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An Improved Deep Learning Inspired Intelligent Algorithm to Detect Lung Cancer

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Abstract:

The use of deep learning algorithms, and in particular Convolutional Neural Networks (CNN), has recently emerged as a better method for automating the process of illness diagnosis. The purpose of this research was to determine whether deep learning-optimized chest CT was useful in diagnosing lung cancer. The study's participants were 90 people who had been diagnosed with lung cancer either in-hospital surgery or puncture. Nodule detection used RCNN, and a common end-to-end picture segmentation model was the Mask Region Convolutional Neural Network (Mask-RCNN) model. The findings revealed that the suggested algorithm model was 71.74 percent accurate in identifying lung lesions in patients with lung cancer, whereas the accuracy of CT diagnosis of lung cancer was 88.37%, the sensitivity was 78.21%, and the specificity was 82.87%.

Keywords: Lung cancer detection, CNN, RCNN, Deep Learning

1. Introduction

Recently, 2.09 million new instances of lung cancer were diagnosed, while 1.76 million individuals died from the disease. Early in the 2000s, four Japanese case-controlled trials revealed that screening with both chest x-rays and sputum cytology successfully reduced lung cancer mortality. Two randomized controlled studies, however, performed between 1980 and 1990, found that screening with chest radiography did not reduce lung cancer mortality. Radiographs of the chest, although their usefulness in lung cancer screening is still up for debate, have the advantages of being less expensive, more readily available, and delivering a lower radiation dosage than low-dose computed tomography (CT). Excessive false positive (FP) readings are another issue with chest CT. It has been observed that low-dose CT screening identifies 96% FPs among nodules, resulting in many unneeded follow-up and invasive investigations. While chest CT has a higher sensitivity, chest radiography is more accurate when it comes to pinpointing the exact location of an issue. Considering these factors, it is clear that enhancing sensitivity while retaining low FP outcomes via the creation of a CAD model for chest radiograph would be beneficial. In recent years, state-of-the-art advancements in radiography have been made thanks to the use of convolutional neural networks (CNN), a subfield of deep learning (DL). In addition, DL-based models have shown potential for nodule/mass identification on chest radiographs9-13, with reported sensitivity values between 0.51 and 0.84 and a mFPI (fraction of positive indications) of 0.02 to 0.34. Further, radiologist performance for identifying nodules was enhanced with these CAD models. It might be difficult for radiologists to see nodules and determine whether they are benign or cancerous in clinical practice. Nodules might have normal anatomical structures masquerading as them, thus radiologists need to pay close attention to their size, form, and marginal features. Because these issues stem from the circumstances themselves and not the radiologist's skill, even highly trained radiologists sometimes get it wrong.

The greatest effect has been shown in the rising or falling prevalence of lung illnesses. This increases the risk of developing lung cancer and other lung diseases [1-3]. Compared to other cancers, lung cancer has a very high incidence and fatality rate, and this trend is only expected to worsen with time. Its growth rate increased to nearly 27% in 2018 [4]. When it is first developing, lung cancer has no outward symptoms. Pulmonary nodules are the primary sign of early lung cancer and may be found using a variety of additional diagnostic procedures. Major symptoms such as fever, hemoptysis, and shortness of breath are indicative of more advanced disease stages. If these individuals don't get therapy at the optimum time, their prognosis is dismal [5, 6]. Because of this, the prognosis of lung cancer patients is greatly influenced by how quickly they are diagnosed and treated. Presently, image detection, especially by computed tomography (CT), is the primary mode of assessment for lung disorders [7]. Cone beam computed tomography (CT) is a popular diagnostic tool that utilizes X-ray technology. Additionally, it is a crucial part of the process of assessing and diagnosing lung illnesses, particularly in the context of evaluating lung function. CT, however, reveals a shortcoming of illness diagnostic methods: the influence of clinicians' own biases and preferences on the interpretation of images captured by their equipment. The outcomes of diagnoses are also influenced to some degree [8]. When evaluating the same CT scan, clinicians with varying amounts of expertise will focus on various details and use alternative lines of reasoning. As a consequence, it's not unusual to get conflicting findings. In addition, the modern society's increased patient volume increases the need for film criticism from medical professionals.

