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NODULE SHADOW BASED LUNG CANCER DETECTION USING DEEP LEARNING

Bhavani K[1*], Gopalakrishna M T[2]

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Abstract

The second leading cause of cancer-related fatalities globally is lung cancer. A method for finding malignant nodules based on shadow detection is provided using 3D computer tomography (CT) images of the lung field. Cancer can be successfully diagnosed at an early stage using this method. The recommended method uses a 3D lung field created from a CT image as its input. The model is built using a three-dimensional convolutional neural network with a focus on shadow identification for cancer detection. A mark and a label are added to the appropriate location in the CT picture when it is determined that the input small area image depicts a nodule. This work uses a model created with two classes, nodules and non-nodules, and applies it to the detection of nodules on a variety of CT images in order to test the classification accuracy. This was done to ensure that the suggested technique would be effective. As a result, the model was able to achieve an F1-score of 93% and an accuracy of 95% with less complexity structure.

Key words: CT, Lung cancer, Nodule shadow, Nodule, CNN.

[1]Department of ISE, Dayananda Sagar College of Engineering, Bangalore, India

[2]Department of AI&ML, SJB Institute of Technology, Bangalore, India

*Corresponding author: bhavanik7@gmail.com

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1. Introduction

The number of deaths due to cancer in India in 2021 was 26.7 million. It grows rapidly with age and the survival rate declines. Currently, radiologists visually diagnose three-dimensional lung field CT (computer tomography) images by continuously following each slice plane, and diagnose nodule shadows that are the cause of lung cancer [1][2]. However, the number of radiologists in India is only 5% of the total number of physicians, and there is a shortage [India Radiology]. There may be differences in the oversight rate due to nodule presence in CT images.

Deep learning models , particularly Convolutional neural network (CNN) models have demonstrated impressive increases in accuracy during image classification tasks under such conditions in recent years [3][6]. Moreover, work is being done on CNN-based computer-aided diagnostic (CAD) systems. In this context, "second opinion"[4] refers to the distribution to physicians of computer diagnostic reports for medical pictures, particularly CT images. The classification of solid nodule shadows, ground-glass nodule shadows, and non-nodule shadows by CNN utilizing real lung field CT scans using two-dimensional images is done for the aim of supplementing. The inability to use the lung field CT images' original three-dimensional features presents a challenge. As a result, in this paper, a CNN that accepts created 3D pictures as input is used to design a system for detecting nodule shadows, which indicates the presence of cancer, from lung field CT scans. The lung field region is the area that can be clipped as the input. The three-dimensional small region picture that was extracted from the lung field CT image is then fed into the detection model that the three-dimensional CNN built [5]. The relevant area of the lung field CT image is then marked with a rectangle if it is noticeable that the cut-out portion represents a nodule shadow. In this research, utilizing publicly available lung field CT image data sets, a three-dimensional classification experiment is performed to develop a model of nodule shadow images and non-nodule shadow images. Additionally, a rectangular display is used to demonstrate the proposed method's ability to detect nodule shadows using a three-dimensional CNN constructed from the lung field CT image.

