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Lung Cancer Detection Powered by YOLO v11

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ABSTRACT

Lung cancer remains a major cause of cancer-related deaths worldwide, highlighting the need for early and precise detection. This project utilizes YOLOv11, an advanced object detection model, to automatically identify and classify lung nodules in CT scans. The model accurately categorizes nodules into three types: Normal, Benign, and Malignant. Additionally, a TNM classification system is incorporated to assess tumor staging, enhancing the diagnostic process. By leveraging state -of-the-art detection and classification techniques, this approach aims to improve diagnostic accuracy and facilitate early intervention. Performance is evaluated using precision, recall, F1-score, and mAP.

KEYWORDS: *Lung cancer classification, computed tomography, convolutional neural network, CNN–SVM, attention mechanism, computer-aided diagnosis.*

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1. INTRODUCTION

Lung cancer is a major public health concern and one of the most prevalent and fatal cancers globally. While medical advancements have improved treatment options, early detection remains key to increasing survival rates. Deep learning and artificial intelligence have transformed medical image analysis, offering accurate and automated solutions for diagnosing complex diseases. CT scans are essential for lung cancer detection due to their high-resolution imaging, but manual interpretation is time-consuming and subject to human variability. Radiologists must carefully examine multiple CT slices, which can lead to missed or delayed diagnoses.

2. RELATED WORK

Significant progress has been made in lung cancer detection and classification using deep learning techniques. Researchers have introduced multi-model frameworks that integrate convolutional neural networks (CNNs) for cancer subtype classification and survival prediction, utilizing region of interest computation for greater efficiency. Modified architectures like U-Net have been applied for lobe segmentation and candidate nodule extraction, combined with classification models such as AlexNet-SVM to enhance accuracy and sensitivity. Other studies have proposed methods like Lung-RetinaNet, which employs multi-scale feature fusion and context modules to improve the detection and localization of small tumors in CT scans.

3. PROBLEM DEFINITION AND OBJECTIVES

1. Existing lung nodule detection methods encounter difficulties in attaining high accuracy, especially when dealing with small or irregularly shaped nodules.
2. Conventional machine learning approaches fail to capture the intricate characteristics of lung nodules, impacting the sensitivity of diagnosis.
3. Present detection techniques face challenges in handling the varying scales of nodules, frequently missing smaller ones that are critical for the early.

4. SYSTEM ARCHITECTURE

The proposed YOLOv11 architecture follows a structured pipeline consisting of Data Acquisition, Preprocessing, Model Training, and Evaluation to enhance lung nodule detection. The dataset includes Normal, Benign, and Malignant lung nodules, sourced from public datasets like Kaggle and Robo flow.

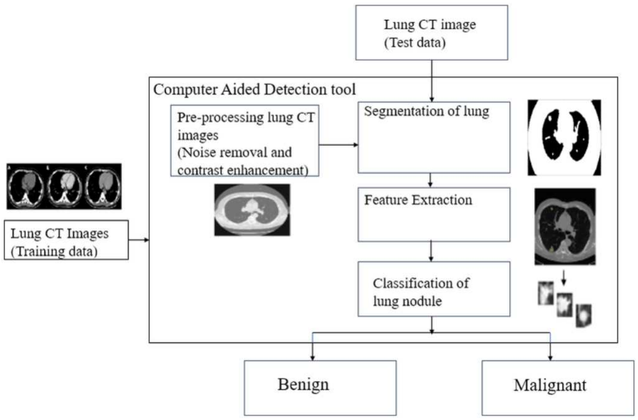

Fig 1: YOLOv11 Architecture

5. DATA PREPROCESSING

Images are resized to 640×640 pixels, and lung segmentation techniques are applied to focus on regions of interest. Data augmentation techniques such as flipping, rotation, and contrast adjustments improve generalization. The YOLOv11 model, a single-stage detection network, efficiently detects lung nodules in a single forward pass, comprising 268 layers and 68,126,457 parameters, optimized for medical imaging. Transfer learning enhances detection accuracy, and the Adam optimizer with a dynamic learning rate ensures optimal convergence. The model is evaluated using Precision, Recall, F1-score, and Mean Average Precision (mAP), with performance validation through training loss, validation loss, and confusion matrices. The optimized YOLOv11 model provides a robust and accurate deep-learning-based solution for lung cancer detection and classification.