Physical factors such as lesion size, attenuation, evaluation, and surrounding cystic airspace have been identified by radiologists as being useful in determining whether lesions are benign or malignant. Quantitatively capturing the tumor's or normal tissue's form, size, volume, and texture is possible using radiological features. With the use of AI, they may be included into a prognostic prediction model [9, 10]. The use of chest CT scans in the detection of cancer faces two main obstacles today. To begin with, a method must be created for chest CT diagnosis that can precisely extract phenotypic traits from pictures. Second, in order to aid in the prognosis and clinical treatment of the illness, the system must determine, from among hundreds of phenotypes, which traits are associated to the underlying genotype and disease behavior [11]. The method model of the Mask Region Convolutional Neural Network (Mask-RCNN) combines detection and classification; it is based on the Faster-Regions with Convolutional Neural Network (Faster-RCNN). Mask-RCNN is the most sophisticated deep learning model, and research shows that it performs well when used to dynamic video identification and segmentation [12]. Mask-RCNN technique has been suggested in other research to help with illness classification and identification [13] due to its automated segmentation impact. Good results have been seen in the automatic detection of pulmonary nodules when using a CNN called a Dual Path Network (DPN) [14], which combines the benefits of aggregation residual transform (ResNeXt) for feature reuse with those of a dense convolutional network (DenseNet) for exploring new features. To sum up, CT detection pictures of lung cancer were processed using the optimization-based Mask-RCNN method for automated segmentation, and lung function tests were performed on lung cancer patients using this technique. Additionally, its identification effects on benign and malignant cancers were evaluated by serum tumor detection. Improvements in clinical diagnosis and therapy for lung cancer patients may be supported by the model's adoption and evaluation, which in turn provides a sound scientific foundation for such efforts.

2. Literature Review

Gene expression data-based approaches are very precise yet costly in 2021. However, there is a radiometric technique that saves money without sacrificing too much precision. Genotype-guided radiomics (GGR) was proposed by P. Aonpong et al. [19] because to its excellent accuracy and inexpensive cost. Pre-processing, feature extraction and selection from radiomics (input features), and prediction are the steps that make up this approach. GGR is a two-step process that employs two models to make its predictions. Estimation of the gene is used in the first model, and then the estimated gene is used in the second model to make recurrence predictions. The CT images and gene expression data from the overall NSCLC radiography dataset are used in this technique. Results from experiments demonstrate that the proposed GGR greatly improves prediction accuracy over both the current radiometric approach and ResNet50, reaching 83.28 percent. Evidence suggests that late-stage diagnosis is the leading cause of illness and mortality in patients with lung cancer. For the ultimate categorization of EGFR mutation status, F. Silva et al. [20] suggested using MLP. The nodule, the lung with the primary nodule, and the other lung are all evaluated for EGFR activity. The strategy presented here may be broken down into two distinct stages. Learning features is the first step.

Second, we use transfer learning strategies to create a comprehensive model of categorization. The LIDC-IDRI and NSCLC-Radiogenomics data sets were used for this analysis.