2. Literature Review

S Arukonda et al [7] provide the evidence to suggest that lung cancer has one of the highest mortality rates of any cancer kind. This is because it is one of the most common types of cancer. The prognosis of the disease has not been particularly encouraging, and a significant contributor to this unfortunate outcome is the tardiness with which the existence of cancer was recognized. Patients who were diagnosed with lung cancer at an earlier stage and received treatment for it have been shown to have a higher survival rate than those who were diagnosed with the disease at a later stage [8]. As a direct result of early detection and following effective treatment, the survival rate of patients with lung cancer is predicted to increase by 20%. [9]. Even while low-dose computed tomography has demonstrated its efficacy in the detection of lung cancer [10] Using CT technology presents a substantial challenge due to the sheer (Large) quantity of scans that radiologists are required to process on a regular basis. When looking at CT scans for microscopic spherical nodules, radiologists encounter a difficult challenge. Also, it takes a long time to determine whether or not the nodules are cancerous. [11]. As a result, it is expected that the CT scans will be analysed using methods [such the computer-aided detection (CAD) approach that will accurately select lung nodules and non-nodules from CT scans based on previously specified features. [12] [13]. When combined with computed tomography, the use of computer-aided design (CAD) systems has proven to be effective in the detection of potential nodules that are of a tiny size, have a poor contrast, and occupy locations with intricate anatomy [14], [15]. The sensitivity of the CAD method to detect candidate nodules is compromised by the high risk of creating false positives [16][19][30]. In order to have a precise and/or accurate evaluation of candidate nodules, it is crucial that such a system be created to reduce the number of false positives. [17]. Raising the sensitivity of an identification and detection model requires feature extraction and nodule classification. This is necessary for the analysis to eventually result in fewer false positives being generated, which is the goal. Suk et al. [18] developed a method for the purpose of Alzheimer's disease and mild cognitive impairment (MCI) diagnosis developed a unique latent and shared feature representation of neuro-imaging data of the brain using Deep Boltzmann Machine (DBM). Wu et al. [19] with the goal of bettering image registration through the use of deep features, created deep feature learning for deformable registration of brain MR images. Xu et al. [20] suggested deep neural networks (DNNs) that may be used for supervised feature extraction in medical picture analysis. Kumar et al [21] For the purpose of determining whether lung nodules are cancerous or benign suggested a “CAD system” that employs deep features generated from the auto encoder. Yaniv et al. [22] Using convolutional neural networks that were trained on data from an archive that was not related to medicine, a system for the medical application of identifying chest diseases in x-rays was presented. According to the findings of that research, the best performance may be achieved by combining deep learning (Decaf) with the characteristics provided by PiCodes. The suggested combination demonstrated the viability of employing deep learning algorithms grounded on nonmedical learning to detect disease in chest x-rays. Ninety-three pictures made up the utilized database. With an AUC of 0.93, 0.89, and 0.79, respectively, for Enlarged Heart, Right Pleural Effusion, and Normal Chest X-Ray Detection, Enlargement, and Classification, they successfully identified abnormal and normal chest x-rays [23]. Suna W. Altaffer et al. [24] deployed three distinct deep learning algorithms—Convolutional Neural Network (CNN), Deep Belief Networks (DBNs), and Stacked Denoising Autoencoder (SDAE)—and compared them to the standard image feature based CAD setup. The CNN structure was made up of eight alternating convolutional and pooling layers. As many as 35 textural and morphological characteristics were retrieved from the old method before being compared to the algorithm. The SVM was trained and classified based on these features given into its kernel. Accuracy for the CNN method was 0.7976, just slightly better than the standard SVM method's 0.7940. The LIDC/IDRI databases (Lung Image Database Consortium and Image Database Resource Initiative) were used, and together they included data on roughly 1018 lung patients [25]. J Tan et al. Using a framework identified lung nodules, and then decreased the number of false positives for the identified nodules by employing a combination of a Deep Neural Network and a Convolutional Neural Network [26]. There are a total of eight layers in the CNN, including four convolutional and four pooling. The filter had a depth of 32 and a size of 3,5. The dataset utilized contains information on around 85 individuals and was obtained from the LIDC-IDRI. A sensitivity of 0.82 was obtained. By using DNN, authors were able to reduce the number of false positives by 0.329 [27]. R. Golan [28] used lung nodules in CT image sub-volumes and provided a framework to train the CNN's weights via back propagation. Using lung nodules that have been labelled by all four radiologists, the approach attained a sensitivity of 78.9% with 20 false positives, and 71.2% with 10 FPs per image.

3. Proposed method

In this study, a 3D-CNN model that can do both classification and detection is developed. The construction of this CNN is shown in Table 1.

Layers	Output size	Structure
Convolution 1	32×32×32×64	[3×3×3,64] [3 × 3 × 3,64]
convolution 2_x	32×32×32×64	3×3max pool. stride2 [3 × 3 × 3,64] [3 × 3 × 3,64⌋
Convolution 3_x	32×32×4×128	[3×3×3,128] [3×3×3,128]
Convolution 4_x	8X8X2X256	[3× 3 × 3,256] [3 × 3 × 3,256]
Convolution 5_x	4×4×1×512	[3×3×3,512] [3×3×3,512]
average pooling	1 x1×1×512	4x4x1
fully combined	4×4×1	2

Table 1: CNN structure

Figure 1 shows an overview of the nodule shadow detection method. First, a small region image of 32 × 32 × 32 pixels is cut out from the field CT image to be detected. At this time, the centre of the small region image is assumed to be within the lung region. Next, the clipped 3D small area image is input to the detection model constructed by CNN as derived from Table 1. The output of the detection model consists of two classes: nodular shadows and non-nodular shadows. Then, if the determination result of the detection model is a nodule shadow, a rectangle is displayed at the clipped portion of the small region image in the lung field CT image.

