our pulmonary segmentation process.; (b)image histogram; (c) The generated image is then processed to generate the final pulmonary division after normalising the picture using the limit value calculated from the histogram.; (d) the complemented image, which is created by flipping the thresholded image's pixel values; (e) a visual representation of the lung region obtained through the segmentation process (f) map represents the final segmentation of the lung; (g) The final segmentation map represents the detected nodules; (h) After noise has been removed, the final image accurately depicts the segmented organs with no extra noise or artefacts.

We use a thresholding technique that is reliant on the chosen target value to separate the lungs from the overall image. The target value is typically not predetermined and requires careful consideration to achieve optimal results. In our method, we use the matching histogram to determine the threshold value to every image slice. In above image displays the histogram of a sample lung image, which shows four distinct peaks. The peak at 0 corresponds to the black color in the backside of the image, while the peak at approximately 60 represents the dark grey peripheral region surrounding the brighter region.

1.3 Lung Nodule Feature Extraction

Due to their distinctive shape in comparison to other lung structures, lung nodules are challenging to identify. This difference in shape is exploited to distinguish nodules from vessels and bronchi, as demonstrated in Figure 1.

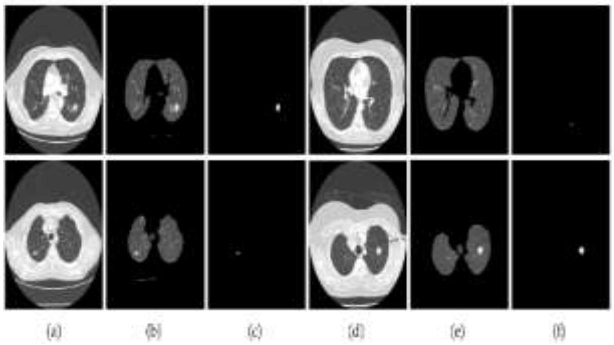


Fig 1.4

In order to accomplish this, we employ a shape identification method that, when applied to the collection of identified structures, recognises spherical shapes based on size and roundness. The region-growing algorithm separates the nodule candidates by returning the centres of the possible node positions, which are subsequently used as seed points. Our system is independent of any nodule template and can identify nodules of any size, in contrast to template-based approaches. Let {c1, c2, c3, …, cn} denote the middle of the circle shape extracted using the RCNN algorithm. We seed the region-growing algorithm, which produces the n nodule candidate regions A1,A2,A3,,An, with the centres discovered by the form identification technique. We compute different nodule features and build a feature vector to distinguish nodules from other interior structures. Several statistical aspects, pattern features, and across-slice properties of the candidate regions are used to create the feature vector. We can accurately distinguish nodules from other tumors using this method.

1.4 Lung Nodule Classification

We used a CNN and a feature vector F to categorise the chosen regions as nodules or non nodules. The model was trained by using the features from a trained dataset and then applied to the testing dataset for classification. We use 2 different CNN models, CNN21 and CNN47, for nodule classification with and without nodule features. For classification without nodule features, the CNN model's own softmax classifier was employed to forecast the class for each and every nodule in the testing dataset. In contrast, when tumor features were employed, a vector containing the 50 node data was added to the CNN-generated feature vector to create a vector with 250 elements. This combined feature vector was then used to assess the nodules in the validation set using an Odd Forest classifier model that had been developed on the training set. The default values were utilised for all other parameters, and the n trees option was set to 1000. For this, we utilised R's random forest package.

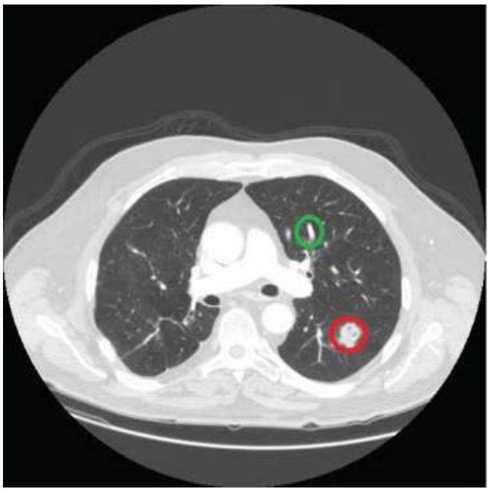


Figure 1.5. A nodule is shown by the area ringed in red, and a non-nodule by the area circled in green.

Several convolutions with ReLU activation, pooling layer, flatten, and a final fully linked softmax layer make up the CNN architecture, which can distinguish between CT scans without and with chest radiography. The complexity of the channel equivariant convolution is different from that the Densenet network. In the complexity of the Densenet network, a bunch of complexity kernels is responsible for a bunch of feature maps, while in the channel equivariant convolution, a complexity kernel is responsible for a feature map, which can substantially lessen the number of parameters. However, this can lead to loss of information between the same group of data. Both the issue of information not being shared within the group and the issue of information not being shared between groups can be resolved by the equivariant operation.

IV Testing Phase: Lung Nodule Disease Prediction

The efficiency of the methods has been assessed after the training process is complete on a total of 10 frames, including imagery out from testing set with obstacles in a variety of challenging environmental circumstances. The trained data collection also includes several other road entities, apart from the obstacles. As part of the evaluation process, the algorithms' precision as well as accuracy in identifying and localising obstacles in the provided frames are examined. The outcomes are contrasted with the test dataset data to assess how well the algorithms worked in actual world situations.

