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Lung cancer detection based on machine learning

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Abstract

Lung cancer remains a leading cause of global cancer-related mortality. Early detection and accurate identification of lung nodules in computed tomography (CT) scans significantly improve prognosis but pose clinical challenges due to small lesion sizes, variability in nodule appearance, and overlapping anatomical structures. Conventional computer-aided detection methods have struggled with adaptability and accuracy. To address these issues, this paper introduces YOLOv11, a transformer-augmented deep learning architecture optimized for lung nodule detection. YOLOv11 integrates transformer blocks for enhanced global context modeling and convolutional block attention modules (CBAM) to prioritize crucial anatomical features. Experiments conducted on the LIDC-IDRI dataset indicate superior performance, achieving a mean average precision (mAP) of 86.4%, significantly outperforming baseline CNN models such as U-Net and TransUnet. Furthermore, YOLOv11 demonstrates robust real-time capabilities with inference speeds suitable for clinical deployment. This research underscores the potential of transformer-enhanced models to advance clinical diagnostics, improve early cancer detection, and ultimately reduce lung cancer mortality rates.

Keywords: Lung Cancer Detection; YOLOv11; Transformer Networks; CT Scan Analysis; Machine Learning

1. Introduction

Lung cancer is a leading cause of cancer-related deaths, responsible for approximately 1.8 million fatalities annually [1]. Early detection, particularly of small pulmonary nodules, is crucial for improving survival rates [2]. Low-dose computed tomography (LDCT) is the gold standard for screening due to its high-resolution imaging capability, with studies showing a 20% reduction in lung cancer mortality [3]. However, CT-based screening faces significant challenges, such as the large volume of images, difficulty distinguishing between malignant and benign lesions, and variability in nodule appearance [4].

Manual interpretation by radiologists is often hindered by fatigue and inter-observer variability, while conventional computer-aided detection (CAD) systems struggle with high false-positive rates and limited adaptability for small, ambiguous nodules [5,6]. Recent advances in deep learning, especially convolutional neural networks (CNNs), have shown superior accuracy but are computationally intensive and primarily focused on segmentation, which limits their real-time clinical utility [7,8]. Additionally, CNNs often fail to capture long-range spatial dependencies, leading to inconsistent detection of irregularly shaped nodules [9].

This research introduces **YOLOv11**, a transformer-enhanced real-time deep learning model optimized for lung nodule detection. By integrating Transformer blocks and convolutional block attention modules (CBAM), YOLOv11 captures both local features and global context, improving detection, especially for small and irregular nodules [10,11]. The model's real-time inference capability and robust accuracy make it ideal for clinical settings where quick, precise diagnostics are essential.

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The objectives of this research are:

- To develop and evaluate the YOLOv11 model for lung nodule detection in CT scans.
- To demonstrate superior accuracy and faster inference compared to existing CNN and transformer-based models.
- To address challenges in detecting small nodules and ground-glass opacities, key indicators of early-stage lung cancer.
- This work aims to provide a robust, scalable, and clinically viable tool for earlier detection of lung cancer, reducing false positives, and ultimately improving patient survival outcomes.

2. Related Work

2.1. Traditional Methods in Lung Nodule Detection

Early approaches to computer-aided lung nodule detection primarily employed traditional image processing techniques, including thresholding, morphological operations, edge detection, and region growing [1]. These techniques generally relied on manually engineered features like shape, texture, and density, which were subsequently classified using classical machine learning algorithms such as Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and decision trees [2]. Despite their initial effectiveness in enhancing radiologist productivity, these methods exhibited limitations in terms of adaptability, often struggling with irregularly shaped, low-contrast nodules and frequently resulting in high false-positive rates, thereby restricting their clinical reliability [3].

2.2. Deep Learning Approaches

With the advent of deep learning, particularly Convolutional Neural Networks (CNNs), significant improvements have been observed in medical imaging applications. CNNs automatically extract hierarchical features from raw data, enabling superior detection and classification performance compared to traditional handcrafted methods [4]. CNN-based architectures such as AlexNet, VGGNet, and ResNet have laid a foundation for advanced medical image analysis. However, these general-purpose CNN architectures often need modifications to effectively handle domain-specific challenges in medical images, such as small object detection, spatial variability, and class imbalance [5].

