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Lung CT Image Diagnosis Model Based on a Convolutional Neural Network

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Abstract. Lung disease is still a great threat in the world. There are many problems in manually computed tomography (CT) image diagnosis, including strong subjectivity and low efficiency. This study constructed a lung nodule detection model based on you only look once version 8 nano (yolov8n) to provide computer-aided diagnosis technology support for early screening of lung cancer. The lidc-idri lung CT data set was used to complete the preprocessing steps, such as HU value normalization, multi-doctor label de duplication, and Yolo format label conversion. The input image was uniformly scaled to 512 × 512 resolution, the model superparameters were optimized, and 50 epochs of training were completed. The experimental results show that the accuracy rate of the model in the validation set is 0.704, the recall rate is 0.443, the mAP50 is 0.497, and the reasoning time of a single CT slice is 1.4ms. The model can realize the rapid detection of pulmonary nodules, effectively reduce the burden of doctors, reduce the risk of missed diagnosis and false detection, and has the potential for clinical auxiliary diagnosis. Finally, the future improvement and optimization directions are discussed, including the introduction of a hybrid local channel attention mechanism and the use of image enhancement technology based on super-resolution generation of a countermeasure network.

Keywords: convolutional neural network, lung CT images, YOLOv8n, Pulmonary nodule detection

1. Introduction

In recent years, artificial intelligence technology has developed rapidly, has been applied in various fields, and has played an important role and has important value. At present, lung diseases still pose a great threat worldwide. Chronic respiratory diseases are the fourth leading cause of death in the world, and lung cancer is the cancer with the highest incidence and mortality. Traditional lung CT image diagnosis requires doctors to observe and judge the images themselves, which may lead to some problems, such as the difficulty for doctors to learn to read CT images, the complexity and dryness of the theory, and the difficulty of digestion and absorption [1]. The use of artificial intelligence for diagnosis can first enhance the image, and then use the neural network model for image diagnosis, which can improve the efficiency of diagnosis, reduce the cost, and ensure the accuracy of judgment. Therefore, with the help of artificial intelligence technology, it is of great

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significance to develop a neural network model that can assist in the diagnosis of lung diseases and assist clinicians in reducing the treatment burden of lung diseases [2].

At present, scholars have conducted some research on the application of artificial intelligence in CT image diagnosis. Based on SAM foreground detection, some scholars constructed a segmentation model for lung nodule detection considering heterogeneous missed detection and blurred edges, which enhanced the expression ability of the model for key features and significantly improved the generalization of the model [3]. Other scholars have constructed seg-LANet, a pneumonia CT image classification network fused with segmentation information. The backbone of the model network uses the encoder of LA-UNet, and then extracts features of different scales through the Inception module. Finally, the high accuracy of 74.6% and 91.3% on the two classification tasks is achieved, respectively [4]. Other scholars have proposed a modular design model of space extractor-time encoder-integrator-classifier (STIC) based on deep learning, which combines the advantages of a convolutional neural network and a gated cyclic neural network, and helps doctors improve the diagnosis effect [5]. These studies can help doctors diagnose and reduce the burden of lung disease treatment.

Based on this, this paper uses the method of deep learning convolutional neural network, and uses YOLOv8n to build the model of lung nodule detection in lung CT images, aiming to achieve the purpose of using a lightweight model for lung CT image diagnosis, while ensuring high accuracy, so as to assist doctors in diagnosis.

2. Methods

2.1. Data preprocessing

2.1.1. LIDC-IDRI dataset

Lung Image Database Consortium and Image Database Resource Initiative(LIDC-IDRI), jointly created by the National Cancer Institute (NCI), FDA, and FNIH, is the most commonly used public data set for lung CT pulmonary nodule detection [6]. The LIDC-IDRI dataset included 1010 patients and 1018 chest CT images, including 7371 labeled lesions, including 2669 nodules ≥ 3mm. The image format is DICOM 3D CT sequence, and the annotation format is an XML file, which contains the doctor's annotation corresponding to each nodule [7].

Figure 1 shows a CT image in the LIDC-IDRI dataset. The upper left corner shows the pulmonary nodule information marked by the doctor.

