Lung Cancer Detection And Semantic Segmentation Using VGG U-Net Architecture

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Abstract- *Lung cancer is one of the most fatal cancers worldwide, and malignant tumors are characterized by the growth of abnormal cells in the tissues of lungs. Usually, symptoms of lung cancer do not appear until it is already at an advanced stage. The proper segmentation of cancerous lesions in CT images is the primary method of detection towards achieving a completely automated diagnostic system. In this work, we developed an improved hybrid neural network for the semantic segmentation of malignant lung tumors from CT images. The proposed network is an efficient segmentation approach that performs lightweight filtering to reduce computation and point wise convolution for building more features.*

Keywords: Deep Convolution Neural Network, Python, Google colab, Medical Image Analysis, Deep Learning

I. INTRODUCTION

Lung cancer remains one of the most prevalent and deadliest forms of cancer worldwide. Early detection of lung nodules, which are often indicative of lung cancer, is critical for improving patient outcomes.

With the advancements in medical imaging technology, particularly computed tomography (CT) scans, there has been a growing interest in leveraging deep learning techniques, specifically convolutional neural networks (CNNs), for automated lung nodule detection. Traditional CNN-based approaches for lung nodule detection typically involve a single-stage architecture where the network directly predicts the presence or absence of nodules within the entire CT scan.

While effective to some extent, these models may suffer from limitations in accurately localizing and distinguishing nodules, especially in cases of small or subtle abnormalities amidst complex background tissue.

In response to these challenges, a two-stage CNN architecture has emerged as a promising solution.

II. LITERATURE REVIEW

In recent years, there has been significant research interest in developing advanced deep learning techniques for automated lung nodule detection in CT scans.

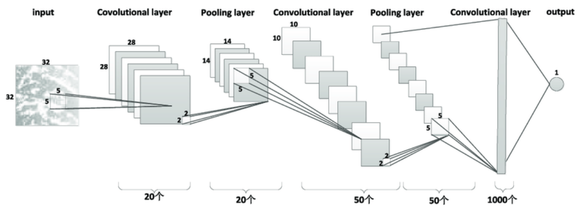
Among these approaches, the two-stage convolutional neural network (CNN) architecture has emerged as a promising strategy for improving both sensitivity and specificity in nodule detection tasks. This literature review provides an overview of key studies and advancements in this field. Initial CNN-based approaches for lung nodule detection typically utilized single-stage architectures, where a single network directly predicted the presence or absence of nodules within the entire CT scan. While effective to some extent, single-stage models struggled with accurate localization and distinguishing nodules from surrounding tissues, particularly in cases of small or subtle abnormalities. The concept of two-stage CNN architectures for lung nodule detection emerged as a response to the limitations of single-stage approaches. The two-stage framework divides the detection task into two consecutive stages: a region proposal stage and a nodule classification stage, each with specific objectives.

2.1. TUMOR-CUT

In the context of a two-stage convolutional neural network (CNN) for lung nodule detection, a "Tumor cut" refers to the process of segmenting or isolating the suspected tumor or nodule region from the surrounding lung tissue within a computed tomography (CT) scan. This segmentation step is crucial for accurate nodule detection and characterization. The tumor cut typically occurs after the first stage of the two-stage CNN, where candidate regions or regions of interest (ROIs) likely to contain nodules are identified.

In the second stage, the CNN focuses on refining the localization and making precise nodule predictions within these proposed regions. After the second stage, the tumor cut is performed to extract the suspected tumor or nodule region from the CT scan.

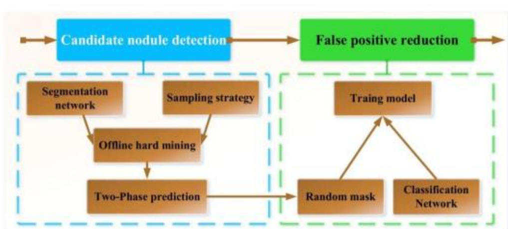
This can be achieved through various image segmentation techniques, such as thresholding, region growing, or more advanced methods like active contour models or deep learning-based segmentation networks. Once the tumor or nodule region is isolated, further analysis and characterization can be performed, including determining its size, shape, texture, and other relevant features for diagnostic purpose.