According to experiments, it outperforms other methods in terms of its predictive power. Early detection will be the primary factor in survival and quality of life for patients with lung cancer in 2020. Automatic lung cancer detection was suggested by H. Yu et al. [12] using the "Adaptive Hierarchical Heuristic Mathematical Model (AHHMM)". There are five phases to this procedure. To begin, a picture must be obtained. Pre-processing is the next phase. In the third stage, binarization occurs. Thresholding and categorization come up next. Last but not least, a Deep Neural Network for extracting and detecting features (DNN). Furthermore, pre-classification photos were clustered using a modified version of K-means. The experimental findings of this approach on the lung cancer dataset [21] demonstrate an accuracy of 96.67%. Screening is often used by radiologists for a variety of CT scans to ensure thorough analysis. It's possible that automated algorithmic solutions may be useful, but figuring out how to work with doctors to implement them is another obstacle. To address this issue, O. Ozdemir et al. offer a method using low-dose CT scans. [22] The CT images are analyzed in real time, and the system returns standardized ratings. Specifically, they are three-dimensional convolutional neural networks trained on data from an entire system. Preprocessing, the CADe module for segmentation, and the CADi module for interpreting results are the steps that make up this technique (CADx). This is because the success of CADx is tied to that of CADe, hence the two systems must be built and tuned together. These datasets are used in this method: LIDC-IDRI, LUNA-16, and Kaggle. In practical use, this method is superior. A 96.5% accuracy rate in diagnosing lung cancer is achieved by using the suggested methodology.

Early detection of lung cancer may save lives, according to research published by Q. Zhang et al. [23]. Radiologists have a difficult, time-consuming, and repetitive job in the early diagnosis of lung cancer nodules. They suggested adding the "vesselness filter" to the "Multi-Scene Deep Learning Framework (MSDLF)" for better precision and fewer false positives. The primary goal of this study is to locate big nodes (those with diameters more than 3 millimeters). It's a model created using four channels of CNN. Data set preparation, parenchyma segmentation, vascular removal, standardization of data sets, CNN construction, segmentation, and classification, and normalized spherical sampling are all parts of this procedure. This strategy use the LIDC-IDRI dataset. In a time-consuming and laborious process, radiologists must manually draw lung nodules, as noted by A. Masood et al. [24]. To aid radiologists, a 3D Deep Convolutional Neural Network (3DDCNN) is included in the system. In comparison to cutting-edge technology, theirs performs well. Accurate detection of lung nodules is achieved by combining deep learning with cloud computing. For its design, they relied on the mRPN (Multi-Regional Proposal Network). Training datasets, data enhancement, pre-processing, suggested model architecture, training procedure, cloud-based 3DDCNN CAD system are all part of the methodology. This approach utilizes the ANODE09, LUNA-16, and LIDC-IDRI SHANGHAI Hospital datasets. Data analysis demonstrates that the provided model can diagnose lung cancer with a 98.5% degree of accuracy. Lung cancer mortality risk prediction was suggested by H. Guo et al. [25] using the Knowledge-based Analysis of Mortality Prediction Network (KAMP-Net). A Convolutional Neural Network is trained with the use of data augmentation in this approach (CNN). They hypothesized that by adding more data, they might boost CNN's efficiency. Mortality risk is calculated by using a combination of CNN and SVM classification findings, with the SVM classifier being trained using the clinical measures. Clinical parameters have been gathered by hand measurement. Multi-Channel Image Coding, Network Design and Deployment, Deep Learning and Clinical Expertise are all parts of this procedure. Data from the National Lung Screening Trial (NLST) is used for this technique. With the use of deep learning, S. Pang et al. [26] were able to determine the subtype of lung cancer shown in CT scans taken from patients at Shandong Province Hospital. By using picture preprocessing techniques like "rotation, translation, and transformation," they were able to increase the size of the training data set and therefore address the issue of a lack of data acquired from the patient. In order to classify the lung cancer photos, the scientists trained the "densely connected convolutional networks (DenseNet).

At last, they combine the results of many classifications using the adaptive boosting (adaboost) method. This strategy employs data from Shandong Provincial Hospital. Based on the experimental assessment, the suggested model is able to identify lung cancer with an accuracy of 89.85%. Correct categorization of malignant lung nodes and feature score regression are essential for automated lung node analysis. For a fully automated study of pulmonary nodules, L. Liu et al. [27] presented the MTMR-Net model. The Siamese network's architecture is also mapped out in this form. There are three primary components to the suggested architectural technique. The first piece is a module that extracts features. One convolution layer, one Res Block A, and three Res Block B made up the architecture. The second part is the categorization section. It had one and only one layer that was interconnected throughout. The module that deals with regression is the third. It had two levels, both of which were linked together. Multi-Task Learning for Lung Nodule Analysis, Margin Ranking Loss for Discriminating Marginal Nodules, and Joint Training of MTMR-Net are all features of the MTMR-Net model. The experimental results assessment demonstrates that the suggested model can identify lung cancer dataset with 93.5% accuracy [28]. By far the most accurate, sensitive, and specific technique was "MTMR-NET," which was compared well to other cutting-edge approaches.

