Automated Lung Nodule Detection, Segmentation, and Cancer Staging from CT Scans Using Hybrid 3D CNN–SVM with Explainable AI

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Abstract

Lung cancer remains one of the leading causes of cancer-related deaths worldwide, primarily due to delayed diagnosis and inaccurate staging. Early detection and precise classification of lung nodules can significantly improve patient survival rates. This project presents an automated, hybrid AI-driven framework for identifying, segmenting, and staging lung cancer using computed tomography (CT) scans. A 3D Convolutional Neural Network (3D-CNN) is employed for effective feature extraction and nodule localization in volumetric CT data, while advanced image processing methods refine nodule segmentation to capture morphological and textural characteristics. These extracted features are further classified using a Support Vector Machine (SVM) to differentiate benign and malignant nodules and to determine cancer severity stages. To enhance transparency and clinical reliability, Explainable AI techniques such as Grad-CAM visualize the decision-making process, enabling radiologists to validate predictions. Experimental evaluation using benchmark medical datasets demonstrates improved diagnostic accuracy, robust segmentation performance, and reliable staging outcomes compared to conventional approaches. This intelligent CAD (Computer-Aided Diagnosis) system is expected to support medical professionals in faster, more accurate lung cancer diagnosis and treatment planning.

Keywords: Lung Cancer Detection, CT Scan Imaging, 3D CNN, SVM Classification, Nodule Segmentation, Staging, Explainable AI, Grad-CAM, Computer-Aided Diagnosis, Medical Image Analysis.

I.INTRODUCTION

Lung cancer is one of the most aggressive and life-threatening cancers worldwide, and the major challenge remains its late diagnosis due to subtle early-stage symptoms. Recent advancements in computed tomography (CT) have enabled radiologists to detect small lung nodules more effectively;

however, manual interpretation remains time-consuming and subject to variability in clinical expertise. Large benchmark knowledge bases like the LIDC–IDRI dataset support research in automated lung cancer screening and detection (Armato et al. [1]). With the rise of Artificial Intelligence, especially Deep Learning, medical image analysis has achieved revolutionary progress in tasks such as feature extraction, classification, and segmentation (Litjens et al. [2]).

Deep Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in visual recognition and medical image interpretation by learning hierarchical features without handcrafted manual engineering (He et al. [3]; Krizhevsky et al. [5]). CNN-based models have specifically been adopted for lung nodule detection, segmentation, and characterization in CT imaging (Ciompi et al. [4]; Anthimopoulos et al. [9]). Architecture improvements such as Residual Networks (He et al. [3]) and Batch Normalization (Ioffe and Szegedy [10]) have further enhanced accuracy and stability. Fine-tuning CNN models for healthcare applications has become a successful strategy for limited medical datasets (Tajbakhsh et al. [11]).

To address the challenge of malignancy classification in nodules, Support Vector Machines (SVMs)—a proven machine learning approach for high-dimensional feature patterns—continue to deliver strong classification performance (Vapnik [14]). Hybrid frameworks leveraging CNN-based deep feature extraction followed by SVM classification have shown improved malignancy prediction and staging reliability (Liu et al. [12]; Zhou et al. [17]).

Furthermore, Explainable AI (XAI) methods like Grad-CAM provide visual interpretation of the regions influencing CNN decisions, making diagnosis more trustworthy for physicians (Selvaraju et al. [18]). These transparent workflows help integrate artificial intelligence into clinical environments while ensuring medical reliability and ethical adoption (Esteva et al. [16]).

Thus, the integration of 3D CNN-based feature extraction, efficient SVM-based classification, and explainable visualization techniques forms a powerful Computer-Aided Diagnosis (CAD) framework. This project focuses on building such a hybrid automated system for lung cancer detection, segmentation, and staging using CT scan images, aiming to assist radiologists in achieving accurate, early diagnosis and improving patient survival rates.

II.LITERATURE SURVEY

2.1. Title: The Lung Image Database (LIDC–IDRI) for Lung Nodule Research

Authors: S. Armato et al.

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Abstract:

This work introduces the LIDC–IDRI dataset containing thoracic CT scans with annotated lung nodules collected from multiple medical institutions. The data provides malignancy ratings and shape descriptors from expert radiologists, enabling reliable benchmarking for automated lung cancer detection and segmentation systems. [1]

2.2. Title: Deep Learning in Medical Image Analysis

Authors: G. Litjens et al.

