AI-Powered Deep Learning Framework for Automated Detection and Segmentation of Pulmonary Nodules from HRCT Thorax Scans

MACSE519
Machine Learning and Applications

Team members:

1. Shah Harsh Parag 25MAI0040

Guided by:

Dr. Mythili T

Paper Name	Author Name & Publish Date	Findings	Limitations	Project Workflow Mapping	Reviewed By
A 3D Probabilistic Deep Learning System for Detection and Diagnosis of Lung Cancer Using Low-Dose CT Scans	Onur Ozdemir, Rebecca L. Russell, Andrew A. Berlin, 21 JAN 2020	3D CNN-based CADe + CADx combined system; eliminates false-positive reduction stage	Only works with low-dose CT; does not differentiate types of nodules/cancers	Detection + Malignancy Classification	Harsh
A Machine Learning Approach to Volumetric Computations of Solid Pulmonary Nodules	Y. Han Zhou, H. Chen Huang, Y. Yu, H. Shang Jian, 29 AUG 2025	Faster performance (~60s saved per scan); mean absolute deviation ~8%	Focused on nodules ≤2 cm; low-dose CT only	Volume Measurement (ROI Extraction + Regression Head)	Harsh
A Unified Multi-Scale Attention-Based Network for Automatic 3D Segmentation of Lung Parenchyma & Nodules	Muhammad Abdullah, Furqan Shaukat, 3 JUN 2025	Attention-based U-Net with residual + dilated conv; superior Dice/IoU on LUNA16	Evaluated only on LUNA16; unknown inference time; no ablation studies	Lung Segmentation + Nodule Segmentation	Harsh
CLIP-Lung: Textual Knowledge-Guided Lung Nodule Malignancy Prediction	Yiming Lei, Zilong Li, Yan Shen, Junping Zhang, Hongming Shan 2023, arXiv	Multimodal (images + text) improves malignancy prediction & interpretability	Requires annotated reports; may not generalize without quality text	Feature Fusion + Explainability	Harsh
RadImageNet: An Open Radiologic Deep-Learning	Xueyan Mei, PhD Zelong Liu, MS Philip M.	Domain-specific pretraining improves transfer	Limited modality coverage	Pretraining for 3D Encoder	Harsh

Research Dataset	Robson, PhD Brett Marinelli, MD Mingqian Huang, MD Amish Doshi, MD Adam Jacobi, MD Chendi Cao, PhD Katherine E. Link, BS Thomas Yang, BSA Ying Wang, PhD Hayit Greenspan, PhD Timothy Deyer, MD Zahi A. Fayad, PhD Yang Yang, PhD 2022/2023	learning for medical imaging			
CSF-Net: Cross-Modal Spatiotemporal Fusion Network	Yin Shen, Zhaojie Fang, Ke Zhuang, Guanyu Zhou, Xiao Yu , Yucheng Zhao, Yuan Tian , Ruiquan Ge, Changmiao Wang, , Xiaopeng Fan , Ahmed Elazab 2025	Integrates longitudinal CTs + clinical data	Complex training, requires temporal data	Longitudinal Tracking + Feature Fusion	Harsh

LMLCC-Net: A Semi-Supervised Deep Learning Model for Lung Nodule Malignancy Prediction from CT Scans using a Novel Hounsfield Unit-Based Intensity Filtering	Adhora Madhuri, Nusaiba Sobir, Tasnia Binte Mamun, Taufiq Hasan,2025	Uses pseudo-labeling & consistency regularization Using Semi supervised Learning	May propagate pseudo-label errors	Candidate Reduction + Low-label Settings For malignancy score	Harsh
Transformer /Attention-Based Segmentation (SW-UNet, hybrids)	Xiao Liu, Peng Gao, Tao Yu, Fei Wang, and Ru-Yue Yuan2024	Improves small nodule segmentation using attention	High computational demand	Alternative Segmentation	Harsh

Gap Analysis

Computational and Efficiency Gaps

The literature reveals significant computational challenges across multiple studies. Training times ranging from 13-18 hours for ensemble 3D CNN models represent a major barrier to practical deployment. Resource-intensive architectures, while achieving high accuracy, struggle with real-time processing requirements and present difficult trade-offs between model size and performance.

