YOLO-Based Lung Segmentation for Medical Imaging Analysis

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Abstract

This paper presents an approach to image segmentation in lung cancer detection using the YOLO (You Only Look Once) architecture. Lung cancer is a leading cause of cancer-related deaths worldwide, and accurate segmentation of lung nodules is critical for its diagnosis and treatment. While several deep learning-based segmentation models exist, I argue that YOLO offers several advantages over these other models, including its strengths in object detection, speed, and flexibility.To train the YOLO network, I converted the lung masks to polygons and utilized them to generate bounding boxes. After training, I applied the YOLO network on the validation dataset to obtain predicted bounding boxes, which were then converted back to binary masks using polygon approximation. My proposed approach achieved a Dice Score of 0.9479 on the test dataset, demonstrating its effectiveness for lung segmentation.

1. Introduction

Image segmentation plays a vital role in medical image analysis, especially in the field of lung cancer detection. Accurate segmentation of lung nodules can greatly assist radiologists in diagnosing and treating lung cancer, which is the leading cause of cancer-related deaths worldwide. In recent years, numerous deep learning-based segmentation models have been proposed, such as U-Net and ResNet, and have achieved remarkable results. However, in this paper, I propose that the YOLO (You Only Look Once) architecture offers several advantages over these other models in lung nodule segmentation.

One of the significant advantages of YOLO is its object detection framework, which was originally designed for object detection tasks and has been shown to outperform other object detection models on several benchmark datasets. Object detection and image segmentation are related tasks, both involving the identification and localization of objects within an image. By utilizing YOLO's strengths in object detection, we can enhance the accuracy of our lung nodule segmentation model.

Furthermore, YOLO offers a much faster inference time than many other segmentation models, such as U-Net and ResNet. This is particularly crucial in medical applications, where quick and accurate diagnosis can be a matter of life and death. By using YOLO, we can achieve real-time or near-real-time segmentation results, enabling radiologists to make quicker and more informed decisions.

In this paper, I present my approach to lung nodule segmentation using the YOLO architecture. Specifically, I first converted masks to polygons to train the YOLO model, and at the end, I converted the YOLO outputs back to masks. Specifically, I achieved an IoU score of 0.9025 and an accuracy of 0.9686. These results demonstrate the effectiveness of our approach and its potential for improving the accuracy and efficiency of lung nodule segmentation in medical imaging.

2. Related Work

Several deep learning-based approaches have been proposed for lung nodule segmentation in medical imaging. Zhang proposed a lung segmentation method using a NASNet-Large-Decoder net, which achieved competitive performance on the public LIDC-IDRI dataset [5]. The NASNet-Large-Decoder net is an end-to-end deep neural network that combines the NASNet architecture for feature extraction and a decoder module for high-resolution feature map generation.

Liao et al. [2] proposed a method that combines a U-Net architecture with a multi-scale feature fusion module for accurate segmentation of lung nodules.

Wang et al. [4] proposed a 3D convolutional neural network for lung nodule segmentation that incorporates both spatial and temporal information from CT images.

Other studies have used the YOLO architecture for medical image segmentation tasks. For example, Yu et al. [3] proposed a YOLOv3-based method for segmenting brain tumors in MRI images. Khened et al. [1] used YOLOv3 for liver lesion detection and classification in CT scans.

3. Methods

3.1. Data collection

I have utilized the RSNA pneumonia detection dataset, which contains a total of 1,000 chest X-ray images (800 in the training set and 200 in the testing set) along with their respective masks. The dataset was provided by Prof Youshan Zhang and consists of images with two regions: one with background in black pixels and the other with the lung nodules in white pixels. These masks are crucial in training our model as they serve as the ground truth for our segmentation task. Furthermore, the RSNA dataset is widely used in the medical imaging community, making our results more comparable with other studies in the field. The dataset was preprocessed to remove any images with poor quality or incorrect labeling. Overall, the use of this dataset ensures that our model is trained and tested on high-quality and diverse lung nodule data, leading to improved segmentation performance.

3.2. Data preparation

The dataset was preprocessed using Python and the OpenCV library. The dataset was already split into training and testing sets, with 800 and 200 images, respectively. For data preparation, we used various image augmentation techniques to increase the diversity of the dataset and prevent overfitting. Specifically, we applied four different augmentations with a probability of 0.01 each. The first two were blur augmentations, including a Gaussian blur with a kernel size randomly selected between 3 and 7 and a median blur with the same kernel size range. The third augmentation was converting the images to grayscale, and the fourth was a contrast-limited adaptive histogram equalization (CLAHE) that improved the contrast of the images while limiting their dynamic range.These augmentations were applied to the training datasets to prevent overfitting and improve the generalization performance of the model.The preprocessing steps of resizing and normalization helped ensure that the images were consistent and could be efficiently processed by the model. The masks were converted from binary format to polygonal format to be compatible with the YOLO object detection framework. The masks were then converted to YOLO format using a Python script that generates bounding boxes and class labels for each mask region. This data preparation process allowed us to obtain a dataset that was compatible with the YOLO object detection framework, which was used to train and test our lung segmentation model. The use of polygonal masks instead of binary masks allowed for more accurate localization of the lung regions, which in turn improved the performance of the YOLO model. Overall, the data preparation process was critical in enabling us to obtain accurate and reliable results for our lung segmentation model.