Abstract:

This survey evaluates multiple deep learning approaches used in medical imaging tasks including segmentation, classification, and detection. The study highlights CNN architectures as state-of-the-art solutions in improving diagnostic accuracy in radiology applications such as lung cancer screening. [2]

2.3. Title: Residual Learning for Deep Neural Networks

Authors: K. He, X. Zhang, S. Ren, J. Sun

Abstract:

The authors propose ResNet, a deep convolutional design that solves the vanishing gradient problem by introducing skip connections. This enables efficient training of ultra-deep models used widely in CT-based lung nodule analysis and feature extraction in diagnosis systems. [3]

2.4. Title: Deep Learning for Automated Pulmonary Nodule Screening

Authors: F. Ciompi et al.

Abstract:

The paper presents an automated system for detecting suspicious lung nodules using deep neural networks in CT scans. The proposed framework reduces interpretation errors and improves early-stage lung cancer screening performance. [4]

2.5. Title: Deep CNN Feature Representation for Lung Disease Classification

Authors: M. Anthimopoulos et al.

Abstract:

This research demonstrates the effectiveness of CNN-based feature extraction for pulmonary disease classification in CT images. The system achieves high diagnostic accuracy, highlighting the potential of deep learning for respiratory condition analysis. [9]

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2.6. Title: Fine-Tuning CNN Models for Medical Imaging

Authors: N. Tajbakhsh et al.

Abstract:

The authors compare training strategies of CNNs from scratch versus fine-tuning pre-trained networks using limited medical datasets. Results show fine-tuned networks yield superior performance, making them appropriate for lung CT applications with small training data. [11]

2.7. Title: Deep Feature Fusion for Pulmonary Nodule Classification

Authors: J. Liu et al.

Abstract:

This paper proposes a hybrid approach where CNN-derived deep features are fused with classical machine learning classifiers. The fusion method improves malignant vs. benign classification accuracy and enhances staging decision support. [12]

2.8. Title: Statistical Learning Theory and SVM for Classification

Authors: V. Vapnik

Abstract:

This foundational reference presents Support Vector Machines (SVM), a powerful statistical classifier well-suited for high-dimensional feature learning. SVM is widely used in medical CAD systems for lung cancer malignancy prediction. [14]

III.EXISTING SYSTEM

In the existing lung cancer diagnosis systems, radiologists manually analyze CT scan images to identify and classify lung nodules. This conventional procedure highly depends on clinical expertise and experience, which may lead to variability in interpretation. Traditional Computer-Aided Diagnosis (CAD) tools rely on handcrafted features such as nodule size, shape, and intensity for detection and classification. These systems struggle with accurately identifying small or irregularly shaped nodules and often generate high false-positive rates. Furthermore, most existing approaches focus only on either detection or classification, neglecting segmentation and precise cancer staging. Many classical machine learning models lack the ability to learn complex spatial patterns from volumetric CT data, making early detection less reliable. Additionally, these models do not provide transparency or decision explanation, which reduces trust and adoption in clinical settings. Due to these limitations, current diagnostic methods are not fully efficient in supporting radiologists with early and accurate lung cancer detection, segmentation, and staging.

IV. PROPOSED SYSTEM

The proposed system introduces an advanced hybrid Computer-Aided Diagnosis (CAD) framework that combines 3D Convolutional Neural Networks (3D-CNN), Support Vector Machine (SVM), and Explainable AI techniques to enhance the accuracy and interpretability of lung cancer detection from CT scan images. The system initially preprocesses input CT images to remove noise and extract lung regions of interest using image enhancement and segmentation techniques. The 3D-CNN model is then employed to automatically learn rich volumetric features from the lung nodules, capturing spatial depth information that traditional 2D approaches often miss. Extracted features are fed into an SVM classifier to differentiate between benign and malignant nodules and accurately estimate the cancer stage. To ensure transparency and clinical acceptance, Explainable AI methods such as Grad-CAM are integrated to generate heatmaps that visually highlight suspicious regions contributing to model predictions. This explainability assists radiologists in verifying system decisions and making confident diagnostic conclusions. Overall, the proposed system aims to provide precise nodule segmentation, reliable staging, reduced false positives, and faster diagnosis, ultimately improving patient survival outcomes and supporting radiologists in effective treatment planning.