3. Image Segmentation Based on Mask-RCNN Algorithm Model

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The Mask-RCNN algorithm model is a convolutional neural network model that may be used for object recognition and image segmentation [15]. It is based on the Faster-RCNN algorithm. It effectively separates the CT image into its constituent parts by combining target identification and segmentation methods. In order to increase the accuracy of the picture while segmenting the boundaries, the Mask-RCNN method swaps out the original region of interest (ROI) pooling layer with a superior ROI Alignment layer [16]. The new network architecture, whose foundation is presented in Figure 1, employs a fully convolutional network for picture segmentation.

Replacement with the ROI Alignment layer successfully preserves the image's spatial information by realizing the mutual correlation between output pixels and input pixels. Using the following equations, we can determine where in the original CT picture the target pixel should be placed.

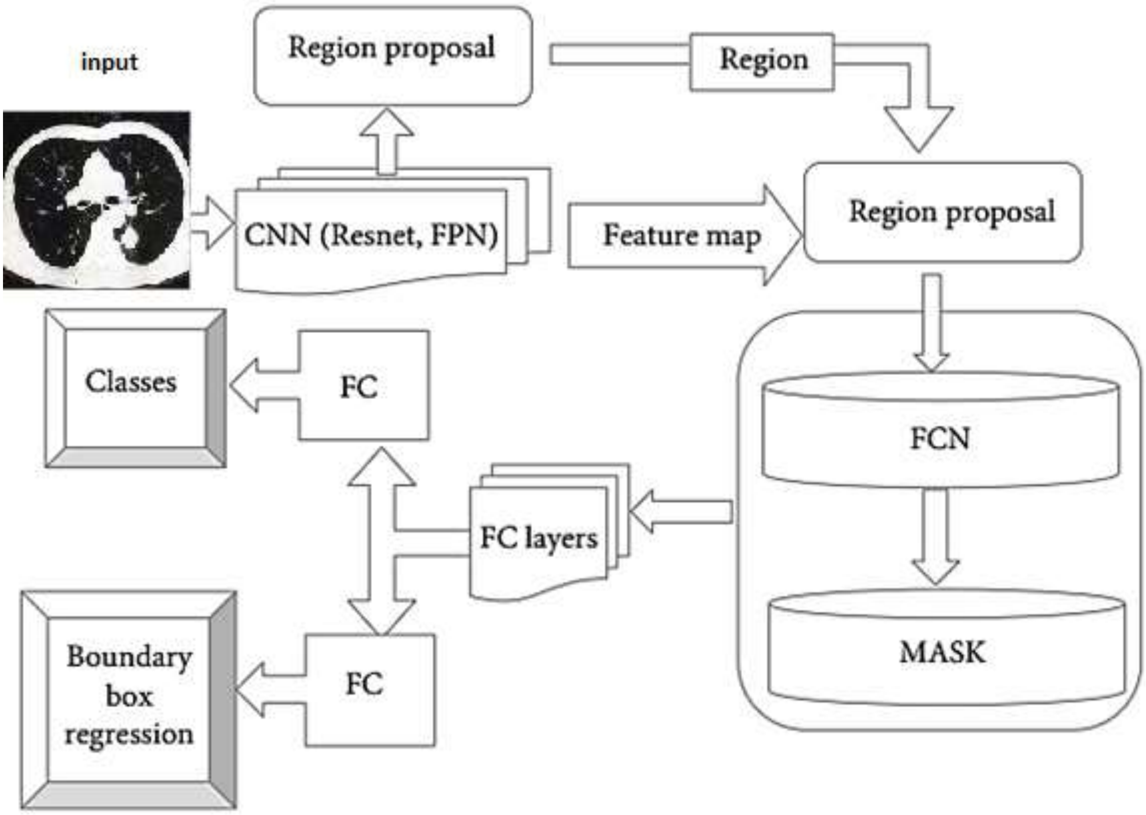

Figure 1: Proposed Mark-RCNN Algorithm

With a focus on patients who had been pathologically diagnosed with lung cancer at our institution, we gathered a series of chest X-rays from patients over time. These chest x-rays have been annotated by radiologists to show the locations of cancerous growths in the lungs. The radiograph annotations were used to develop and verify a deep learning-based model for lung cancer detection on radiographs. After training the model, it was put to the test against a new collection of data in an effort to identify lung tumors. The Ethical Committee of the Graduate School of Medicine at Osaka City University has evaluated and approved the study's protocol (No. 4349). The Ethical Committee of Osaka City University Graduate School of Medicine disregarded the requirement for further informed permission since the radiographs had been taken during routine clinical practice and patients had given approval for their use in research. It is important to note that all procedures were carried out in conformity with all applicable rules and regulations.

For this reason, we decided to implement a CNN framework based on a segmentation strategy. When compared to detection (which presents a bounding box) and classification methods, segmentation provides a greater amount of data (which determine the malignancy from a single image). In clinical settings, the maximal tumor diameter is of utmost importance. This makes it challenging to quantify using detection techniques that give a bounding box, since the maximum diameter of the tumor often corresponds with an oblique direction rather than the