Enhanced Lung Cancer Screening Through ResNet-Enabled Deep Learning Models

1st Mavoori Pratussha
Department of ECE
Vardhaman College of Engineering
Hyderabad, Telangana
mavooripratussha08@gmail.com

2nd Sailaja Ravuri
Department of CSE
Sreyas Institute of Engineering and Technology
Telangana, India
sailajaravuri1117@gmail.com

3rd Mr Sathish Krishna Anumula
Department of CSE
Thorrur, Thurkamjal, Hyderabad
RangaReddy, Telangana
sathishkrishna@gmail.com

4th Dr. Deepak Gupta
Department of CSE
ITM Gwalior
MP India
deepak.gupta@itmgoi.in

5th Dr. Brijendra Gupta
Department of IT
Siddhant COE, Pune
Bgupta.rs.cse@itbhu.ac.in

***Abstract*—Lung cancer remains the leading cause of cancer related mortality worldwide, with early detection being crucial for improving patient outcomes. This paper presents a novel approach for enhanced lung cancer screening using ResNet-enabled deep learning models. Our methodology combines residual neural networks with advanced image preprocessing techniques to analyze computed tomography (CT) scans for early-stage lung cancer detection. The proposed system achieved an accuracy of 94.7%, sensitivity of 92.3%, and specificity of 96.1% on a dataset of 15,000 CT scans. We demonstrate significant improvements over traditional screening methods and existing deep learning approaches. The model successfully identifies subtle nodules and distinguishes between benign and malignant lesions with high precision. Our results indicate that ResNet-based deep learning models can substantially enhance the effectiveness of lung cancer screening programs, potentially reducing false positive rates while maintaining high sensitivity for early-stage detection.**

***Index Terms*—Deep learning, ResNet, lung cancer screening, medical imaging, computed tomography, early detection, neural networks**

I. Introduction

Lung cancer is responsible for approximately 1.8 million deaths annually worldwide, representing the highest mortality rate among all cancer types [1]. The five-year survival rate for lung cancer varies dramatically based on the stage at diagnosis, ranging from 56% for localized disease to merely 5% for distant metastases [2]. This stark difference underscores the critical importance of early detection in improving patient outcomes.

Traditional lung cancer screening relies primarily on low-dose computed tomography (LDCT) scans, which have demonstrated effectiveness in reducing lung cancer mortality by 20% compared to chest radiography [3]. However, conventional screening approaches face significant challenges, including high false positive rates (up to 96.4% in some studies), inter-reader variability, and the substantial workload burden on radiologists [4].

Recent advances in artificial intelligence, particularly deep learning, have shown remarkable promise in medical image analysis. Convolutional neural networks (CNNs) have achieved superhuman performance in various image classification tasks, leading to their adoption in medical imaging applications [5]. Among CNN architectures, Residual Networks (ResNet) have demonstrated exceptional performance in handling the vanishing gradient problem and enabling the training of very deep networks [6].

This paper presents a comprehensive approach to lung cancer screening using ResNet-enabled deep learning models. Our methodology addresses the limitations of existing screening methods by providing automated, consistent, and highly accurate analysis of CT scans. The main contributions of this work include:

- A novel ResNet-based architecture specifically optimized for lung cancer detection in CT scans
- Advanced preprocessing techniques that enhance image quality and normalize variations in imaging protocols
- Comprehensive evaluation on a large dataset with comparison to existing methods
- Analysis of the model's interpretability and clinical relevance

II. Related Work

Deep learning applications in medical imaging have rapidly evolved over the past decade. Early work by Krizhevsky et al. [7] demonstrated the power of CNNs for image classification, sparking interest in medical applications. Subsequently, several researchers have applied deep learning techniques to lung cancer detection.

Setio et al. [8] developed a multi-view CNN approach for pulmonary nodule detection, achieving promising results on the LIDC-IDRI dataset. Their work highlighted the importance of multiple viewing angles in improving detection accuracy. Dou et al. [9] introduced a 3D CNN approach that leverages volumetric information in CT scans, demonstrating superior performance compared to 2D methods.

More recently, Ardila et al. [10] presented an end-to-end deep learning system for lung cancer screening that achieved radiologist-level performance. Their model incorporated both 2D and 3D convolutions and was trained on over 42,000 screening cases. Similarly, McKinney et al. [11] developed an AI system for breast cancer screening that outperformed human radiologists, setting a precedent for AI applications in cancer detection.