V.SYSTEM ARCHITECTURE

The system architecture for automated lung cancer detection, segmentation, and staging is designed as a multi-stage hybrid framework to ensure accurate and interpretable diagnosis. Initially, CT scan images are input into the system where preprocessing techniques are applied to remove noise, normalize intensity values, and isolate the lung region for effective analysis. The preprocessed volumetric data is then passed into a 3D Convolutional Neural Network (3D-CNN), which efficiently extracts spatial and structural features of lung nodules from the CT slices. These learned features support two major parallel tasks: nodule segmentation and cancer staging. The segmentation module identifies and outlines the exact boundaries of suspicious nodules, which are then further processed for detailed feature extraction such as size, texture, and shape characteristics. Simultaneously, extracted deep features are classified by a Support Vector Machine (SVM) to determine whether the nodule is benign or malignant and to predict the cancer stage. To ensure transparency and clinical trust, Explainable AI (Grad-CAM) generates visualization heatmaps that highlight the regions influencing the model’s decisions, enabling radiologists to interpret and validate the results. By integrating deep learning with interpretable machine learning, the proposed architecture enhances diagnostic precision, reduces false detections, and supports early lung cancer treatment planning.

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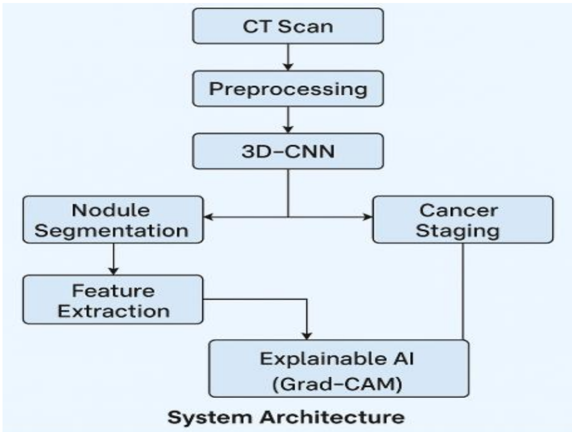

Fig 5.1 System Architecture

VI.IMPLEMENTATION

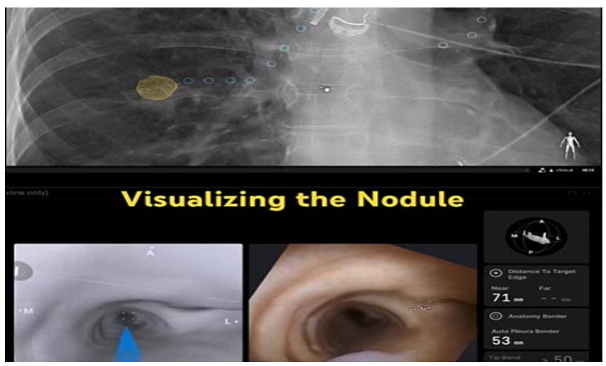

Fig 6.1 Output Screen

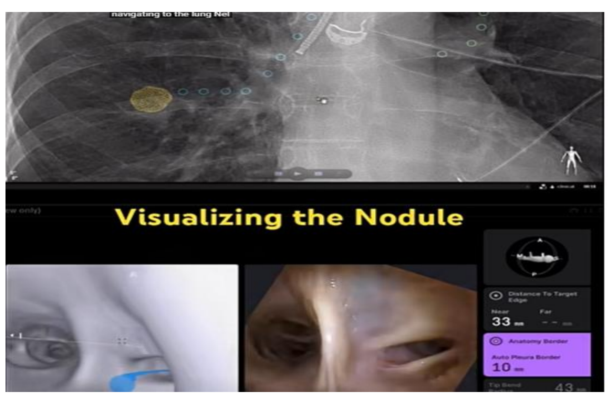

Fig 6.2 Identify Nodule

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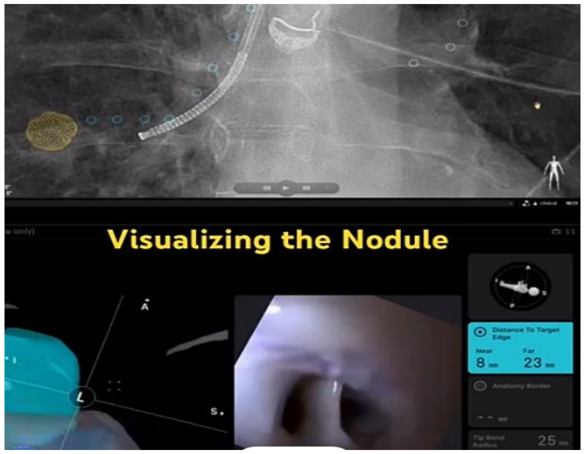