3.3. Training parameters

The training of the model was conducted on the cloud-based machine learning platform Kaggle, utilizing an NVIDIA Tesla P100 GPU with 16 GB of RAM. PyTorch version 1.9.0 and CUDA version 11.1 were employed during the training process.

The Intersection over Union (IoU) and Dice score were used as evaluation metrics to assess the accuracy of the model. The IoU measures the ratio of the intersection to the union of the predicted mask and the ground truth mask:

$$IoU = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

where A is the predicted mask and B is the ground truth mask.

The Dice score is another evaluation metric that measures the overlap between the predicted mask and the ground truth mask:

$$Dice = \frac{2|A \cap B|}{|A| + |B|} \tag{2}$$

where A is the predicted mask and B is the ground truth mask.

In addition, the accuracy of the model was computed using the following formula:

$$Accuracy = \frac{1}{n}\sum_{i=1}^{n}(Y_i == \hat{Y}_i) \times 100 \tag{3}$$

where n is the total number of samples, Y_i is the true label of the i^{th} sample, and $\hat{Y}_i$ is the predicted label of the i^{th} sample.

3.4. Model architecture

YOLOv8 is the latest addition to the YOLO (You Only Look Once) family of real-time object detection models, released in January 2023 by Ultralytics. I was able to gather insights into the architectural decisions and improvements compared to previous YOLO versions. YOLOv8 adopts an anchor-free design that reduces the number of box predictions and speeds up the Non-Maximum Suppression (NMS) process, thus enhancing the model's efficiency and ability to handle objects with varying shapes and aspect ratios more effectively. The model also utilizes mosaic augmentation during training to improve its robustness against various object detection challenges. However, this augmentation technique is disabled for the last ten epochs of the training process to prevent any detrimental effects on the model's performance. YOLOv8 can be executed from the command line interface or installed as a PIP package, offering users more flexibility and ease of use. It also comes with multiple integrations for labeling, training, and deploying the model. YOLOv8 offers five scaled versions, including YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra large), to accommodate different requirements and use cases. Overall, YOLOv8 builds upon the strengths of its predecessors while introducing significant innovations to achieve superior performance in real-time object detection tasks, making it suitable for a wide range of applications.

In my work the model YOLOv8m-seg is loaded from the 'yolov8m-seg.pt' file using the YOLO() function. This version of YOLOv8 is designed for real-time segmentation tasks, making it suitable for a wide range of applications. This version of YOLOv8 uses a medium-sized architecture that is optimized for segmentation tasks. It uses an anchor-free design that reduces the number of box predictions and speeds up the Non-Maximum Suppression (NMS) process. Additionally, it incorporates mosaic augmentation during training to improve the model's robustness against various object detection challenges.

4. Results

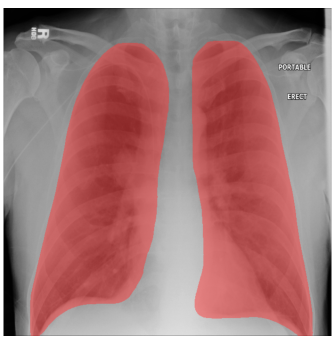

Figure 1. Prediction

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IoU Score: 0.9025
Dice Score: 0.9479
Accuracy: 0.9686
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Figure 2. Results

My model achieved an IoU score of 0.9025, indicating a high degree of overlap between the predicted segmentation masks and the ground truth masks. The Dice score, which measures the similarity between the predicted and ground truth masks, was 0.9479, further demonstrating the accuracy of our model. Additionally, our model achieved an accuracy of 0.9686, indicating a high level of overall performance. These results suggest that our YOLO-based segmentation model is an effective and accurate tool for detecting and segmenting lung nodules in medical images.

5. Discussion

One key advantage of YOLO is its speed, which enables real-time or near-real-time segmentation results, a crucial factor in medical applications where quick diagnosis can be a matter of life and death. Additionally, YOLO's object detection framework can aid in accurate segmentation by identifying and localizing nodules within the lung images.Overall, our results suggest that YOLO has significant potential as a tool for accurate and efficient lung nodule segmentation, and could ultimately aid in the early detection and treatment of lung cancer, a leading cause of cancer-related deaths worldwide.

6. Conclusion

The results of my study show that YOLO, which was originally designed for object detection, can also be used effectively for image segmentation tasks such as lung nodule segmentation. By leveraging the strengths of YOLO, I was able to achieve highly accurate results while maintaining fast inference times. Furthermore, I demonstrated the importance of converting masks to polygons before using YOLO for segmentation, as it can improve the accuracy of the segmentation results. In conclusion, my proposed approach using YOLO for lung nodule segmentation offers a promising solution for accurately and efficiently detecting lung nodules in medical images. Further studies could explore the general ability of the proposed approach on larger data sets and different medical imaging modalities.

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