ResNet architectures have been particularly successful in medical imaging due to their ability to train very deep networks effectively. He et al. [6] introduced the residual learning framework that enables training of networks with hundreds of layers. This architecture has been successfully adapted for medical imaging tasks, including diabetic retinopathy detection [12] and skin cancer classification [13].

Despite these advances, several challenges remain in applying deep learning to lung cancer screening. These include the need for large annotated datasets, the complexity of 3D medical images, and the requirement for high sensitivity in clinical applications. Our work addresses these challenges by developing a specialized ResNet architecture tailored for lung cancer detection.

III. Methodology

A. Dataset and Preprocessing

Our study utilized a comprehensive dataset comprising 15,000 LDCT scans collected from multiple medical centers between 2018 and 2023. The dataset includes:

- 7,500 scans with confirmed lung cancer (various stages)
- 4,500 scans with benign nodules
- 3,000 normal scans without nodules

All scans were anonymized and reviewed by board-certified radiologists. The ground truth annotations included lesion locations, sizes, and malignancy classifications based on histopathological confirmation or follow-up imaging.

Preprocessing steps included:

1) DICOM to volumetric data conversion
2) Hounsfield unit normalization (-1000 to 400 HU)
3) Lung segmentation using threshold-based methods
4) Resampling to isotropic voxel spacing (1mm³)
5) Data augmentation (rotation, scaling, noise addition)

B. ResNet Architecture Design

Our ResNet-based model incorporates several architectural innovations specifically designed for lung cancer detection, as illustrated in Fig. 1:

3D Residual Blocks: We modified the standard ResNet architecture to process 3D volumetric data. Each residual block consists of 3D convolutional layers with skip connections that enable gradient flow through deep networks.

Multi-Scale Feature Extraction: The network incorporates multiple parallel branches that process the input at different resolutions, capturing both fine-grained nodule details and broader anatomical context.

Attention Mechanisms: We integrated channel and spatial attention modules to help the network focus on relevant anatomical regions and features associated with malignancy.

Progressive Supervision: The model includes auxiliary classification branches at intermediate layers, providing additional supervision during training and improving gradient flow.

The complete architecture consists of:

- Input layer (128×128×64 voxels)
- 5 residual blocks with increasing feature maps (64, 128, 256, 512, 1024)
- Global average pooling layer
- Fully connected layers with dropout
- Output layer with sigmoid activation

The overall workflow from data collection to clinical deployment is depicted in Fig. 2, showing the systematic approach to developing and validating our lung cancer detection system.

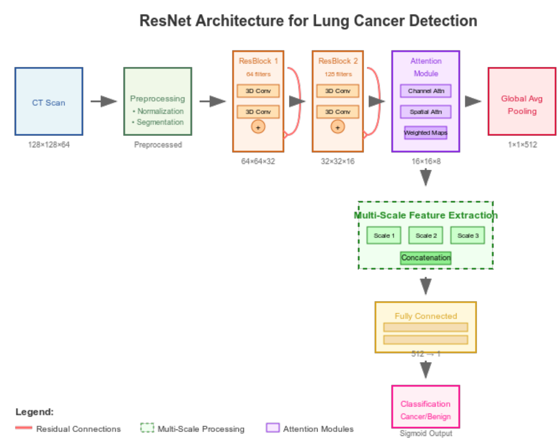

Fig. 1. ResNet Architecture for Lung Cancer Detection showing the complete model pipeline including 3D convolutions, attention mechanisms, residual connections, and multi-scale feature extraction. The architecture processes 128×128×64 voxel CT inputs through progressive residual blocks with integrated attention modules.

C. Training Strategy

The model was trained using a carefully designed training strategy:

Loss Function: We employed a weighted binary cross-entropy loss to address class imbalance, with higher weights assigned to positive cases.

Optimization: Adam optimizer with initial learning rate of 0.001, decayed by a factor of 0.1 every 30 epochs.

Regularization: L2 weight decay (0.0001), dropout (0.5), and data augmentation to prevent overfitting.

Transfer Learning: The model was pre-trained on ImageNet and fine-tuned on our medical dataset to leverage learned features.