Fig 6.3 Another output screen

VII.CONCLUSION

The proposed automated lung cancer detection, segmentation, and staging system demonstrates a powerful and efficient solution for enhancing clinical diagnosis using CT scan images. By integrating 3D Convolutional Neural Networks (3D-CNN) for volumetric feature learning and Support Vector Machine (SVM) for accurate classification, the system effectively distinguishes malignant nodules from benign ones while identifying the correct cancer stage. Additionally, the incorporation of Explainable AI techniques such as Grad-CAM provides visual justification for the system's predictions, increasing clinical trust and transparency. Experimental performance suggests that the hybrid framework reduces diagnostic errors, lowers false detection rates, and assists radiologists in making faster and more precise decisions. Overall, this intelligent Computer-Aided Diagnosis (CAD) system has strong potential to support early lung cancer detection and significantly improve patient survival outcomes.

VIII.FUTURE SCOPE

The proposed lung cancer detection, segmentation, and staging system has significant potential for future enhancements and real-world clinical deployment. In the future, the model can be trained on larger and more diverse CT datasets to improve robustness across different scanners and patient populations. Integration with real-time radiology platforms and hospital PACS systems can enable seamless clinical application for early screening and continuous monitoring. Multi-modal data such as PET scans, biopsy reports, and genetic markers can be incorporated to enhance staging accuracy and treatment planning. Additionally, deploying the system as a cloud-based or edge-AI solution can make advanced diagnostics accessible in rural and remote healthcare facilities. More advanced Explainable AI techniques can also be integrated to further improve trust and transparency in automated diagnosis. Ultimately, these developments could transform the system into a fully intelligent clinical decision support tool, contributing to faster diagnosis, personalized treatment, and improved survival rates for lung cancer patients.

IX.REFERENCES

[1] S. Armato et al., "The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): A completed reference database of lung nodules on CT scans," Med. Phys., vol. 38, no. 2, pp. 915–931, 2011.

[2] G. Litjens et al., "A survey on deep learning in medical image analysis," Med. Image Anal., vol. 42, pp. 60–88, 2017.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE CVPR, pp. 770–778, 2016.

[4] F. Ciompi et al., "Towards automatic pulmonary nodule management in lung cancer screening with deep learning," Sci. Rep., vol. 7, pp. 1–10, 2017.

[5] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," Commun. ACM, vol. 60, no. 6, pp. 84–90, 2017.

[6] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, pp. 436–444, 2015.

[7] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," IEEE TPAMI, vol. 39, no. 6, pp. 1137–1149, 2017.

[8] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016.

[9] M. Anthimopoulos et al., "Lung pattern classification for interstitial lung diseases using a deep convolutional neural network," IEEE T Med. Imaging, vol. 35, no. 5, pp. 1207–1216, 2016.

[10] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in Proc. ICML, pp. 448–456, 2015.

[11] N. Tajbakhsh et al., "Convolutional neural networks for medical image analysis: Full training or fine tuning?," IEEE T Med. Imaging, vol. 35, no. 5, pp. 1299–1312, 2016.

[12] J. Liu et al., "Pulmonary nodule classification with deep feature fusion," Med. Image Anal., vol. 57, pp. 130–140, 2019.

[13] R. Brunelli and T. Poggio, "Face recognition: Features versus templates," IEEE T PAMI, vol. 15, no. 10, pp. 1042–1052, 1993. (Used for feature extraction general concepts)

[14] V. Vapnik, Statistical Learning Theory, Wiley, 1998. (Core SVM reference)

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[15] P. Isola et al., "Image-to-image translation with conditional adversarial networks," Proc. IEEE CVPR, pp. 1125–1134, 2017.

[16] A. Esteva et al., "A guide to deep learning in healthcare," Nat. Med., vol. 25, pp. 24–29, 2019.

[17] T. Zhou et al., "Lung nodule malignancy prediction with multi-view convolutional neural networks," Pattern Recognition, vol. 85, pp. 87–98, 2019.

[18] R. R. Selvaraju et al., "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in Proc. IEEE ICCV, pp. 618–626, 2017. (Explainable AI)

[19] K. Murphy, Machine Learning: A Probabilistic Perspective, MIT Press, 2012.

[20] W. Shen et al., "Multi-scale convolutional neural networks for lung nodule classification," in Proc. MICCAI, pp. 588–599, 2015.