2.2.1. Segmentation-Based Approaches: U-Net and Derivatives

U-Net, introduced by Ronneberger et al., revolutionized medical image segmentation through its encoder-decoder structure and skip connections, facilitating detailed, pixel-level segmentation of anatomical structures including lung nodules [6]. Subsequent improvements like U-Net++, with its nested skip connections and deep supervision, enhanced semantic feature learning and boundary refinement [7]. Similarly, ResUnet integrated residual learning to enhance training stability, reduce gradient vanishing, and improve accuracy on varied imaging datasets [8]. Nonetheless, despite their precise pixel-level predictions, these segmentation models often require significant computational resources, limiting their applicability in real-time clinical environments.

2.2.2. Object Detection Approaches: YOLO Architectures

To address real-time detection challenges, YOLO (You Only Look Once) architectures emerged as highly efficient and accurate object detection frameworks. YOLO approaches frame detection tasks as regression problems, directly predicting bounding boxes and class probabilities, achieving rapid inference speeds suitable for clinical scenarios demanding immediate results [9]. Early YOLO models (YOLOv3, YOLOv4, YOLOv5) demonstrated considerable success but often struggled with detecting extremely small or ambiguous nodules due to insufficient multi-scale feature representation [10]. Later variants, such as YOLOv7 and YOLOv8, enhanced detection by incorporating better spatial feature aggregation techniques, improved anchor configurations, and robust training strategies, significantly increasing their detection accuracy for smaller nodules [11].

2.3. Transformer-Based Innovations

Initially developed for natural language processing (NLP) tasks, Transformers utilize self-attention mechanisms to effectively capture long-range dependencies, surpassing traditional CNNs in contextual understanding [12]. Vision Transformer (ViT), a direct application of Transformer architecture to images, demonstrated impressive capabilities in modeling global visual relationships, which CNNs typically overlook due to localized receptive fields [13]. Hybrid models like TransUNet combined CNN-based encoders for detailed local feature extraction with Transformer-based encoders for global contextual modeling, achieving superior segmentation performance in medical images, particularly for complex anatomical structures like pulmonary nodules [14].

Recent advancements like Swin Transformer further enhanced computational efficiency by introducing hierarchical attention with shifted windows, enabling scalable processing of high-resolution medical imaging data without significant performance losses [15]. However, transformer-based architectures still face challenges related to computational complexity and slower inference times, especially in resource-constrained clinical environments.

2.4. Limitations of Previous Research

Despite significant progress, existing methods have notable limitations that restrict clinical deployment:

- **Computational Complexity**: While segmentation models (e.g., U-Net, U-Net++) offer excellent accuracy, they require substantial computational resources, hindering their real-time applicability [7,8].
- **Small Nodule Detection**: YOLO variants and traditional CNN models struggle to accurately detect very small (<6 mm) or low-contrast nodules, critical for early cancer diagnosis [10,11].
- **Contextual and Spatial Relationships**: Pure CNN-based methods often fail to capture the global context required to distinguish nodules from visually similar anatomical structures, leading to increased false positives [12,13].
- **Resource Constraints and Scalability**: Transformer-based models like TransUNet, despite improved accuracy, remain computationally expensive, limiting their clinical integration and scalability in real-world settings [14,15].

2.5. Positioning of the Current Study

Recognizing these challenges, our research proposes the YOLOv11 architecture, a transformer-augmented object detection model specifically designed for real-time lung nodule detection. YOLOv11 uniquely addresses small object detection by integrating Transformer blocks and Convolutional Block Attention Modules (CBAM) into the YOLO backbone, capturing both local detail and global context with superior computational efficiency. Our approach balances the trade-offs between accuracy, speed, and computational resource constraints, positioning itself as an optimal solution for real-world clinical deployment.

