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A Better Deep Learning-Inspired Algorithm For Lung Cancer Detection

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Abstract:

Using deep learning algorithms, especially Convolutional Neural Networks (CNN), has become a more effective way to automate illness diagnosis. This research aimed to see if deep learning-optimized chest CT scans could help diagnose lung cancer. The study involved 90 people diagnosed with lung cancer through surgery or biopsy. A model called RCNN was used for nodule detection, and a common picture segmentation model called Mask-RCNN was also used. The results showed that the suggested algorithm was 71.74% accurate in identifying lung lesions in lung cancer patients, compared to CT scans which had an 88.37% accuracy rate. The sensitivity of the algorithm was 78.21%, and the specificity was 82.87%.

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

1. Introduction

Recently, there have been 2.09 million new cases of lung cancer diagnosed, resulting in 1.76 million deaths from the disease. In the early 2000s, four Japanese case-controlled trials found that screening with both chest x-rays and sputum cytology reduced lung cancer mortality. However, two randomized controlled studies from the 1980s to 1990s showed that screening with chest radiography did not reduce lung cancer mortality. Although the effectiveness of chest radiography in lung cancer screening is debatable, it has advantages such as lower cost, greater availability, and lower radiation dosage compared to low-dose computed tomography (CT).

However, chest CT screening presents challenges with excessive false positive (FP) readings, where low-dose CT screening identifies 96% FPs among nodules, leading to unnecessary follow-ups and invasive investigations. Although chest CT has higher sensitivity, chest radiography is more accurate in identifying the precise location of an issue. Given these factors, there is a clear need to enhance sensitivity while maintaining low FP outcomes by developing a CAD model for chest radiography.

In recent years, advancements in radiography have been achieved through the use of convolutional neural networks (CNNs), a subfield of deep learning (DL). DL-based models have shown promise for identifying nodules/masses on chest radiographs, with reported sensitivity values ranging from 0.51 to 0.84 and a fraction of positive indications (mFPI) of 0.02 to 0.34. Furthermore, these CAD models have improved radiologists' performance in identifying nodules.

Identifying nodules can be challenging for radiologists, as they may resemble normal anatomical structures. Therefore, radiologists must pay close attention to factors such as size, shape, and marginal features. Even highly trained radiologists may make errors due to the nature of the circumstances rather than their skills.

The prevalence of lung diseases has a significant impact on the risk of developing lung cancer and other lung diseases. Lung cancer has a high incidence and fatality rate, which is expected to worsen over time, with a growth rate reaching nearly 27% in 2018. Lung cancer often has no outward symptoms in its early stages, and pulmonary nodules are the primary sign of early lung cancer. Major symptoms such as fever, hemoptysis, and shortness of breath indicate more advanced disease stages. Prompt diagnosis and treatment significantly affect the prognosis of lung cancer patients.

Currently, computed tomography (CT) imaging is the primary mode of assessing lung disorders. Cone-beam CT is a popular diagnostic tool that utilizes X-ray technology and is crucial for evaluating lung function. However, a limitation of CT imaging is the influence of clinicians' biases and preferences on image interpretation, leading to varying diagnoses.

Radiologists have identified physical factors such as lesion size, attenuation, and surrounding cystic airspace as useful in determining whether lesions are benign or malignant. Quantitatively capturing the tumor's form, size, volume, and texture using radiological features can aid in developing prognostic prediction models. Artificial intelligence (AI) can incorporate these features into prognostic prediction models.

However, there are two main obstacles to using chest CT scans in cancer detection. Firstly, a method must be developed to precisely extract phenotypic traits from chest CT images. Secondly, the system must determine which traits are associated with the underlying genotype and disease behavior among hundreds of phenotypes. The Mask Region Convolutional Neural Network (Mask-RCNN) model, based on Faster-Regions with Convolutional Neural Network (Faster-RCNN), is a sophisticated deep learning model that combines detection and classification. This model has shown promise in dynamic video identification and segmentation and has been suggested for illness classification and identification due to its automated segmentation impact.

In conclusion, the optimization-based Mask-RCNN method has been used to process CT images of lung cancer for automated segmentation, and lung function tests have been performed on lung cancer patients using this technique. The adoption and evaluation of this model could support improvements in clinical diagnosis and therapy for lung cancer patients, providing a solid 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

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.