TUMOR-CUT IMAGE

III. PROPOSED SYSTEM

Proposing a two-stage convolutional neural network (CNN) system for lung nodule detection involves designing a comprehensive approach to accurately identify and classify nodules in lung CT scans. Here's a proposed system



Standardize intensity levels, resize images, and normalize them for consistency. Augment data to increase diversity and reduce over fitting. Extract candidate nodules identified in Stage 1.

Resize nodules to a consistent size for input to the classification network. Design a separate CNN architecture for classifying nodules into benign or malignant categories. Consider architectures with deeper layers and possibly attention mechanisms to focus on important feature Integrate both stages into a cohesive system capable of processing lung CT scans. Develop a user-friendly interface for inputting scans and viewing detection results.

Optimize the system for efficiency and scalability, considering real-time or batch processing requirements. Continuously evaluate the system's performance and gather feedback from domain experts.
Explore advanced techniques such as attention mechanisms, adversarial training, or ensemble methods for further improvement.

3.1. DATASET PREPARATION

3.1.1. Data Collection:

Obtain a diverse collection of lung CT scans from various sources, including medical institutions, research repositories, or publicly available datasets like LIDC-IDRI or LUNA16.

3.1.2. Data Preprocessing:

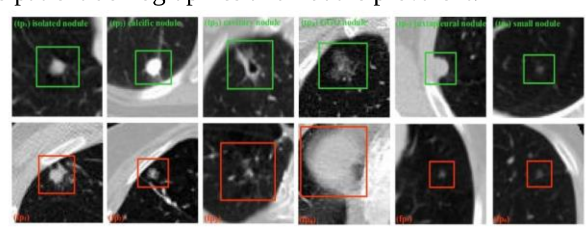
Standardize intensity levels across all CT scans to mitigate variability. Resize images to a consistent resolution for uniformity. Normalize pixel values to a common scale (e.g., [0, 1]) for improved convergence during training.

3.1.3. Data Augmentation:

Augment the dataset to increase diversity and prevent over fitting. Apply transformations such as rotation, translation, scaling, and flipping to generate additional training samples. Adjust augmentation parameters to preserve anatomical realism while introducing variability.

3.1.4. Dataset Splitting:

Divide the dataset into training, validation, and test sets to evaluate model performance effectively. Ensure an appropriate distribution of data across sets, considering factors like patient demographics and nodule prevalent.



SAMPLE DATASET

3.2. CNN DEEP NET CLASSIFIER

To implement a two-stage convolutional neural network (CNN) for lung nodule detection with a deep classifier, you'll need to design and train two separate CNN models: one for candidate nodule detection and another for nodule classification. Here's a high-level overview of each stage:

CNN Architecture: Design a CNN architecture suitable for detecting candidate nodules in lung CT scans. This CNN should output a probability map highlighting potential nodule locations.

Input Preprocessing: Preprocess the input lung CT scans by resizing, normalizing, and standardizing intensity levels to ensure consistency across scans.

Training Data: Prepare a dataset of annotated lung CT scans with labeled nodule regions for training. Use data augmentation techniques to increase dataset diversity and prevent over fitting.

Evaluation: Evaluate the performance of the two-stage CNN system on a separate test set. Measure metrics such as sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC-ROC) to assess the system's effectiveness.

IV. PERFORMANCE ANALYSIS

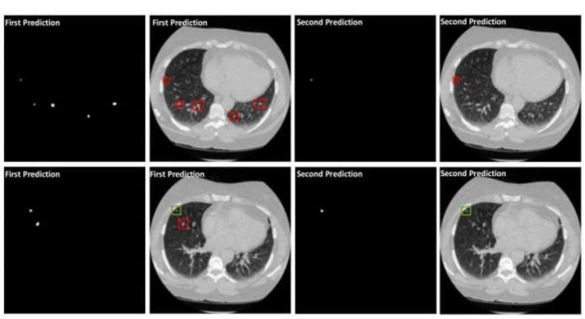
Performing analysis on the performance of a two-stage convolutional neural network (CNN) for lung nodule detection involves evaluating its effectiveness in detecting nodules accurately while minimizing false positives. Here's a comprehensive approach to performance analysis:

4.1. Positive Predictive Value (PPV) and Negative Predictive Value (NPV):

Compute the positive predictive value (PPV) and negative predictive value (NPV) of the system.PPV represents the proportion of true positive detections among all positive detections, while NPV represents the proportion of true negative regions among all negative detections.