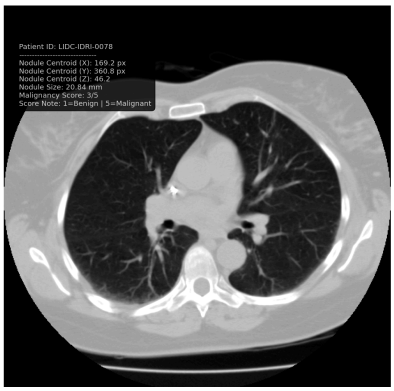

Figure 1. Lung CT images and lung nodule labeling information (picture credit: original)

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2.1.2. HU value normalization

In order to convert the original 3D CT scan data into 2D slice images and normalized labels required for YOLO training, the following data preprocessing steps are carried out in this paper.

After reading all CT scanning samples, the training set and test set were divided according to 8:2. For each patient's 3D CT scan, 2D slices were processed one by one along the Z axis.

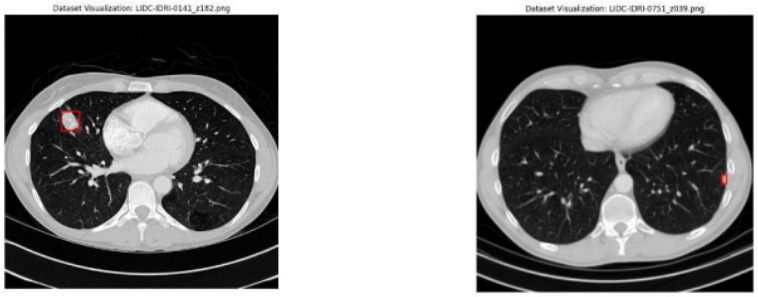
CT image normalization is to map the original Hu value to a fixed value range, which can eliminate the difference in value distribution caused by different scanning equipment and scanning parameters. The value of lung CT has clear clinical significance, air is -1000 Hu, soft tissue and nodules are 0~400hu, and bone>400 Hu. Therefore, first truncate the Hu value (retain the range of -1000~400), and then map the value to [0,255] by normalization. Finally, the image is converted into a PIL image and reduced to a 512 × 512 size

2.1.3. Nodule labeling processing

For the current slice, all pulmonary nodules marked by doctors are extracted and converted to the format of "category + normalized center point + width and height" required by the YOLO model.

First, the nodules in the current image layer are screened out, the nodule mask is generated, and the nodule bounding box is calculated. For multiple doctors labeling the same nodule, if the intersection over Union (IOU) of the labeling boxes of different doctors is greater than 0.5, it is considered that the labeling is the same nodule, and only one of them is retained. Finally, the coordinate information is normalized to the range of 0-1 to meet the requirements of the Yolo format.

Finally, the slice image with nodules and the corresponding annotation information are saved in PNG format. Figure 2 shows the processed CT images of two cases, and the pulmonary nodules are marked with red boxes.



(a) (b)

Figure 2. Processed CT images (a) The pulmonary nodules were large and easy to detect; (b) Nodules are small and difficult to detect (picture credit: original)

2.2. Convolutional neural network

2.2.1. Principle of the convolutional neural network

A convolutional neural network includes an input layer, a convolution layer, an activation layer, a pooling layer, and a full connection layer. The convolution kernel slides on the image for feature extraction, and the pooling layer downsamples the image to reduce the size, while retaining the key information, and the final output of the full connection layer.

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Using a convolutional neural network to detect pulmonary nodules can realize automatic feature learning without manual intervention, and directly extract features layer by layer from CT images. Shallow convolution and deep convolution can learn different-scale features, respectively, which fundamentally solves the limitations of artificial features. A convolutional neural network can accurately magnify the small features of small lesions and suppress the interference of lung background, blood vessels, and texture through sliding window scanning of a convolutional kernel and feature extraction of multiple receptive fields.

2.2.2. YOLOv8n

YOLOv8n is a nano ultra-lightweight end-side model of the YOLOv8 series released by Ultralytics on January 10, 2023. It is a real-time visual AI benchmark model built by the YOLO series for low computing power and embedded devices. It is one of the preferred baseline models for end-to-end real-time target detection and lightweight AI landing in the current industry while minimizing the number of parameters and calculations and retaining the full range of architecture innovation and multitasking capabilities of YOLOv8 [8].