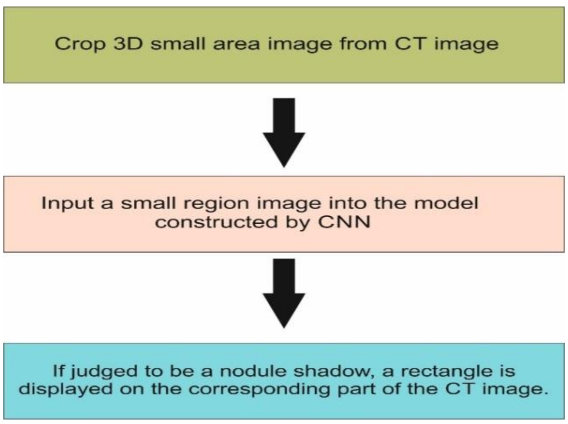

Figure 1: Outline of nodule shadow detection method

In this study, a detection model is built using the three-dimensional CNN displayed in Table 1.The accuracy of the classification of this model is then validated in order to confirm the detection accuracy of the nodule shadow detection approach. Using the model, nodule shadow detection on lung field CT images was carried out, and the model's efficacy was confirmed.

4. Method

4.1 Dataset used

In this paper, lung field CT image data that are publicly available in LUNA16 (Lung Nodule Analysis 2016) [LUNA] for detection experiments [29] is used. First, according to the 3D coordinates specified in the annotation data, the 3D image of 32×32×32 pixels is divided into a nodule shadow image and a non-nodule shadow image and cut out. At this time, 1,351 nodule shadow images and 1,351 non-nodule shadow images are prepared, and these are used as a data set for model construction. Figure 2 shows an example of a nodule shadow image and a non-nodule shadow image.

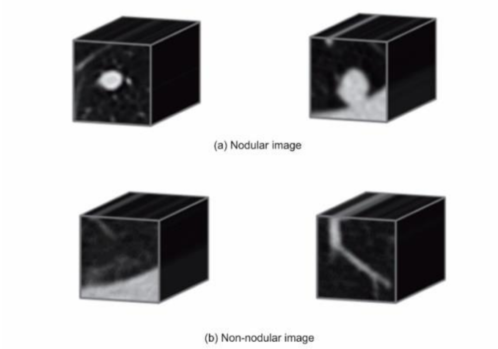

Figure 2: Small area image example of LUNA dataset

4.2 Verification of classification accuracy

The dataset is initially separated into training data for model training and test data for determining classification accuracy. A three-dimensional image that has been moved from the given coordinate position in the original training data is clipped in order to correlate to the displacement of the nodule shadows, as illustrated in Figure 3. Thus, a nine fold expansion of the training data is achieved.

Experiments with various learning rates and mini-batch learning with a batch size of 16 were conducted as training conditions for the detection model.

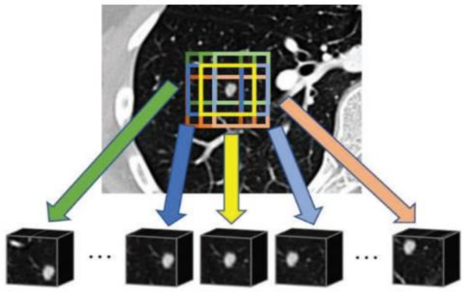

Figure 3: Generation of displaced images

One of the metrics taken into account for rating labeling prototypes is accuracy. In a general sense, accuracy is determined by the portion of estimations that the model may be accurate in. Properly, accuracy takes the following definition: it indicates in percentage how many of all predictions were accurate. A single metric known as the F1-score is created by taking the harmonic mean of the two assessment matrices, Precision and Recall. Precision also called specificity counts the proportion of predictions that are accurate out of everything that has been forecasted as being positive. Recall also called sensitivity tells us how many of the real positives the model was able to identify. The F1-score is given by the formula

f1-score = 2 * recall * precision / (recall + precision)

Based on the aforementioned metrics, the confusion matrix produced by the model is shown in figure 4.

	precision	recall	f1-score	support
0	0.94	0.99	0.96	90
1	0.98	0.89	0.93	53
accuracy			0.95	143
macro avg	0.96	0.94	0.95	143
weighted avg	0.95	0.95	0.95	143

0.951048951048951

Figure 4: Confusion matrix

Figure 4 shows that the F1-score is 93 and that the accuracy rate is 95. Further, the test data indicated a high accuracy rate of 95.1% or more for both nodular and non-nodular shadows.

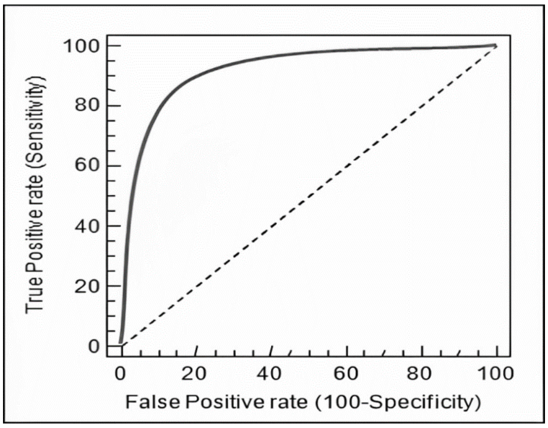

Figure 5: AUC/ROC curve

The detection model converges to roughly 98% while the accuracy rate for the training data typically approaches 100% as seen in figure 5. A model with a simplified structure was utilised to obtain the above results.