6. FEATURE ENCODING AND EMBEDDING

Objectness score: YOLOv11 computes the objectness score to estimate the probability of an object being present in each grid cell. This score is derived using the sigmoid activation function, ensuring values range between 0 and 1 for precise detection.

$$\sigma = \sigma(t0)$$

7. MODEL DESIGN

Class prediction: The model applies the softmax function to compute the probability distribution across predefined categories (Normal, Benign, Malignant), ensuring that the total class probabilities always sum to 1 for accurate classification.

$$pi = \Sigma\ ei\ t\ C\ j=1 \cdot et\ (2)\ j$$

where C represents the total number of possible classes.

Loss Function: YOLOv11 employs a composite loss function to enhance detection accuracy and classification precision by reducing errors in object localization and category prediction.

$$L = L\ box + Lobj + Lcls$$

Where: The Lbox term handles bounding box regression loss, ensuring accurate localization of lung nodules. The Lobj component manages objectness score loss, optimizing detection confidence and reducing false predictions. The Lcls term controls classification loss, guaranteeing precise differentiation between Normal, Benign, and Malignant categories.

8. TRAINING AND EVALUATION

Lung cancer remains one of the leading causes of death worldwide, where early detection of lung nodules significantly improves survival rates. This paper presents the training and evaluation of the YOLOv11 (You Only Look Once version 11) object detection model for automated lung nodule detection using CT scan images. The model is trained on annotated medical imaging datasets and evaluated using standard performance metrics such as precision, recall, F1-score, and mean Average Precision (mAP).

Training Process
- Input image size: 640×640
- Batch size: 16 or 32
- Epochs: 50–200
- Optimizer: SGD / Adam
- Learning rate: 0.001

Tools & Frameworks
- Python
- PyTorch
- Ultralytics YOLO framework Hardware
- GPU (NVIDIA RTX series recommended)

9. RESULTS

This section presents the results from training the YOLOv11-based model for lung cancer detection. The model's performance is assessed using key metrics, including loss functions, precision, recall, and mean Average Precision (mAP). The findings highlight a notable improvement in detection accuracy, reinforcing the model's ability to differentiate between normal, benign, and malignant cases effectively. A custom dataset of 1500 annotated lung images, sourced from Kaggle and labeled via Roboflow, ensures high-quality data for training. Each image is resized to 416×416 pixels, with advanced preprocessing and augmentation techniques applied to enhance dataset diversity. The model is trained with a learning rate of 0.001 and a batch size of 32 for 20 epochs, completing training in approximately 0.932 hours. A key strength of this approach is its capability to achieve high accuracy in lung cancer detection. The chosen learning rate of 0.001 strikes a balance between adaptability and preventing overfitting. Validation accuracy and overall accuracy serve as crucial benchmarks for evaluating deep learning models in image classification, enabling quantitative comparisons across different architectures and variations.