The Backbone network uses a new C2F module to replace the C3 module of YOLOv5. By adding branch connections and cross-layer gradient flow, the feature extraction ability is significantly improved under lightweight constraints, and the down-sampling module is optimized to further reduce the computational overhead. Based on the PAN-FPN multi-scale fusion architecture, the Neck is fully reconstructed with the C2F module, which strengthens the fusion ability of shallow detail features and deep semantic features, significantly improves the recall rate of small target detection, and adapts to the common small target recognition scenarios on the end side. The detection Head part adopts the industry-leading Anchor-Free decoupling detection head, completely abandoning the design of the previous generation of preset anchor frame, and directly predicting the target center point, which not only simplifies the training process but also reduces the amount of post-processing calculation. At the same time, the classification and regression branches are completely decoupled to achieve task-independent optimization, which significantly improves the convergence speed and detection accuracy of the model.

3. Results

Use the processed CT image data to train YOLOv8. Set the epochs to 50, the positioning loss to 10, the classification loss to 1.0, and the input image size to 512. The following is the chart of results after completing the training and testing.

Figure 3 shows the val/box_loss curve. The regression loss of the bounding box of the validation set indicates the position deviation between the predicted nodule bounding box and the real nodule marking box. The lower the value, the more accurate the positioning of the nodule by the model.

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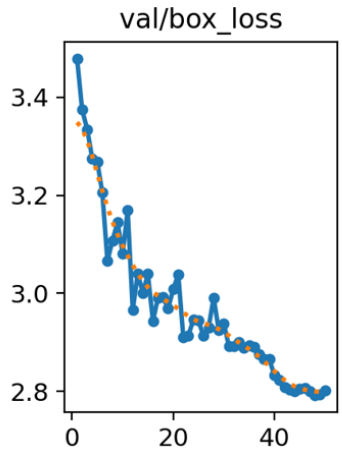

Figure 3. Validation set bounding box regression loss (picture credit: original)

Figure 4 shows the val/cls_loss curve. The classification loss of the validation set indicates the error of the model in judging the binary classification problem of "whether it is a pulmonary nodule". The lower the value, the more accurate the classification, and the lower the probability of missed or false detection.

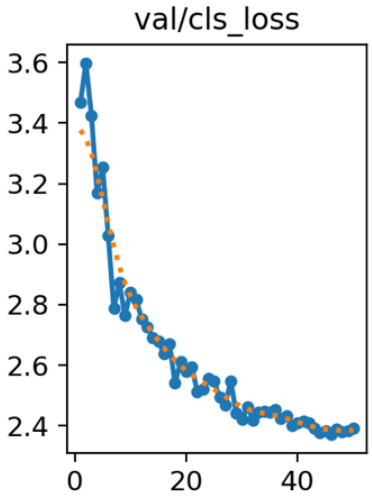

Figure 4. Verification set classification loss (picture credit: original)

Figure 5 shows the val/dfl_loss curve, verifying the focus loss of the distribution set and the auxiliary loss of yolov8, specifically optimizing the positioning accuracy of the bounding box. Especially for small targets such as pulmonary nodules, the lower the value, the more accurate the prediction of the distribution of the bounding box.

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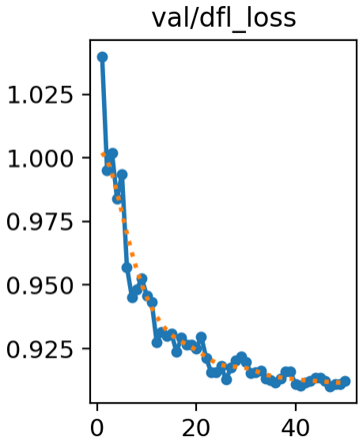

Figure 5. Verification set distribution focus loss (picture credit: original)

Figure 6 shows the metrics/mAP50 (b) curve, which is the core comprehensive detection index of the model. The average accuracy when the IOU threshold is 0.5 measures the positioning and classification ability of the model. The higher the value, the better the comprehensive detection performance.