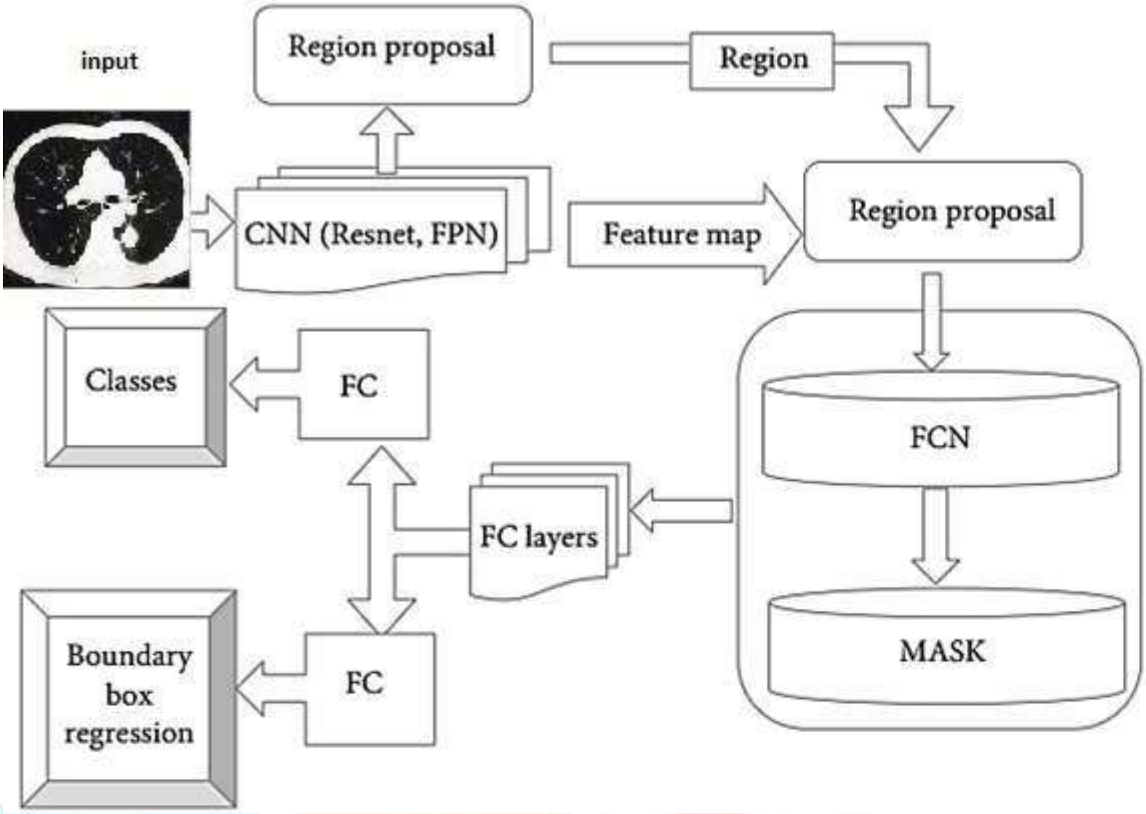

Figure 1: Proposed Mark-RCNN Algorithm

The Mask-RCNN algorithm model is a type of convolutional neural network (CNN) used for object recognition and image segmentation. It is built upon the Faster-RCNN algorithm and effectively divides the CT image into its individual parts by combining target identification and segmentation techniques. To improve the accuracy of image segmentation, the Mask-RCNN method replaces the original region of interest (ROI) pooling layer with a superior ROI Alignment layer. This new network architecture, illustrated in Figure 1, employs a fully convolutional network for image segmentation.

Replacing the ROI pooling layer with the ROI Alignment layer successfully preserves spatial information by considering the correlation between output and input pixels. Using specific equations, we can determine the original position of the target pixel in the CT image.

We collected a series of chest X-rays from patients who had been pathologically diagnosed with lung cancer at our institution. These X-rays were annotated by radiologists to indicate the locations of cancerous growths in the lungs. The radiograph annotations were used to develop and validate a deep learning-based model for lung cancer detection on radiographs. The study protocol was evaluated and approved by the Ethical Committee of the Graduate School of Medicine at Osaka City University (No. 4349). Since the X-rays were part of routine clinical practice and patients had given consent for their use in research, further informed consent was waived by the Ethical Committee. All procedures were conducted in compliance with applicable rules and regulations.

For this study, we opted to implement a CNN framework based on a segmentation strategy. Unlike detection methods that provide a bounding box, segmentation provides more detailed data, which is crucial for determining malignancy from a single image. In clinical settings, the maximal tumor diameter is highly important, and detection techniques with bounding boxes can be challenging as the tumor's maximum diameter often aligns with an oblique direction. To address this, we constructed our CNN based on a standard encoder-decoder framework. The bottleneck structure of this design decreases feature map resolution and enhances the model's resistance to noise and overfitting.

