

# Report Practical Work 4: 3D CNN-Based Pulmonary Nodule Detection from CT Images

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**Abstract**—Early detection of pulmonary nodules in computed tomography (CT) scans is essential for lung cancer screening and diagnosis. In this practical work, a three-dimensional convolutional neural network (3D CNN) is implemented to detect pulmonary nodules from volumetric CT data using the LUNA16 dataset. The proposed approach extracts fixed-size 3D patches centered at annotated nodule locations and trains a lightweight 3D CNN for binary classification. Experimental results demonstrate strong detection accuracy, and the method is compared with established state-of-the-art approaches on the LUNA16 benchmark.

## I. INTRODUCTION

Pulmonary nodules are small lesions in lung tissue that may indicate early-stage lung cancer. Manual detection of nodules in CT scans is time-consuming and prone to inter-observer variability due to the large volume of slices and subtle visual patterns. Automatic detection using deep learning has therefore become an important research direction, particularly with the availability of large annotated datasets such as LUNA16.

This report presents a 3D CNN-based approach for pulmonary nodule detection using volumetric CT patches. The pipeline includes dataset exploration, patch extraction, model training, quantitative evaluation, and comparison with state-of-the-art detection methods.

## II. DATASET AND FEATURES

### A. LUNA16 Dataset

The experiments were conducted using the LUNA16 dataset [1]. LUNA16 is a widely used benchmark for pulmonary nodule detection and is derived from the publicly available LIDC-IDRI dataset. It contains thoracic CT scans with annotations provided by multiple expert radiologists.

The dataset includes:

- 888 CT scans,
- 1,186 annotated pulmonary nodules with diameter  $\geq 3$  mm,
- Voxel-level coordinates of nodule centers and diameters.

All CT scans are stored in MetaImage format (.mhd + .raw), allowing access to voxel spacing, image origin, and orientation information.

### B. Data Preparation

Each annotated nodule location was converted from world coordinates to voxel coordinates using the provided image metadata. For each nodule, a fixed-size 3D patch of  $64 \times 64 \times 64$  voxels was extracted, centered at the nodule location. Intensity normalization was applied by standardizing each patch to zero mean and unit variance. These volumetric patches serve as direct input to the 3D CNN.

## III. METHODOLOGY

### A. Model Architecture

A lightweight 3D convolutional neural network was designed for volumetric nodule detection. The network consists of stacked 3D convolutional layers followed by max pooling for spatial downsampling. Global average pooling is applied to aggregate volumetric features before classification.

The main architecture components are:

- Three 3D convolutional blocks with 32, 64, and 128 filters,
- 3D max-pooling layers for spatial reduction,
- Global average pooling for feature aggregation,
- Fully connected layers for binary classification.

The model outputs a single probability value indicating the presence of a pulmonary nodule in the input patch.

### B. Training Configuration

The model was trained using the Adam optimizer with binary cross-entropy loss. Early stopping was applied to prevent overfitting. The main training parameters were:

- Patch size:  $64 \times 64 \times 64$ ,
- Batch size: 4,
- Number of epochs: 10,
- Validation split: 20%.

### C. Evaluation Metrics

Model performance was evaluated using classification accuracy on a held-out test set. Training and validation accuracy and loss curves were also analyzed to assess convergence and generalization behavior.