horizontal or vertical. To generate segmentation17, we built our CNN on top of a standard encoder-decoder framework. The bottleneck structure of the encoder-decoder design decreases the feature map's resolution and increases the model's resistance to noise and overfitting18. The utilization of both a standard chest radiograph and a black-and-white inversion of a chest radiograph is another distinguishing feature of this DL-based model. This enhancement draws on the expertise of radiologists to improve upon the status quo. To confirm the existence of lung lesions that overlap visual blind areas, black-and-white inversion is often used. Because of our belief that this enhancement would be useful for this model as well, we first trained a CNN architecture on both the original and inverted pictures, and then we trained an ensemble model with the two CNNs combined (see Figure 20). The online Supplemental Fig. S1 provides further context and details about the model. The model was built from scratch and trained and validated using fve-fold cross-validation using chest radiographs from the training dataset. The best-performing model was selected after 100 iterations of Adam learning (learning rate=0.001, beta 1=0.9, beta 2=0.999, epsilon=0.00000001, decay=0.0).

Table 1: Dataset Demographics

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Characteristic	Training dataset	Test dataset
Patients (n)	629	151
Men	408 (65%)	94 (62%)
Women	221 (35%)	57 (38%)
Mean age ± SD (years)		
Men	70 ± 8	70 ± 8
Women	69 ± 10	69 ± 10
Chest radiographs (n)	629	151
No. of malignant nodules/masses	652	159
Mean nodule/mass size ± SD (mm)	38 ± 21	33 ± 21

4. Performance Evaluation

According to the statistics, lung illnesses and cancer in particular have become clinically nonnegligible major concerns with high rates of occurrence and death. The percentage of global mortality attributable to lung cancer in 2018 was around 18% [17, 18]. Lung cancer has a greater death rate than other illnesses. Preventing and treating lung cancer early on is crucial to its successful therapy. The death rate from lung cancer may be drastically decreased with better diagnostic techniques. Chest x-ray (CXR), computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), sputum cytology, and breath analysis are some of the seven methods now used in the clinical diagnosis of lung cancer [19, 20]. Diverse biomarkers are tapped by the various lung cancer detection methods. There are benefits and drawbacks to using these approaches. CXR and CT scans, for instance, expose patients to a little amount of radiation, whereas MRI and PET scans have their own set of shortcomings when it comes to identifying and diagnosing lung nodules [21, 22].