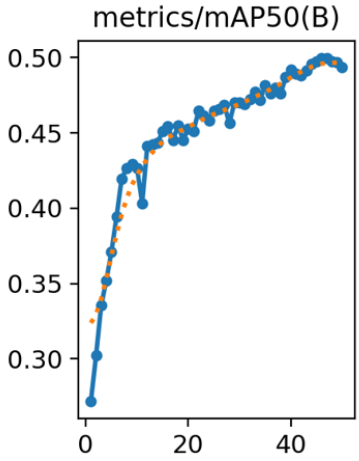

Figure 6. Metrics/mAP50 (B) (picture credit: original)

Figure 7 shows the metrics/mAP50-95 (b) curve, the core indicator of positioning accuracy, which means that the IOU threshold is from 0.5 to 0.95, and the average accuracy is taken every 0.05. It focuses on measuring the precise positioning ability of the model to the nodule boundary box. The higher the value, the more accurate the positioning is.

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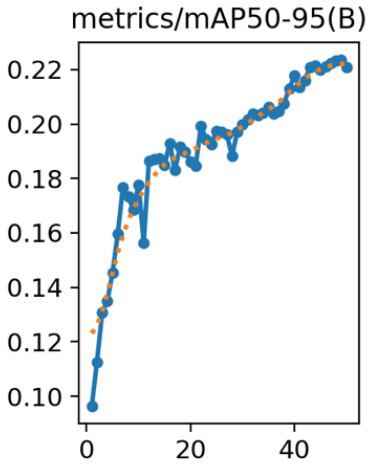

Figure 7. Metrics/mAP50-95 (B) (picture credit: original)

After the completion of 50 epochs, the final results are shown in Table 1:

Table 1. Table of model test results

Precision	Recall	mAP50	mAP50-95
0.704	0.443	0.497	0.223

Figure 8 shows the effect of using the model to detect pulmonary nodules after model training. It can be seen that three pulmonary nodules were detected, and only one was not detected because the pulmonary nodules were small.



Figure 8. Example of pulmonary nodule detection effect (picture credit: original)

4. Discussion

In this study, a pulmonary CT pulmonary nodule detection model was constructed based on the lightweight YOLOv8n convolutional neural network, which achieved an accuracy of 0.497 mAP50 and 0.704, and verified the feasibility of the lightweight convolutional neural network model in the

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rapid detection of pulmonary nodules. At the same time, there are still some problems to be improved in the research, which are analyzed below.

According to the experimental results, it can be seen that the recall rate of the model for the detection of pulmonary nodules is low, only 0.443. It is speculated that the reason is that some small pulmonary nodules account for a small proportion in the 512 × 512 resolution CT images, and the feature information is weak, which is not easy to detect. Secondly, mAP50-95 is only 0.227, which indicates that the boundary box of nodules detected by the model does not fit the actual boundary box of nodules. It may be because the shape and boundary shape of pulmonary nodules differ greatly, and the fixed loss function is difficult to adapt to the boundary detection of all forms of nodules. Finally, the study was only verified on the LIDC-IDRI dataset, and did not test the model generalization on other datasets.

To solve the above problems, it can optimize these aspects in the future. First of all, the mixed local channel attention module can be introduced to improve the sensitivity of the model to the characteristics of micro nodules [9]. This module can replace the global spatial pooling in the traditional channel attention through the mixed pooling operation of multi-scale local windows. It can realize the adaptive weighting of channel features of multiple receptive fields while preserving the local details of micro nodules, and strengthen the expression of features related to pulmonary nodules. Secondly, image enhancement technology based on super-resolution generative adversarial network (SRGAN) can be used for image preprocessing to overcome the problems of noise and artifacts in the image, strengthen the detailed features of tiny nodules in the image, accurately restore the boundary contour of nodules, including fine features such as lobulation and burr, so that the model can learn more accurate boundary distribution rules, and solve the problem of poor detection effect from the root [10].