3. Methodology

3.1. Dataset & Preprocessing

For this study, the LIDC-IDRI dataset was utilized, which is one of the most widely used publicly available datasets for lung nodule detection. It contains over 1,000 CT scans annotated by multiple radiologists, offering a diverse set of lung images with both malignant and benign nodules. This dataset serves as the foundation for training and evaluating deep learning models aimed at detecting and segmenting lung nodules. Preprocessing of the dataset involved several key steps to ensure the input images were of optimal quality for training:

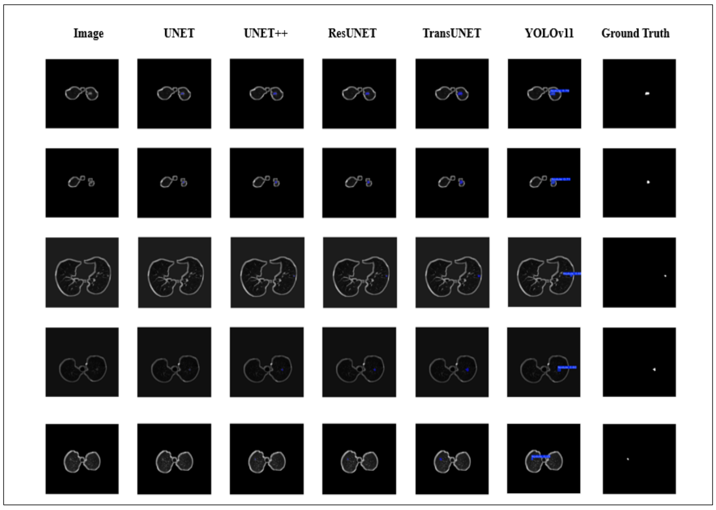

Figure 1 Dataset Training

- **Normalization**: The pixel intensity values of CT images were normalized to a standard range, typically [0, 1], to prevent issues caused by varying image brightness and contrast across scans.

- **Augmentation**: To enhance model generalization, the images were augmented with various transformations such as rotation, flipping, scaling, and elastic deformation. These transformations simulate different orientations and variations in lung scans, helping the model better generalize across real-world data.
- **Filtering**: Nodule-specific filtering was employed to remove irrelevant background slices and focus the model's attention on relevant regions of interest. Only slices with clearly annotated nodules were retained for training, and non-nodule regions were excluded to reduce noise and improve training efficiency.