4.2. Receiver Operating Characteristic (ROC) Curve and Area under the Curve (AUC):

Plot the ROC curve by varying the decision threshold of the CNN system and calculating the true positive rate (sensitivity) versus the false positive rate. Calculate the area under the ROC curve (AUC), which represents the overall performance of the system across different thresholds. A higher AUC indicates better performance.



PREDICTION IMAGE

V. PERFORMANCE METRICS

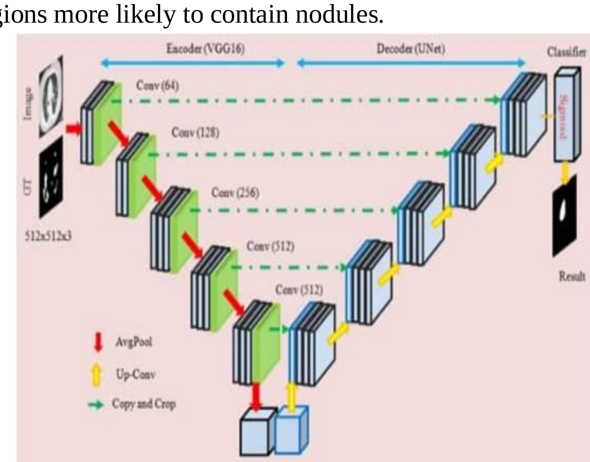
In the context of a two-stage convolutional neural network (CNN) for lung nodule detection, matrices are instrumental for various purposes, including data representation, feature extraction, and model evaluation.

Input Data Representation: Matrices are used to represent the input lung CT scans. Each CT scan is typically represented as a 3D matrix, where each element corresponds to a voxel (3D pixel) in the scan, encoding information about density or intensity.

Feature Extraction: Convolutional layers in the CNN process input data through convolutions with learnable filters. These convolutions result in feature maps, which can be represented as matrices. Feature maps capture local patterns and structures in the input data.

Model Parameters: Model parameters, such as weights and biases in the CNN layers, are stored in matrices. These matrices are learned during the training process through optimization techniques like gradient descent.

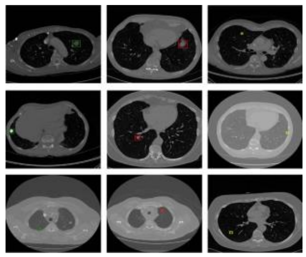
Output Representation: The output of the candidate nodule detection stage is typically a probability map or binary mask highlighting potential nodule locations. These outputs can be represented as matrices, where higher values correspond to regions more likely to contain nodules.



ENCODER AND DECODER

VI. RESULT

For a project involving a two-stage convolutional neural network (CNN) for lung nodule detection, the results typically include the performance metrics of the model, such as accuracy, precision, recall and possibly the area under the receiver operating characteristic curve.



TUMOUR IMAGE ACCURACY

F1-score: Harmonic mean of precision and recall, providing a balance between the two metrics.

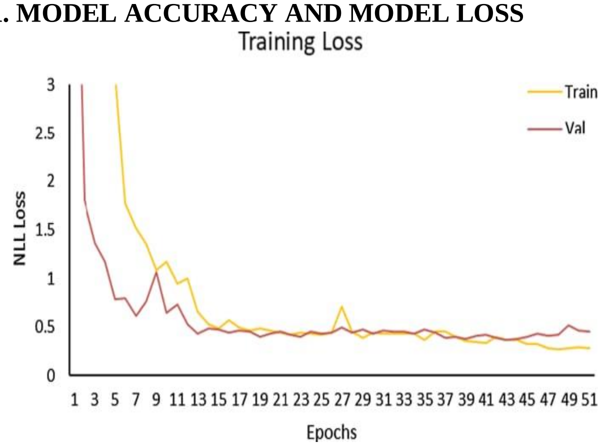
AUC-ROC: Area under the receiver operating characteristic curve, which measures the model's ability to distinguish between classes. Comparison with Baseline or Previous

Methods: Compare the performance of your two-stage CNN with baseline models or existing methods if available.

Qualitative Results: Provide examples of correctly classified lung nodules and instances where the model failed to detect or misclassified nodules.