Dataset and Validation Limitations

A critical limitation across the reviewed studies is the heavy reliance on standard datasets like LUNA16 and LIDC-IDRI for validation. This creates a validation bottleneck where most systems are optimized for these specific datasets, potentially limiting generalizability. The scarcity of diverse, large-scale datasets is particularly problematic, with some studies having access to only 398 cancer-positive cases for training.

Clinical Integration Challenges

Perhaps the most significant gap identified is the disconnect between research achievements and clinical implementation. Most studies fail to address integration into existing radiology workflows, handling of low-quality scans in real-world scenarios, or deployment challenges in clinical environments. This represents a critical barrier to practical adoption.

Methodological Limitations

The literature shows recurring issues with false negative propagation when detection modules fail, limitation to specific CT scan types (primarily low-dose), and lack of longitudinal tracking capabilities. Additionally, most systems lack explainability features necessary for clinical trust and regulatory approval.

Proposed Ideas and Research Directions

Hybrid Multi-Stage Architecture

A promising direction involves combining the efficiency of YOLO-based detection systems with the accuracy of 3D CNN classification models. This hybrid approach would implement adaptive computation, using lightweight screening for initial assessment followed by detailed analysis only for suspicious cases. Integration of attention mechanisms and self-supervised pre-training would enhance both efficiency and performance.

Multi-Modal Integration System

Building on emerging approaches like CLIP-Lung, future systems should integrate CT images with clinical reports, longitudinal patient data, demographics, and clinical history. Graph neural networks could model structural relationships between different data modalities, providing more robust and comprehensive analysis.

Edge-Optimized Deployment Solutions

Addressing clinical deployment challenges requires developing lightweight models suitable for real-time processing, implementing progressive inference architectures, and using knowledge distillation techniques to compress large models while maintaining accuracy. Federated learning frameworks would enable multi-center training while addressing data privacy concerns.