4.3 Nodule detection

Results of nodule shadow identification using the detection model created are shown in Figures 6 and 7. This detection was carried out in accordance with the flow in Figure 1. The red rectangles in Figures 6 and 7 reflect the areas where nodule shadows were detected by the detection model, while the yellow rectangles represent the coordinates given positions in the annotation data. The small region images sliced along the yellow rectangles for each of Figures. 6 and 7 are included in one of the test data.

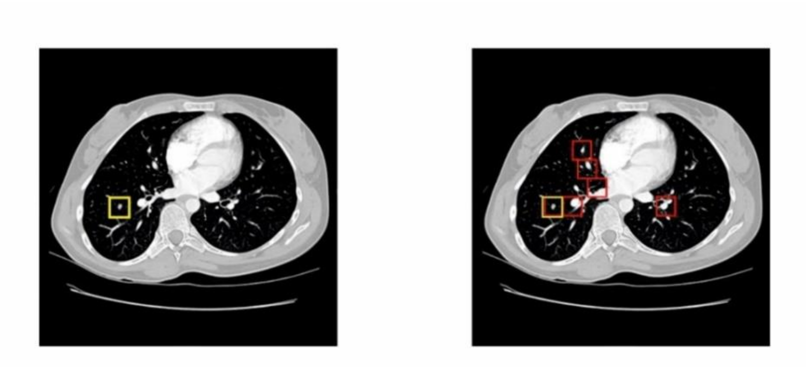

Figure 6: Detection result 1

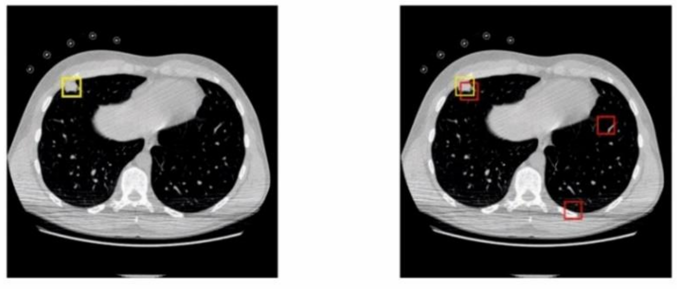

Figure 7: Detection result 2

It is proven that nodular shadows could be found in Figure 7 by using the mismatched images from Figure 3 in the training data. Erroneous detection, however, was localised in regions that resembled nodule shadows and appeared as white dots on the slice plane of the CT image, particularly in Figure 3.

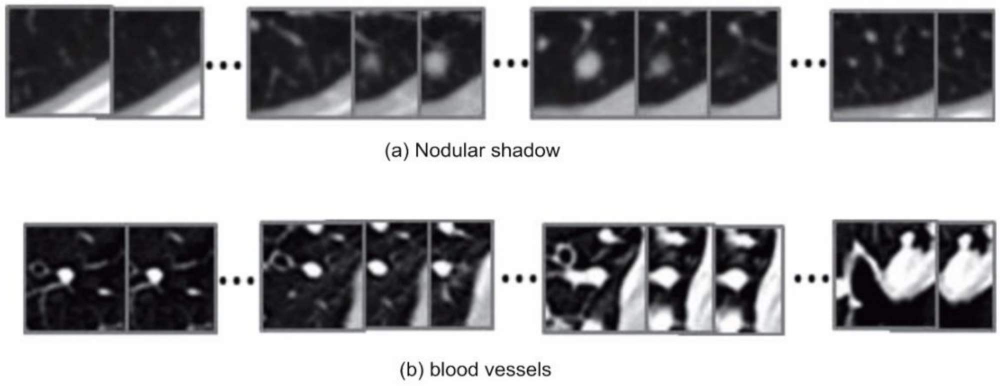

Figure 8: Example of a small area image divided for each slice plane

Blood vessels are depicted by white dots. As seen in Figure 8, blood vessels are visible virtually across the whole slice segment, but nodule shadows only appear as continuous white spots in some slice portions.

5. Conclusion

In order to aid radiologists in diagnosis, a system is suggested in this study for detecting lung cancer using nodule shadows, which aids cancer detection from lung field CT scans using a three-dimensional CNN. To further verify the efficiency of the detection model, nodular shadow detection was actually carried out. As a result, a detection model is built with an F1 score of 93 on cancerous cases, 96 on benign cases and an accuracy score of 95. In order to further improve the detection model's accuracy and F1-score, it is planned to deploy a CNN with a deeper structure in the future.

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