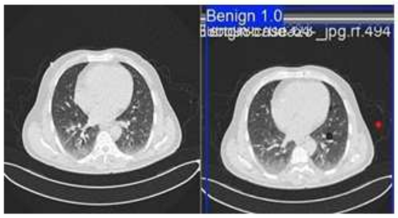

Fig 2. Detection of Benign case

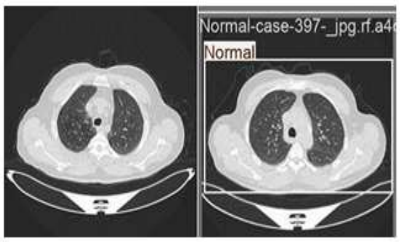

Fig 3. Detection of Normal case

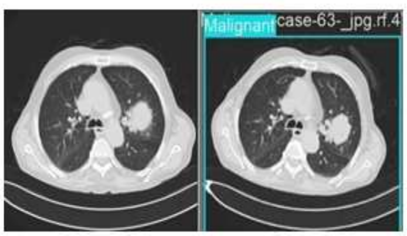

Fig 4. Detection of Malignant case

The provided images validate the successful lung cancer detection achieved using the trained YOLOv11 model. The first image corresponds to a benign case, where the model has accurately identified a localized, non- cancerous tumor. While benign tumors do not spread, they may still require medical attention. The second image represents a normal case, confirming the absence of any abnormalities, with the model correctly classifying it as free of lung cancer. The third image depicts a malignant case, where an irregular, cancerous mass has been detected and appropriately labeled. Malignant tumors are aggressive and can spread rapidly, highlighting the importance of early detection. The model efficiently differentiates between normal, benign, and malignant cases, demonstrating its potential in assisting lung cancer diagnosis by precisely encoding and classifying tumor boundaries. The training process exhibited a consistent reduction in box loss, classification loss, and distribution focal loss (DFL loss), signifying effective learning. Similarly, validation losses showed a steady decline, confirming that the model generalizes well to unseen data, further strengthening its reliability.

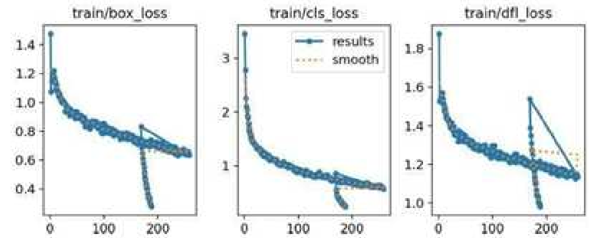

Fig 5. Represents the loss curves of training process

The training process exhibits a steady decline in box loss, classification loss, and distribution focal loss (DFL loss), indicating effective learning, as shown in Fig 5.

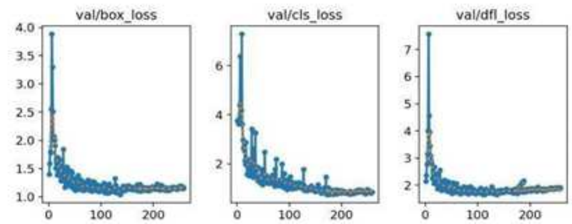

Fig 6. Represents the loss curves of validation process

The validation losses also followed a similar decreasing trend, confirming good generalization on unseen data. Box Loss is decreased from an initial value of 1.4 to below 0.4, ensuring precise bounding box localization. Classification Loss is started at 3.0 and reduced below 1.0, showing improved confidence in class assignments.

further optimizing the model's prediction reliability. These results confirm that the model efficiently learns and adapts, leading to enhanced accuracy

10. FUTURE WORK

Future improvements include:

- Integration with LLMs
- Spatial-awareness and Aspect Ratio Sensitivity
- Data-Efficient Training
- Real-time Inference
- Comparative Analysis

11. CONCLUSION

In conclusion, our study has explored the utilization of the YOLOv11 model for lung cancer detection, demonstrating its effectiveness in distinguishing between nor- mal, benign, and malignant cases. By leveraging the power of deep learning and real-time object detection, the model achieved high accuracy and reliability in detecting lung abnormalities. The steady reduction in loss values, coupled with improvements in precision, recall, and mean Average Precision (mAP), confirms the model's robust learning ability and strong generalization performance.

Furthermore, the results indicate that our approach surpasses traditional classification methods by providing real-time processing capabilities, making it a promising tool for automated lung cancer diagnosis. However, real- world implementation presents challenges, such as variations in CT scan quality and dataset biases, which future work should address through enhanced augmentation techniques, hyperparameter tuning, and larger, more diverse datasets. By refining these aspects, the proposed model can further improve diagnostic accuracy, ultimately assisting radiologists in early lung cancer detection and advancing medical imaging technologies.

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