5. Conclusion

In this study, a pulmonary nodule detection model based on YOLOv8n was constructed for the pain points in lung CT images, which are small in size, difficult to extract features, and difficult to detect. By preprocessing the LIDC-IDRI data set and optimizing the model input resolution and loss function weight strategy, the final model achieved a mAP50 of 0.497 on the validation set, while maintaining a high accuracy of 0.704 and a single image reasoning speed of 1.4ms, which realized the accurate and rapid detection of pulmonary nodules. It can effectively reduce the workload of doctors, and reduce the missed diagnosis and false detection of pulmonary nodules.

Finally, the deficiencies and improvements of the research are discussed. First, the recall rate of the model still has room to improve; the detection ability of micro nodules is insufficient, and the boundary positioning of nodules is not accurate enough. The study was only validated on the public data set, and the model generalization test was not completed on the clinical real-world data. In order to solve these problems, some possible solutions are proposed, including the introduction of a hybrid local channel attention mechanism and the use of image enhancement technology based on a super-resolution generative adversarial network.

References

[1] Zhang, X., Wang, J., Zhou, D., Ji, B., Chen, L., Cheng, L., & Li, X. (2014). The application of "recognizing diseases by signs" in the teaching of CT diagnosis of lung diseases. Journal of Local Surgery, 23(05), 558–559.

[2] Gao, R., Liu, M., Yang, C., & Zhang, Y. (2025). Research progress of deep learning in detection and evaluation of pulmonary nodules. Shanxi Medical Journal, 54(03), 201–205.

DOI: 10.54254/2753-8818/2026.33023

[3] Li, J. (2025). Research on deep learning driven pulmonary CT image diagnosis technology of pulmonary nodules (Master's thesis). Inner Mongolia University of Science and Technology.
[4] Lan, A. (2024). Research on CT image aided diagnosis of pneumonia based on deep learning (Master's thesis). Chongqing University.
[5] Gao, R., Zhao, S., Aishanjiang, K., Cai, H., Wei, T., Zhang, Y., Liu, Z., Zhou, J., Han, B., Wang, J., Ding, H., Liu, Y., Xu, X., Yu, Z., & Gu, J. (2021). Deep learning for differential diagnosis of malignant hepatic tumors based on multi-phase contrast-enhanced CT and clinical data. Journal of Hematology & Oncology, 14(1), 154.
[6] Armato, S. G., III, McLennan, G., Bidaut, L., McNitt-Gray, M. F., Meyer, C. R., Reeves, A. P., Zhao, B., Aberle, D. R., Henschke, C. I., Hoffman, E. A., Kazerooni, E. A., MacMahon, H., Van Beek, E. J. R., Yankelevitz, D., Biancardi, Alberto M., Bland, Peyton H., Brown, Matthew S., Engelmann, Roger M., & Clarke, Laurence P. (2015). Data from LIDC-IDRI [Data set]. The Cancer Imaging Archive.
[7] Armato, S. G., III, McLennan, G., Bidaut, L., McNitt-Gray, M. F., Meyer, C. R., Reeves, A. P., Zhao, B., Aberle, D. R., Henschke, C. I., Hoffman, E. A., Kazerooni, E. A., MacMahon, H., Van Beeke, E. J., Yankelevitz, D., Biancardi, A. M., Bland, P. H., Brown, M. S., Engelmann, R. M., Laderach, G. E., ... Croft, B. Y. (2011). The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): A completed reference database of lung nodules on CT scans. Medical Physics, 38(2), 915–931.
[8] Jocher, G., Chaurasia, A., & Qiu, J. (2023). Ultralytics YOLOv8 (Version 8.0.0) [Computer software]. Zenodo.
[9] Xue, F., Tong, Y., Chen, X., Qin, X., & Yang, M. (2026). Small target forest fire monitoring model based on improved YOLOv8n. Journal of Northwest A&F University of Science and Technology (Natural Science Edition), 54(09), 49–58.
[10] Zhu, W., Wang, X., Xing, J., Xu, X. S., & Yuan, M. (2025). YOLOv8-BCD: A real-time deep learning framework for pulmonary nodule detection in computed tomography imaging. Quantitative Imaging in Medicine and Surgery, 15(9), 8189–8204.