Table 2: Segmentation Performance

Sensitivity by location	
Pulmonary apices	0.52 (0.33–0.71)
Pulmonary hila	0.64 (0.36–0.86)
Chest wall	0.52 (0.32–0.72)
Heart	0.56 (0.22–0.89)
Sub-diaphragmatic space	0.50 (0.00–1.00)
Non-overlapped lesions with normal anatomical structures	0.87 (0.79–0.93)
Sensitivity by margin	
Traceable edge	0.87 (0.81–0.93)
Untraceable edge	0.21 (0.06–0.35)

Lung nodules are an essential indicator of early-stage lung cancer, thus catching the illness as soon as possible is crucial for patients' chances of survival. Serum tumor markers in conjunction with imaging techniques may also be used to diagnose lung cancer [23, 24]. Tumor markers are substances that can be used to reflect the occurrence and development of tumors and monitor the tumor's response to treatment. These substances may be naturally present in malignant tumor cells, abnormally produced by malignant tumor cells, or produced by the host in response to tumor stimulation. Using immunological, biological, or chemical techniques, tumor markers may be discovered in the excreta, bodily fluids, and tumorous tissue of cancer patients. Results showed that CT was 88.37% accurate, 82.91% sensitive, and 87.43% specific for diagnosing lung cancer. Serum tumor markers had an 87.34 percent success rate, an 81.44 percent sensitivity, and an 86.7 percent specificity in the detection of lung cancer. CT based on deep learning and blood tumor markers enhanced accuracy to 97.94%, sensitivity to 98.12%, and specificity to 100%.

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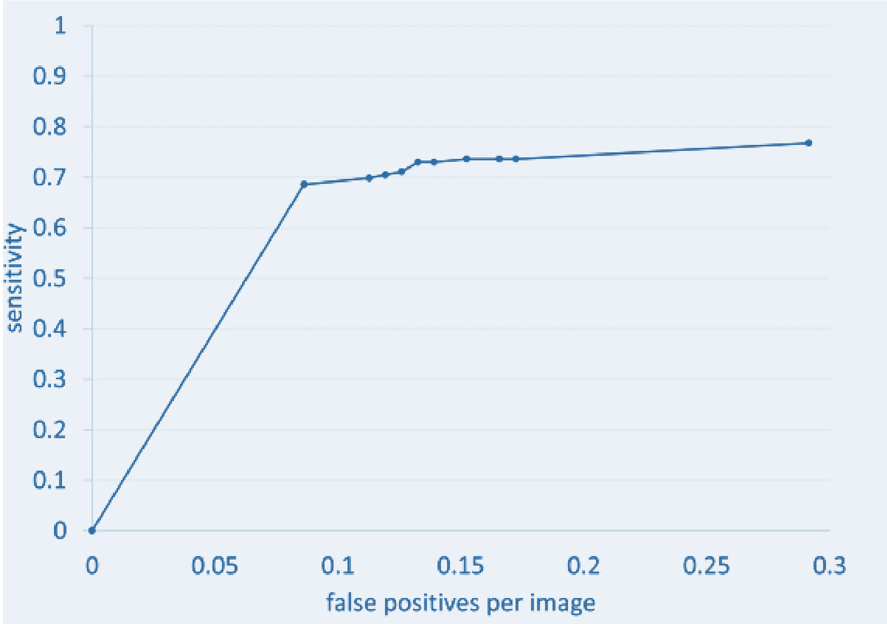

Figure 2: Segmentation Accuracy of the Proposed Approach

At present, the most effective technique to detect lung cancer clinically is CT imaging, which can express detailed information about the location and size of lung nodules. In the early stage of cancer, low-dose CT screening can effectively find tumors in the lungs. Compared with traditional radiography technology, it reduces the mortality of patients with lung cancer by 20.0%, and the positive rate of screening has been significantly improved [25]. When the nodules are small, other inspection methods have limitations in diagnosing, while CT can effectively diagnose the patient. Most lung nodules are small in size, about 3 mm in diameter. Radiologists can classify nodules into malignant and benign based on CT. This involves a detailed examination of 3D lung voxels by slicing them into multiple 2D slices [26, 27]. Because CT contains a large amount of information, the analysis must be more precise in order to divide the nodules into malignant and benign. Usually, the possibility of human error in the analysis and diagnosis of CT images will affect detection results of lung nodules [28]. Therefore, the automatic and intelligent diagnosis of lung cancer is important.

