

Volumetric Pulmonary Nodule Detection Using 3D Convolutional Neural Networks

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Abstract—Early detection of pulmonary nodules is a critical task for lung cancer diagnosis. Computed Tomography (CT) scans provide volumetric information that can be exploited using three-dimensional deep learning models. In this work, we explore the LUNA16 dataset and propose a simple yet effective 3D convolutional neural network to perform volumetric pulmonary nodule detection based on 3D patches extracted from CT scans.

I. INTRODUCTION

Lung cancer remains one of the leading causes of cancer-related mortality worldwide. Early detection of pulmonary nodules significantly increases the chances of successful treatment. Computed Tomography (CT) imaging is commonly used to detect such nodules, as it provides detailed volumetric information of the lungs.

With the recent advances in deep learning, convolutional neural networks (CNNs) have shown promising results in medical image analysis. While many approaches rely on two-dimensional slices, volumetric data naturally motivates the use of three-dimensional models. In this report, we focus on a simple 3D deep learning approach for pulmonary nodule detection using the LUNA16 dataset.

II. DATASET EXPLORATION

The experiments are conducted on the LUNA16 dataset, which is derived from the LIDC-IDRI database. Each sample consists of a chest CT scan stored as a volumetric image, along with expert annotations indicating the location of pulmonary nodules.

Each CT scan is represented as a three-dimensional volume with voxel intensities expressed in Hounsfield Units (HU). Before any modeling step, the dataset was explored by visualizing axial, coronal, and sagittal slices to ensure data integrity and understand the anatomical structure of the lungs.

Annotations provided in the dataset include the world coordinates and diameters of annotated nodules. These coordinates were converted from world space (millimeters) to voxel space using the scan origin and voxel spacing metadata.

III. DATA PREPARATION

Due to the large size of CT volumes, direct processing of entire scans is computationally expensive. Therefore, a patch-based strategy was adopted.

For each annotated nodule, a cubic 3D patch of fixed size ($32 \times 32 \times 32$ voxels) was extracted and labeled as a positive sample. Negative samples were generated by randomly extracting patches far from annotated nodules within the same

volume. A ratio of one positive sample to two negative samples was used to mitigate class imbalance.

Prior to training, voxel intensities were clipped to a lung window range of $[-1000, 400]$ HU and normalized to the interval $[0, 1]$ to stabilize the learning process.

IV. 3D CNN MODEL

A simple 3D convolutional neural network was implemented to classify 3D patches as either containing a pulmonary nodule or not. The network consists of three 3D convolutional layers followed by max-pooling operations, and two fully connected layers.

The model outputs a single probability value indicating the likelihood of nodule presence. Binary cross-entropy loss with logits was used as the training objective, and the Adam optimizer was employed for optimization.

V. EXPERIMENTAL RESULTS

The model was trained on a single LUNA16 subset using an 80/20 train-validation split. Training was conducted for a small number of epochs to avoid overfitting.

The results show a clear decrease in training and validation loss over epochs. The model achieved a validation accuracy of approximately 88%, demonstrating its ability to distinguish between nodule and non-nodule patches. These results indicate that even a simple 3D CNN can effectively leverage volumetric information for pulmonary nodule detection.

VI. CONCLUSION

In this report, we presented a complete pipeline for volumetric pulmonary nodule detection using 3D CT scans. Starting from dataset exploration, we processed medical imaging data, extracted 3D patches, and trained a 3D convolutional neural network.

Although the proposed model is intentionally simple, the obtained results are encouraging. Future work could include training on multiple subsets, incorporating harder negative samples, and extending the approach to full 3D detection or segmentation frameworks.