Discussion of Results: Interpret the performance metrics and discuss any insights gained from the results. Address limitations of the model and potential areas for improvement.

6.1. MODEL ACCURACY AND MODEL LOSS



VII. CONCLUSION

In conclusion, developing a two-stage convolutional neural network (CNN) for lung nodule detection involves a systematic approach to maximize accuracy, especially when working with small datasets.

Gather a small dataset of lung CT scans with annotations and augment it to increase variability. Design a lightweight two-stage CNN architecture suitable for small datasets, incorporating a feature extraction stage and a region proposal classification stage. Utilize transfer learning, data augmentation, dropout, and batch normalization to train the model effectively while preventing over fitting. Assess the model's accuracy using metrics such as precision, recall, F1 score, and AUC-ROC, considering cross-validation for reliable estimates. Experiment with hyper parameters and regularization techniques to optimize model performance. Consider ensemble methods to combine predictions from multiple models and enhance accuracy, if computational resources permit. Continuously refine the model based on evaluation results and advancements in the field of lung nodule detection. By following these steps and adapting the approach to the specific constraints and requirements of the task, a two-stage CNN model for lung nodule detection can be developed with optimized accuracy, even with limited data.

REFERENCES

[1] J. Ferlay et al., “Cancer incidence and mortality worldwide: Sources, methods and major patterns in GLOBOCAN 2012,” Int. J. cancer, vol. 136, no. 5, pp. E359–86, 2015.

[2] B. K and S. M. V, “Techniques for detection of solitary pulmonary nodules in human lung and their classifications—A survey,” Int. J. Cybern. Inform. vol. 4, no. 1. pp. 27–40, 2015.

[3] R. L. Siegel, K. D. Miller, and A. Jemal, “Cancer statistics, 2018,” CA. Cancer J. Clin., vol. 68, no. 1, pp. 7–30, 2018.

[4] D. R. Baldwin, “Prediction of risk of lung cancer in populations and in pulmonary nodules: Significant progress to drive changes in paradigms,” Lung Cancer, vol. 89, no. 1, pp. 1–3, 2015.

[5] I. Sluimer, A. Schilham, M. Prokop, and B. van Ginneken, “Computer analysis of computed tomography scans of the lung: A survey,” IEEE Trans. Med. Imag., vol. 25, no. 4, pp. 385–405, Apr. 2006.

[6] I. R. S. Valente, P. C. Cortez, E. C. Neto, J. M. Soares, V. H. C. de Albuquerque, and J. M. R. S. Tavares, “Automatic 3D pulmonary nodule detection in CT images: A survey,” Comput. Methods Programs Biomed, vol. 124, pp. 91–107, 2016.

[7] M. Z. ur Rehman, M. Javaid, S. I. A. Shah, S. O. Gilani, M. Jamil, and S. I. Butt, “An appraisal of nodules detection techniques for lung cancer in CT images,” Biomed. Signal Process. Control, vol. 41, pp. 140–151, 2018.

[8] J. Zhang, Y. Xia, H. Cui, and Y. Zhang, “Pulmonary nodule detection in medical images: A survey,” Biomed. Signal Process. Control, vol. 43, pp. 138–147, 2018.

[9] W. Zhang, X. Wang, X. Li, and J. Chen, “3D skeletonization feature based computer-aided detection

system for pulmonary nodules in CT datasets," Compute. Biol. Med., vol. 92, pp. 64–72, 2018.

[10] B. Wang et al., "Pulmonary nodule detection in CT images based on shape constraint CV model," Med. Phys., vol. 42, no. 3, pp. 1241–1254, 2015.

[11] S. A. El-Regaily, M. A. M. Salem, M. H. A. Aziz, and M. I. Roushdy, "Lung nodule segmentation and detection in computed tomography," in Proc. 8th Int. Conf. Intel. Compute. Inf. Syst., 2017, pp. 72–78.

[12] A. CS and P. V, "Lung nodule detection and analysis using VDE chest radiographs," Int. J. Compute. Appl., vol. 115, no. 23, pp. 31–36, 2015.

[13] A. A. Rezaie and A. Habiboghli, "Detection of lung nodules on medical images by the use of fractal segmentation," Int. J. Interactive Multimedia Artif. Intel. vol. 4, no. 5, pp. 15–19, Jan. 2017.