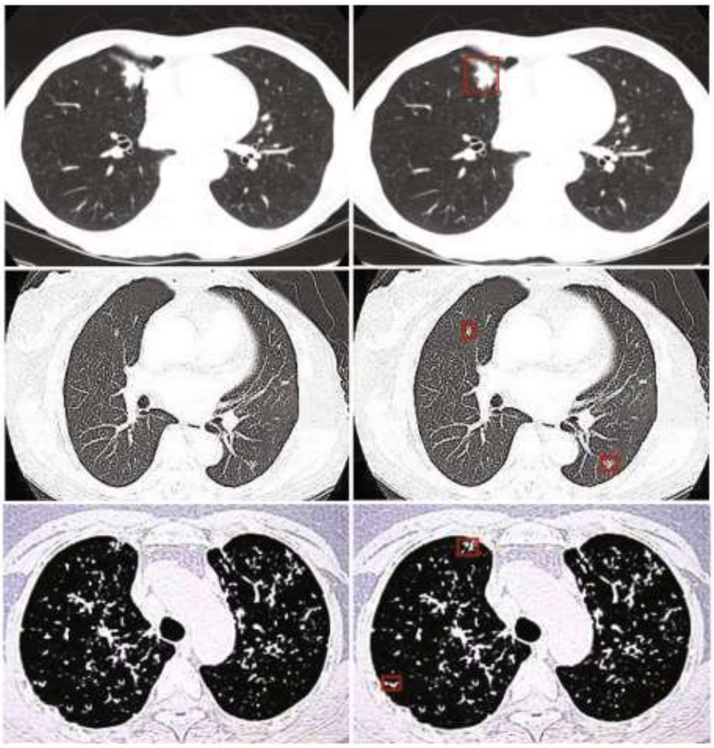

Figure 3: The detection effect of Proposed algorithm on CT images of lung nodules

The model parameter capacity in the training of the Proposed algorithm model is 5.29MB. Compared with other algorithm models, the Proposed algorithm model only uses about a quarter of the parameter capacity of them. According to the experimental results, the Proposed algorithm model had an accuracy rate of 88.74% for the detection of lung lesions in patients with lung cancer. As an auxiliary method for radiologists, deep learning is used to optimize CT imaging to accurately detect and classify malignant tumors, which is an effective method that has been gradually applied in clinical practice. In addition, Mask-RCNN segmentation algorithm was utilized to segment lung CT images in the research. The results showed that Mask-RCNN segmentation algorithm could not identify the boundaries of images accurately, but it could segment CT images, which was consistent with the results of the study conducted by Zhang et al. [29]. The consistency offered some supports to the results of the research.

5. Conclusion

Optimized CT images of pulmonary nodules were obtained from patients with lung cancer and examined in this research. This was accomplished by combining the Mask-RCNN and DPN algorithm. The findings revealed that when Mask-RCNN was used in conjunction with the Proposed algorithm, segmentation effects for lung parenchyma CT images were significantly enhanced, resulting in a significant boost to the diagnostic efficiency of lung cancer CT pictures. While the research has merit, it is important to acknowledge its limitations. The study's strength is compromised by the tiny sample size. A larger sample size is required for confirmation of results in the follow-up. Artificial diagnosis is still required since the only thing that can be done right now is automated identification and labeling of pulmonary nodules, but this does not tell you anything about the nature of the lesions. In conclusion, there is substantial therapeutic merit in promoting the integration of AI algorithms with medical imaging technologies.

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