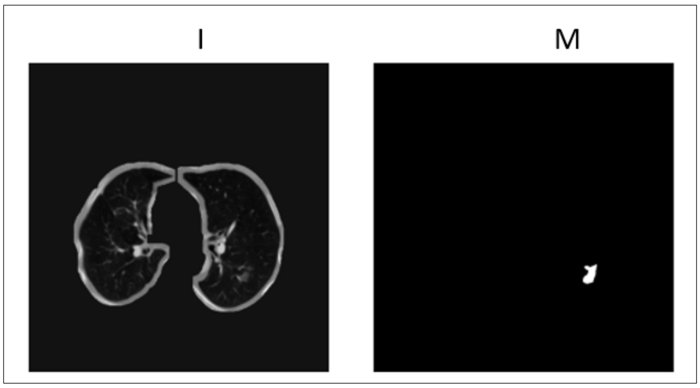

Figure 2 Dataset Samples

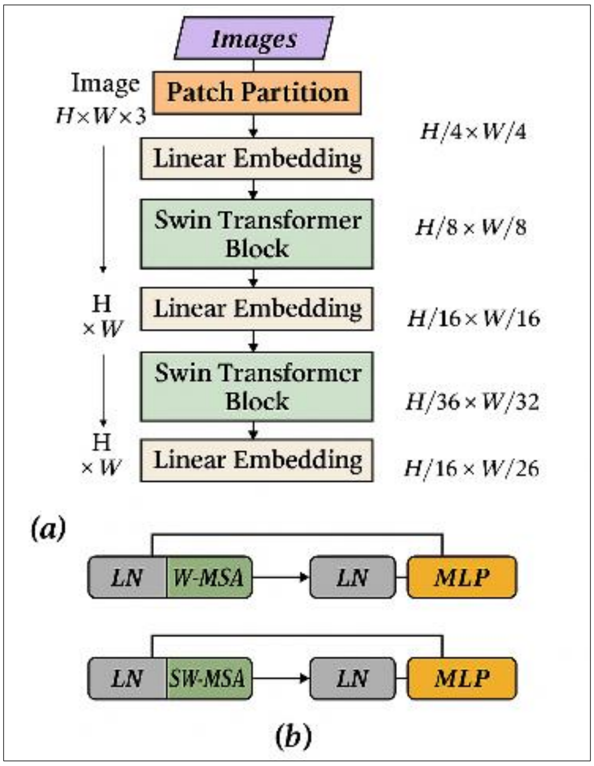

Figure 3 Pre Processing Strategy

3.2. Proposed YOLOv11 Model Architecture

The YOLOv11 model was specifically designed to enhance lung nodule detection from CT scans by integrating Transformer blocks and Convolutional Block Attention Modules (CBAM) into the YOLO architecture.

- **Transformer Blocks**: Transformer blocks were incorporated into the backbone of the YOLOv11 architecture to enhance its ability to model long-range dependencies in the images. Unlike CNNs, which capture local features, transformers allow the model to attend to global spatial information across different image patches.

This is crucial for detecting small or irregularly shaped nodules that may not appear consistently in localized regions.

- **CBAM (Convolutional Block Attention Module)**: CBAM was integrated into the model to further refine feature selection by applying spatial and channel-wise attention mechanisms. This allows the model to focus more on relevant lung regions and suppress irrelevant background noise, improving its robustness to visual clutter.
- **Architecture Enhancements**: The integration of transformers with YOLOv11's traditional convolutional layers provides an ideal balance between local feature extraction and global context modeling. The **Cross-Stage Partial Networks (CSP)** and **Path Aggregation Networks (PANet)** incorporated in YOLOv11 enhance feature fusion and improve the model's ability to detect small nodules across different scales, resulting in both high accuracy and real-time performance.