2.1. Prediction Network

The objective of this detection network is to produce a final bounding box by taking inputs from both the Feature Network and Regional Proposal Network. It includes four Networked layers that are coupled to the classification layer and bounding box regression layer to help produce the final detections.

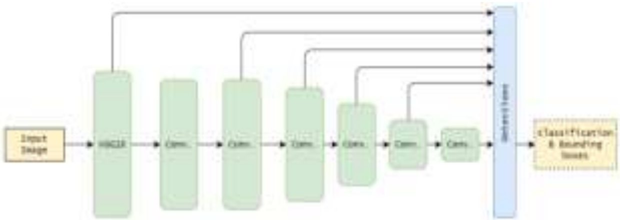
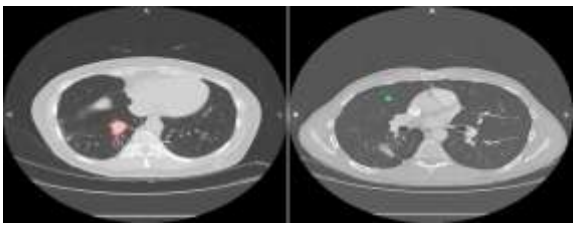


Fig 1.6



Malignant Fig. 1.7 Benign

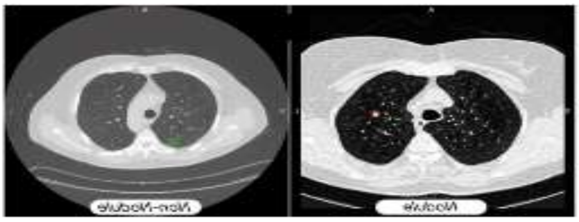


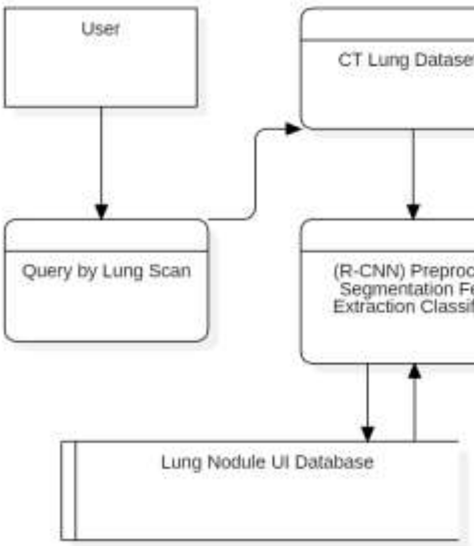
Fig. 1.8

2.2. Algorithm: Improved R-CNN

1. The RGB format of the input CT Lung LUNA Dataset is defined with a 3D Matrix-like RGB format.
2. FRConv(x,y,z,u,v,h,i,j) x = amount of anticipated channels in the displayed picture (3 for RGB)
3. y = the quantity of output channels following the convolution (FRCONV) phase
4. z = The convolution's kernel width
5. u = The convolution's kernel height
6. v = The convolution's step (stride) in the width axis
7. h = The step (stride) height axis.
8. i = added ‘0’ on both side of axis through input.
9. j = added ‘0’ on both side of height through input.
10. ReLU(x) If the input is less than 0, the rectified linear unit's (activation function) output is 0; otherwise, it produces raw output. True or False, x.
11. MaxPooling(x,y,z,u) max-pooling procedure that examines XxY windows and determines its maximum via ZxU stride length.
12. x = Pool filter's width
13. y = Pool filter's height
14. z = Pool stride’s width
15. u = Pool stride’s height
16. FullyConnected(x,y) x = Input image size e.g. 3*256*256 (3 color channels, 256 pixels
17. 256 pixels wide by 256 pixels high)
18. y = fewer output classes than there are input images
19. Loss (x, y) The forecast labels and the actual labels are input into the loss function, which then calculates a number to indicate how well the model performed.
20. x = forecast label
21. y = alive label

Output Segment and Classification (e.g. Nodule:Benign or Malignant and NO Nodule).

DFD:



2. CONCLUSION

Finding pulmonary nodules is essential for the early identification of lung cancer, which is a major global health concern. Automated nodule detection can lessen the radiologists' workload and improve diagnostic accuracy. In order to do this, we suggest an enhanced R-CNN algorithm for identifying lung tumor. A robust system for locating and classifying lung nodules is shown in our project. It involves two models based on deep learning. In order to identify the nodule region in a CT picture as the first step, we first employ an enhanced R-CNN model trained on lung CT scan images. An automated approach utilising two models trained with deep learning was suggested for the detection of lung tumours in CT images. The first model, an Improved R-CNN, was trained with lung CT scan images to detect the nodule region in a CT image. The second model, a segmentation model consisting of RPN and RCNN, was proposed for segmenting the boundaries of the detected nodule region. Following lung segmentation, a significant number of ROIs were collected from the lungs, and the problem of accurate classification was addressed using the form information and the feature of a cluster occurring in successive slices. The suggested technique produced good results, with a sensitivity of 0.9375, accuracy of 0.92, and a Matthews correlation coefficient of 0.8385. In testing, the CNN classifier had a low false positive rate of 0.13 per slice. By limiting the amount of scans that radiologists must perform, this CAD tool may boost their effectiveness that need to be evaluated, and further validation on other clinical data will be conducted to promote its use in lung cancer screening.

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