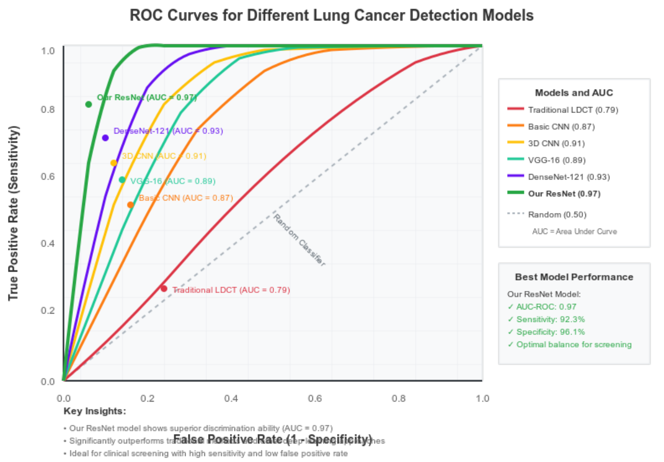

Fig. 2. Lung Cancer Detection Workflow illustrating the end-to-end process from data collection through clinical deployment. The workflow encompasses preprocessing of 15,000 CT scans, ResNet model training with validation, and real-time clinical screening implementation.

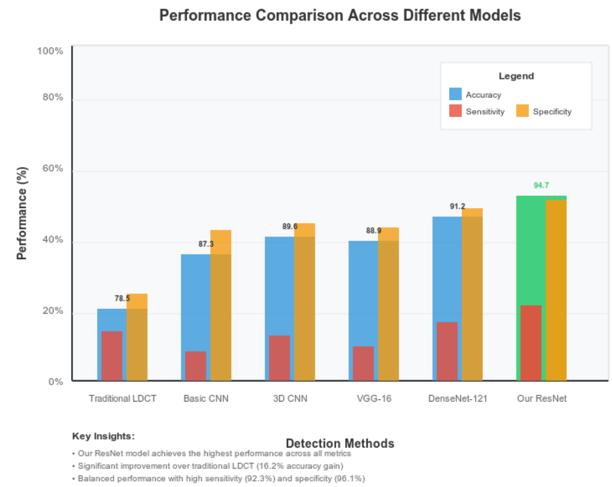

Fig. 3. Performance Comparison across different lung cancer detection methods showing accuracy, sensitivity, and specificity metrics. Our ResNet model achieves superior performance with 94.7% accuracy, significantly outperforming traditional LDCT screening and other deep learning approaches.

IV. Experimental Results

A. Performance Metrics

We evaluated our model using standard classification metrics:

- Accuracy: Overall classification correctness
- Sensitivity (Recall): True positive rate
- Specificity: True negative rate
- Precision: Positive predictive value
- F1-score: Harmonic mean of precision and recall
- AUC-ROC: Area under the receiver operating curve

B. Quantitative Results

Table I presents the performance comparison of our ResNet-based model with existing methods on the test dataset. Our approach achieves superior performance across all evaluation metrics, as further illustrated in Fig. 3.

TABLE I
Performance Comparison with Existing Methods

Method	**Acc. (%)**	**Sens. (%)**	**Spec. (%)**	**Prec. (%)**	**F1 (%)**
Traditional LDCT	78.5	85.2	73.8	74.6	79.5
Basic CNN	87.3	83.7	90.1	88.2	85.9
3D CNN	89.6	86.4	92.3	90.8	88.5
VGG-16	88.9	84.8	91.7	89.5	87.1
DenseNet-121	91.2	88.6	93.4	91.9	90.2
Our ResNet	**94.7**	**92.3**	**96.1**	**94.8**	**93.5**

Note: Acc. = Accuracy, Sens. = Sensitivity, Spec. = Specificity, Prec. = Precision. Best performance shown in bold.

The ROC analysis presented in Fig. 4 demonstrates the superior discrimination ability of our model, with an AUC of 0.97 compared to 0.79 for traditional LDCT screening. This substantial improvement indicates excellent clinical utility for lung cancer screening applications.