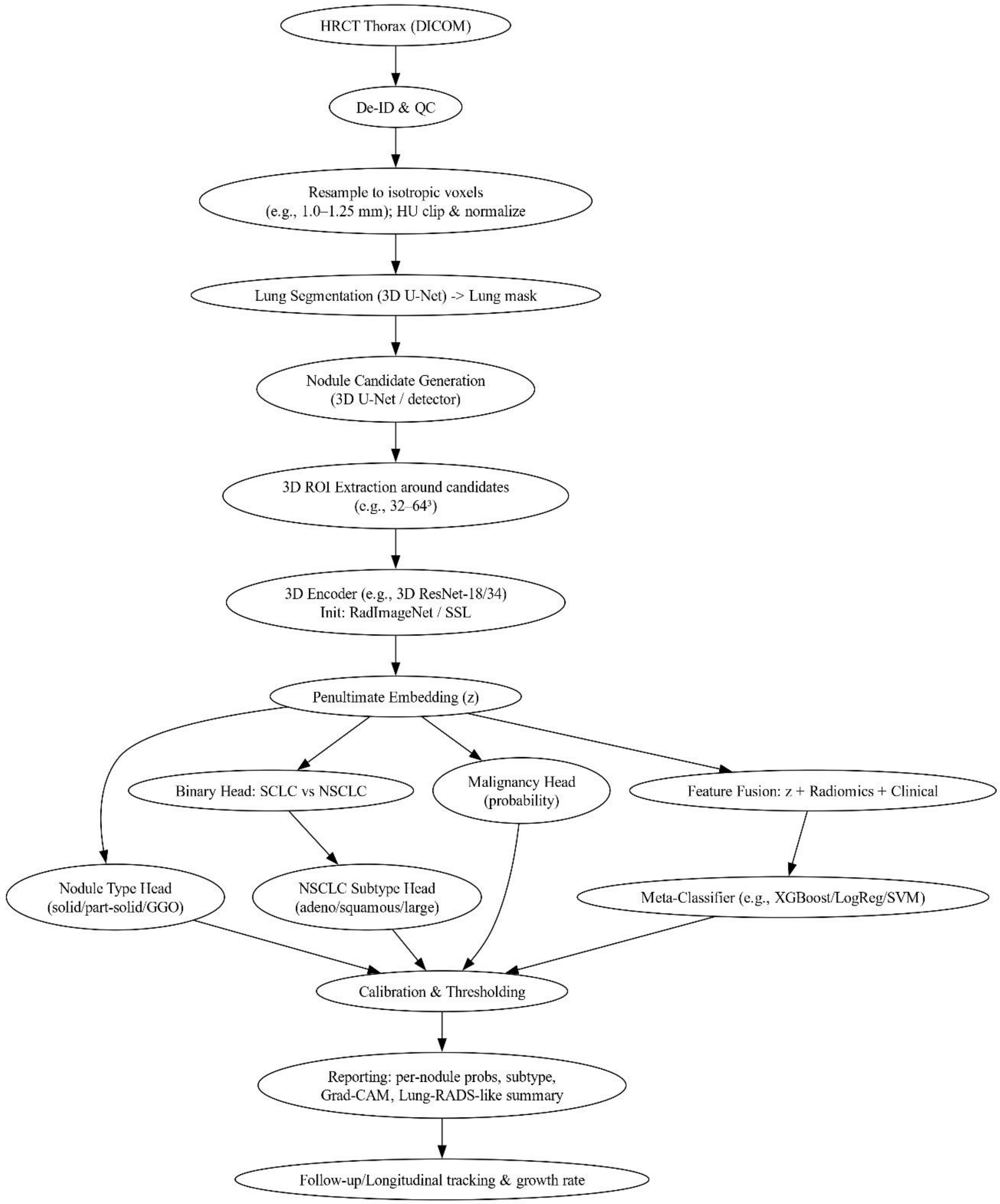
Robust Validation Framework

A comprehensive validation approach should include multi-center, multi-scanner protocols, diverse population datasets, prospective clinical trial designs, and integration testing with existing radiology workflows. This addresses the current over-reliance on limited benchmark datasets.

Explainable AI Integration

Clinical adoption requires attention visualization for radiologist review, natural language explanations for findings, uncertainty quantification for predictions, and interactive interfaces for clinical decision support. These features are essential for building trust and meeting regulatory requirements.

Methodology



Conclusions

Key Findings

The literature demonstrates that 3D CNN architectures consistently achieve high performance with AUC scores ranging from 0.87 to 0.98. Two-stage detection pipelines have emerged as the dominant architectural approach, while LUNA16 remains the primary benchmark despite its limitations. Real-time processing capabilities have been demonstrated but often require accuracy trade-offs.

Critical Research Gaps

The most pressing gaps include the lack of real-world clinical validation, limited dataset diversity affecting generalizability, unresolved computational efficiency versus accuracy trade-offs, missing explainability features, and insufficient handling of edge cases and low-quality scans.

Strategic Implications

The field requires standardized evaluation protocols beyond current benchmarks, with clinical adoption depending more on workflow integration than pure accuracy improvements. Regulatory approval will demand extensive real-world validation, while economic viability hinges on efficient, scalable implementations suitable for widespread deployment.

The analysis reveals that while significant technical progress has been achieved in lung cancer detection using deep learning, the transition from research to clinical practice requires addressing fundamental gaps in validation methodology, computational efficiency, and system integration. Future research should prioritize hybrid architectures, comprehensive validation frameworks, and explainable AI systems to bridge the gap between laboratory success and clinical utility.

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