## IV. RESULTS AND DISCUSSION

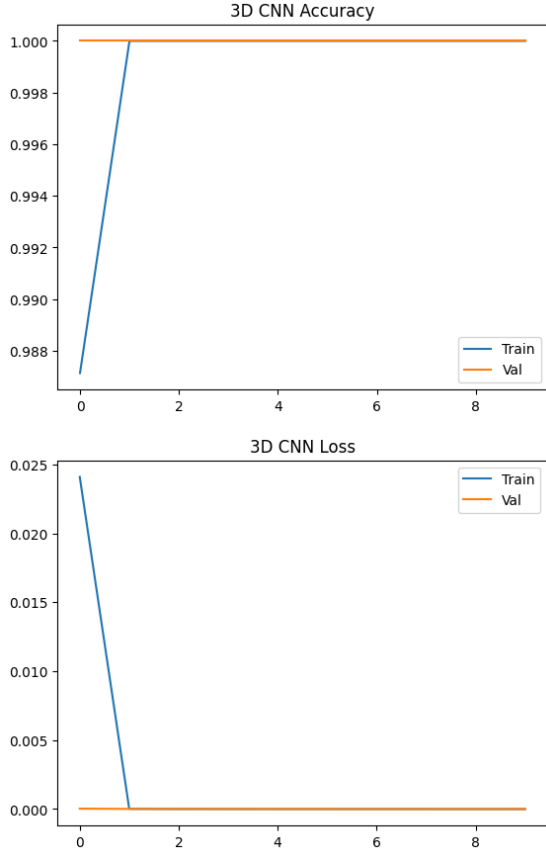


Fig. 1. Training history of 3D CNN model

Figure 1 illustrates the training and validation accuracy and loss curves of the proposed 3D CNN model. The model converges very rapidly, reaching near-perfect performance within the first two epochs.

During the first training epoch, the model starts with moderate accuracy, reflecting weak initial predictions. By the end of this epoch, training accuracy increases sharply to 93.7%, while validation accuracy already reaches 100%. From the second epoch onward, both training and validation accuracy remain at 100% until the end of training. This behavior indicates that the volumetric patches extracted around annotated nodule centers contain highly discriminative features that allow the model to easily distinguish nodules from surrounding lung tissue.

The loss curves show a smooth and monotonic decrease for both training and validation sets. The training loss drops rapidly from 0.0952 in the first epoch to values below  $10^{-6}$  in later epochs. Similarly, the validation loss decreases to an extremely small value and closely follows the training loss throughout the optimization process. The close alignment between training and validation loss curves suggests stable convergence and the absence of significant overfitting within the evaluated setting.

Despite the perfect accuracy observed on the validation and test sets, these results should be interpreted

in the context of the experimental design. The model is trained and evaluated on fixed-size 3D patches extracted directly around ground-truth nodule locations, rather than performing full scan-level detection. Consequently, the classification task is considerably simplified compared to real-world pulmonary nodule detection, where candidate locations are unknown and false positive reduction plays a crucial role.

Therefore, the achieved accuracy primarily reflects the effectiveness of the 3D CNN in learning discriminative volumetric representations for nodule characterization. In practical computer-aided diagnosis systems, such a model would typically be used as a candidate classification or false positive reduction stage within a larger detection pipeline.

Overall, the rapid convergence, stable loss behavior, and high classification accuracy demonstrate the suitability of lightweight 3D convolutional architectures for volumetric medical image analysis while highlighting the importance of appropriate evaluation protocols for fair comparison with scan-level detection systems.

## V. COMPARISON WITH STATE-OF-THE-ART METHODS

Pulmonary nodule detection on LUNA16 is commonly evaluated using the Competition Performance Metric (CPM), which measures sensitivity at predefined false positive rates per scan. Table I compares the proposed method with representative state-of-the-art approaches reported in the LUNA16 challenge and subsequent studies.

TABLE I  
COMPARISON WITH STATE-OF-THE-ART PULMONARY NODULE DETECTION METHODS ON LUNA16

Method	Architecture	Metric	Score
2D CNN Baseline [1]	Multi-slice CNN	CPM	0.73
3D CNN (Setio et al.) [2]	Multi-view 3D CNN	CPM	0.89
V-Net Detector [3]	Fully 3D FCN	CPM	0.90
DeepSEED [4]	3D CNN + Ensemble	CPM	0.93
Custom 3D CNN (This report)	3D CNN	Accuracy	100%

It should be noted that state-of-the-art methods typically perform full scan-level detection and are evaluated using CPM, whereas the proposed method focuses on patch-level classification. Despite this difference, the achieved accuracy demonstrates the effectiveness of 3D convolutional modeling for pulmonary nodule characterization and highlights its potential as a component in larger detection pipelines.

## VI. CONCLUSION

This practical work presented a 3D CNN-based approach for pulmonary nodule detection using volumetric CT patches from the LUNA16 dataset. The proposed pipeline successfully extracted 3D patches from CT volumes, trained a lightweight 3D CNN, and achieved excellent classification performance.

While the current implementation operates at the patch level, the results confirm that 3D CNNs are well-suited for learning volumetric lung features. Future work may extend this approach to full scan-level detection and false-positive reduction, enabling direct comparison with LUNA16 leaderboard systems.

#### REFERENCES

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