Another unique aspect of our DL-based model is the use of both standard chest radiographs and black-and-white inverted chest radiographs. This feature leverages radiologists' expertise to enhance the model's performance. Black-and-white inversion is often used to confirm the existence of lung lesions that may overlap with visual blind areas. Believing this enhancement would benefit our model, we trained a CNN architecture on both original and inverted images, then created an ensemble model combining the two CNNs. The best-performing model was selected after 100 iterations of Adam learning using a five-fold cross-validation on chest radiographs from the training dataset. Further details about the model are provided in the online Supplemental Fig. S1.

Table 1: Dataset Demographics

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%.

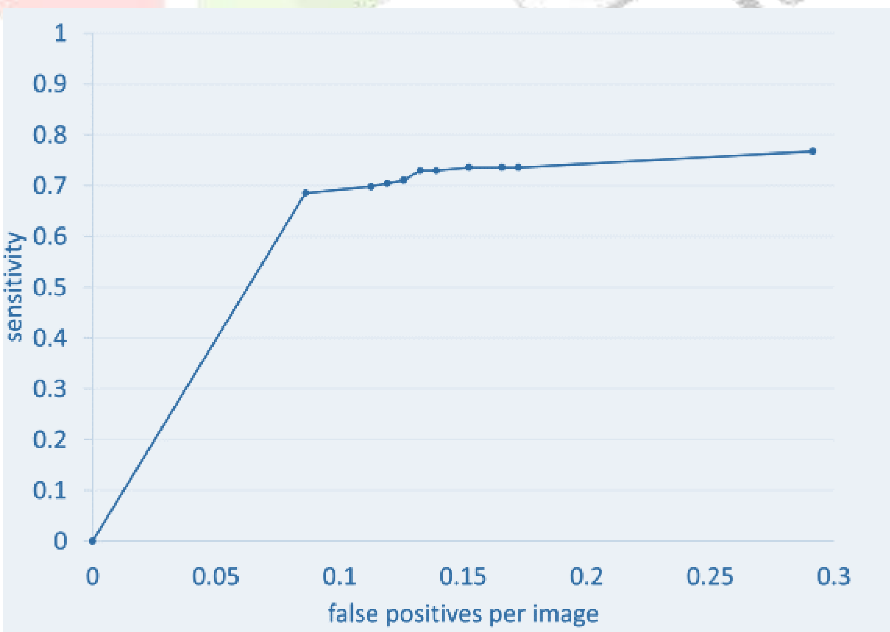

Figure 2: Segmentation Accuracy of the Proposed Approach

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.

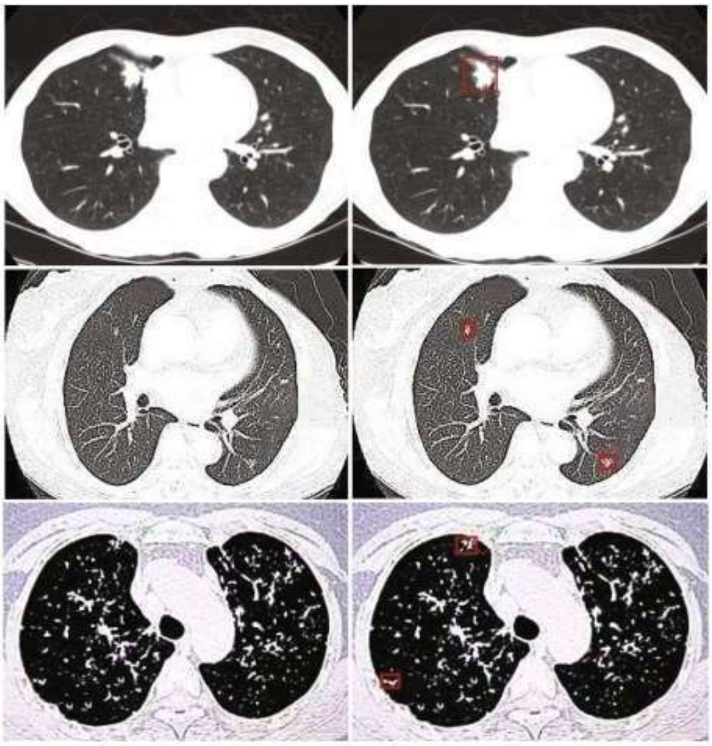

Figure 3: The detection effect of Proposed algorithm on CT images of lung nodules

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

This study examined optimized CT images of lung nodules from lung cancer patients. It combined the Mask-RCNN and DPN algorithm. The results showed that using Mask-RCNN with the proposed algorithm significantly improved the segmentation of lung tissue in CT images, making lung cancer diagnosis more efficient. However, the study's strength is limited by a small sample size. A larger sample is needed to confirm these results. Currently, AI algorithms can only automate the identification and labeling of nodules, but they can't determine their nature. Overall, integrating AI algorithms with medical imaging technology has great therapeutic potential.

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