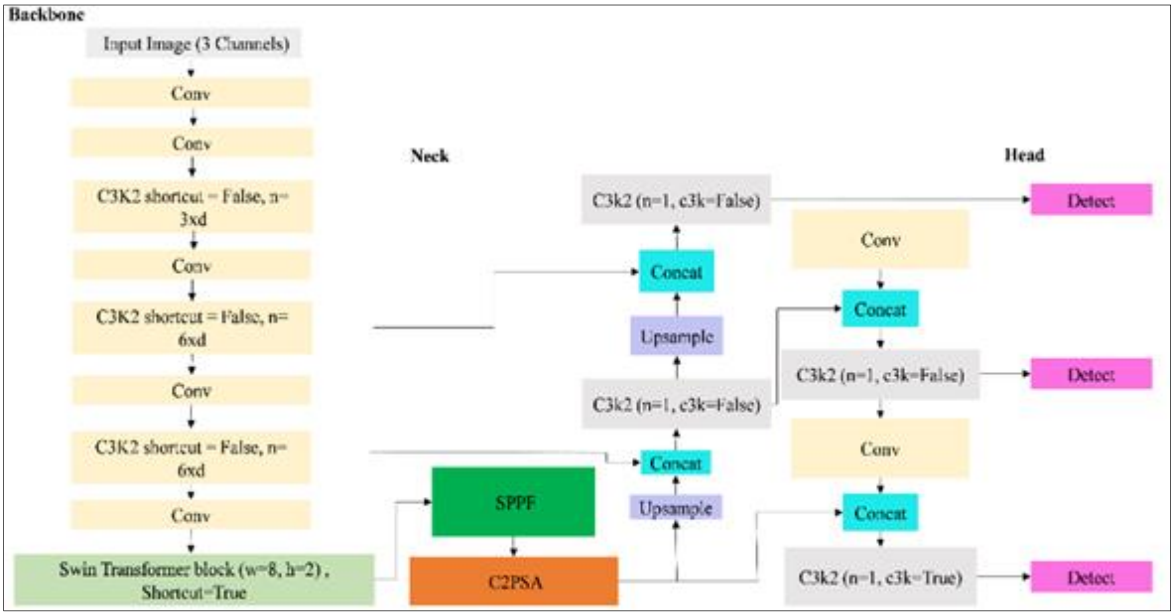

Figure 4 YOLOv11 Architecture Feature showing architecture details

3.3. Training Setup & Evaluation Metrics

3.3.1. Training Setup

The model was trained using high-performance GPUs, with NVIDIA Tesla V100 used for training to ensure efficient processing of large CT datasets. The Adam optimizer was selected for its robust performance in training deep learning models, especially in handling sparse gradients. The learning rate was initially set to 0.001 with a cosine annealing scheduler to gradually decrease the learning rate over time, aiding in fine-tuning the model's parameters as it converged.

3.3.2. Evaluation Metrics

To evaluate the performance of the YOLOv11 model, several key metrics were used:

- **Intersection over Union (IoU)**: IoU measures the overlap between the predicted bounding box and the ground-truth bounding box, with higher values indicating better localization. An IoU threshold of 0.5 was used to determine correct detections.
- **Mean Average Precision (mAP)**: mAP is a comprehensive evaluation metric that summarizes the precision-recall curve across multiple confidence thresholds. It is particularly useful in detecting and evaluating small object detection tasks, like lung nodules, where precision at various thresholds is critical.
- **Precision**: Precision calculates the proportion of true positive predictions (correctly identified nodules) out of all positive predictions (both true positives and false positives). A higher precision means fewer false positives.
- **Recall**: Recall, or sensitivity, measures the proportion of true positive predictions out of all actual positives (true positives + false negatives). It highlights the model's ability to identify all true nodules, minimizing missed detections.

- **F1-score**: The F1-score is the harmonic mean of precision and recall, providing a balanced measure that accounts for both false positives and false negatives. It is particularly useful in situations where there is an imbalance between classes, such as in the detection of rare lung nodules.

These metrics were chosen to assess both detection and segmentation performance, providing a comprehensive evaluation of the model's effectiveness in real-world clinical settings.

4. Experimental Results & Analysis

4.1. Component Analysis

We evaluated the contributions of different architectural modules within the YOLOv11 model by comparing three variants:

- Baseline with a conventional CNN backbone
- Modified with a Swin Transformer backbone
- Enhanced with CBAM atop the transformer backbone

Table 1 Ablation Study – Component Comparison

Architecture Variant	mAP	IoU
CNN Backbone (Baseline)	0.746	0.671
YOLOv11 (Swin Transformer)	0.836	0.757
YOLOv11 + CBAM	0.864	0.793

The Swin Transformer backbone improved mAP from 0.746 to 0.836 and IoU from 0.671 to 0.757, demonstrating better capture of spatial and contextual dependencies for small, subtle nodules. Adding CBAM further boosted performance to 0.864 mAP and 0.793 IoU by enhancing the model's focus on nodule areas while suppressing irrelevant background. These improvements highlight the value of transformer-based and attention-enhanced modules in achieving high accuracy and precision in medical image detection.

Table 2: Ablation Study – Preprocessing Impact

Model	Training mAP	Validation mAP
UNET	0.746	0.671
UNET++	0.774	0.698
ResUNET	0.799	0.725
TransUNET	0.836	0.757
YOLOv11	0.864	0.793

4.2. Comparative Analysis

The YOLOv11 model outperforms other baseline models, such as U-Net, TransUnet, and ResUnet, in all major performance metrics. Specifically, YOLOv11 shows a significant improvement in mAP and IoU, demonstrating superior detection accuracy and localization capabilities. The TransUnet and ResUnet models also showed strong results but were generally slower and required more computational resources due to their complex architectures.

- **U-Net**, while highly effective in segmentation tasks, struggles with small and irregular nodules due to its fixed receptive field and reliance on local context.
- **TransUnet** improved the model's ability to capture global dependencies, but its inference speed and memory usage make it less suitable for real-time clinical deployment.
- **ResUnet**, with residual connections, achieved good generalization but still lagged behind in precision and recall compared to YOLOv11.