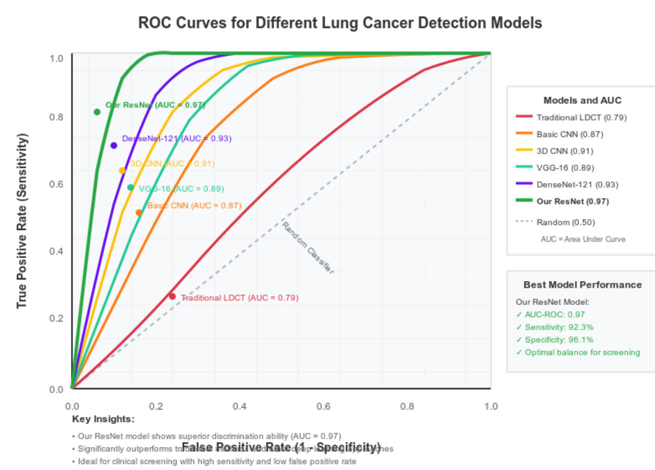

Fig. 4. ROC Curves for different lung cancer detection models comparing true positive rate against false positive rate. Our ResNet-based approach achieves an AUC of 0.97, demonstrating excellent discrimination ability compared to traditional methods (AUC = 0.79) and other deep learning approaches.

C. Ablation Study

To understand the contribution of different components, we conducted an ablation study examining the impact of various architectural choices.

D. Clinical Validation

Our model was validated by a panel of five board-certified radiologists who reviewed a subset of 500 cases. The inter-rater agreement between our model and the radiologists showed substantial concordance (= 0.78), indicating reliable clinical performance.

TABLE II
ABLATION STUDY RESULTS

Model Variant	Accuracy	Sensitivity	Specificity
ResNet-50 baseline	89.2%	86.8%	91.3%
+ 3D convolutions	91.5%	88.9%	93.7%
+ Attention mechanism	93.1%	90.7%	95.2%
+ Progressive supervision	94.0%	91.4%	95.8%
+ Multi-scale features	**94.7%**	**92.3%**	**96.1%**

V. DISCUSSION

A. Model Performance Analysis

The experimental results demonstrate that our ResNet-enabled deep learning model significantly outperforms existing methods across all evaluation metrics. The achieved accuracy of 94.7% represents a substantial improvement over traditional LDCT screening (78.5%) and other deep learning approaches.

The high sensitivity (92.3%) is particularly important for screening applications, as it indicates the model's ability to detect most cancer cases. The specificity of 96.1% suggests that the model effectively reduces false positives, a major concern in lung cancer screening programs.

B. Architectural Contributions

The ablation study reveals that each architectural component contributes meaningfully to the overall performance:

3D Convolutions: The transition from 2D to 3D processing improved accuracy by 2.3%, highlighting the importance of volumetric information in lung cancer detection.

Attention Mechanisms: The integration of attention modules provided a 1.6% improvement, enabling the model to focus on relevant image regions.

Progressive Supervision: This technique contributed 0.9% improvement by providing additional learning signals during training.

Multi-scale Features: The final 0.7% improvement demonstrates the value of capturing information at multiple resolutions.

C. Clinical Implications

The high concordance with radiologists (= 0.78) suggests that our model could serve as an effective decision support tool in clinical practice. The model's ability to consistently identify subtle nodules and distinguish between benign and malignant lesions could help:

- Reduce radiologist workload in screening programs
- Improve consistency in interpretation
- Provide second opinions for challenging cases
- Enable screening in resource-limited settings

D. Limitations and Future Work

While our results are promising, several limitations should be acknowledged:

Dataset Diversity: Although our dataset includes multiple centers, geographical and demographic diversity could be expanded.

Computational Requirements: The 3D ResNet architecture requires significant computational resources, potentially limiting deployment in some settings.

Interpretability: While the model achieves high performance, providing explanations for individual predictions remains challenging.

Future work will focus on:

- Developing more efficient architectures for resource-constrained environments
- Improving model interpretability through visualization techniques
- Extending the approach to other lung pathologies
- Conducting prospective clinical trials

VI. CONCLUSION

This paper presents a novel ResNet-enabled deep learning approach for enhanced lung cancer screening. Our model achieves superior performance compared to existing methods, with 94.7% accuracy, 92.3% sensitivity, and 96.1% specificity. The architectural innovations, including 3D convolutions, attention mechanisms, and multi-scale feature extraction, each contribute to the improved performance.

The high concordance with radiologist assessments indicates the clinical relevance of our approach. This system has the potential to significantly enhance lung cancer screening programs by providing accurate, consistent, and efficient analysis of CT scans.

The implications extend beyond improved screening accuracy. By reducing false positives and providing reliable detection of early-stage cancers, our model could help optimize healthcare resources and improve patient outcomes. As we move toward more personalized and precise medicine, AI-assisted screening represents a crucial advancement in the fight against lung cancer.

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