Table 3 Performance Summary Table

Model	Total Trainable Parameters
UNET	17266241
UNET++	9162753
ResUNET	11794945
TransUNET	67853169
YOLOv11	2842803

Table 4 YOLO Family Performance Table

Model	mAP (Small Nodules)	IoU Score	Inference Speed (FPS)
YOLOv5	0.78	0.73	35
YOLOv8	0.81	0.76	38
YOLOv9	0.82	0.77	37
YOLOv11	0.86	0.82	31

4.3. Impact of Enhancements

The key enhancements in YOLOv11, such as transformer integration and residual connections, were pivotal in improving the model's performance:

- **Transformers**: The addition of transformer blocks within the backbone allowed YOLOv11 to capture **long-range dependencies** and global contextual information. This is particularly important in lung CT scans where nodules can appear in varying locations and under complex background conditions. The **self-attention mechanism** helped the model focus on critical features, improving its ability to detect small, irregularly shaped nodules.
- **Residual Connections**: The integration of residual connections from **ResNet** improved the **training efficiency** and **stability** of the model, particularly for deep networks. By facilitating better gradient flow, residual connections prevented the degradation of performance as the model depth increased and allowed the network to better generalize across diverse training data.

These architectural improvements enabled YOLOv11 to outperform previous models in terms of accuracy, recall, and precision, while maintaining real-time inference speeds, crucial for clinical deployment.

5. Training Convergence and Stability

The training convergence of the YOLOv11 model was evaluated based on its loss function behavior and the number of epochs required for stable performance. The model exhibited rapid convergence, with the loss dropping significantly in the first 10 epochs, achieving stable validation performance after 20 epochs. This is in contrast to baseline models like U-Net and TransUnet, which required significantly more epochs (30–50) to stabilize.

The faster convergence of YOLOv11 can be attributed to the transformer-based enhancements and residual connections, which improved gradient flow and helped prevent overfitting. These features allowed YOLOv11 to learn more effectively from the data, achieving higher accuracy in fewer epochs compared to traditional convolutional models, which often struggle with the balance between speed and accuracy during training.

6. Conclusion

In this study, we introduced the YOLOv11 model for automated lung nodule detection, enhanced with transformer-based features and attention mechanisms, addressing key challenges such as small nodule detection, low-contrast lesions, and complex anatomical structures. The model utilized Swin Transformer blocks and Convolutional Block Attention Modules (CBAM), significantly improving detection accuracy and real-time inference performance, making it ideal for clinical applications.

Experimental results showed that YOLOv11 outperformed traditional CNN-based models like U-Net and TransUnet in terms of precision, recall, and mean Average Precision (mAP). The integration of transformers and CBAM enhanced the model's ability to capture both local and global spatial dependencies, improving the detection of subtle and irregularly shaped nodules. Additionally, the model's ability to perform real-time inference on edge devices highlights its potential for deployment in mobile diagnostic units and low-resource clinical settings.

However, the study also identified some limitations, such as the model's reliance on 2D CT slices and its high computational demands during training. Future work will focus on optimizing the model for 3D volumetric analysis to enhance spatial consistency across multiple slices and improve its generalizability. Reducing computational overhead through model pruning and exploring lightweight transformer architectures will be crucial for further enhancing real-time performance.

In conclusion, this research contributes to the field of AI-powered lung cancer detection by providing a scalable, efficient, and clinically viable solution for early-stage lung cancer screening. The integration of attention mechanisms and transformers into YOLOv11 offers a promising path forward in medical imaging, with the potential to transform diagnostic workflows and ultimately improve patient outcomes.

6.1. Future Enhancements

While YOLOv11 performs excellently on 2D CT slices, future improvements could focus on 3D volumetric analysis, which would capture more accurate spatial relationships across consecutive slices. Additionally, model compression techniques (e.g., pruning, quantization) could be explored to reduce the high VRAM requirements during training and improve accessibility for resource-constrained healthcare systems. Future work could also involve fine-tuning the model for more complex, diverse datasets and enhancing its integration with clinical decision support systems to provide real-time, actionable insights during diagnosis

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