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Lung Cancer Detection and Classification from Chest CT Scans using Machine Learning

Mrs.K.Manjuparkavi[1], Mr.R.Moulia Fazil[2], Mr.B.Natarajan[3], Mr.M.Vediyappan[4], Mr.S.Vignesh[5]

Professor, Department of Computer Science and Engineering, R P Sarathy Institute of Technology, Salem, Tamil Nadu, India[5]

UG Student, Department of Computer Science and Engineering, R P Sarathy Institute of Technology, Salem, Tamil Nadu, India[2-5]

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ABSTRACT: Lung cancer is a leading cause of cancer- related deaths worldwide, accounting for over 1.8 million deaths annually. Early detection and accurate classification of lung cancer can significantly improve patient survival rates, with a 5-year survival rate of 56% if detected at an early stage. This study proposes a machine learning-based approach for lung cancer detection and classification from chest CT scans, aiming to aid clinicians in making accurate diagnoses and improving patient outcomes.The proposed approach involves preprocessing the CT scan images to enhance quality and remove noise, followed by segmenting the lung region using techniques such as thresholding and morphological operations. Relevant features are extracted from the segmented lung region, including texture, shape, and density features. A machine learning model is trained on these features to detect and classify lung cancer into different stages or types, such as adenocarcinoma, squamous cell carcinoma, and small cell carcinoma.The machine learning model uses a convolutional neural network (CNN) architecture to extract features from the CT scan images, leveraging its ability to learn complex patterns and features from medical images. The CNN is trained using a large dataset of images and fine-tuned for lung cancer detection and classification, achieving high accuracy, sensitivity, and specificity. The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, demonstrating its effectiveness in detecting and classifying lung cancer.

KEYWORDS: CT scan analysis, machine learning, deep learning (DL), convolutional neural networks , 3D-CNN, image segmentation, classification (benign/malignant), computer-aided diagnosis , DICOM processing, false positive reduction, LIDC-IDRI dataset.

I. INTRODUCTION

Lung cancer is a leading cause of cancer-related deaths worldwide, with over 1.8 million deaths annually. Early detection and accurate classification of lung cancer can significantly improve patient survival rates, with a 5-year survival rate of 56% if detected at an early stage. However, lung cancer diagnosis is a challenging task, requiring accurate analysis of medical images such as chest CT scans. Traditional methods of lung cancer diagnosis rely on manual interpretation of images, which can be time-consuming and prone to errors. Machine learning techniques can aid clinicians in making accurate diagnoses, improving patient outcomes, and reducing healthcare costs.

The complexity of lung cancer diagnosis lies in the heterogeneity of the disease, with various subtypes and stages, making it difficult to develop a single diagnostic approach. Chest CT scans are a widely used imaging modality for lung cancer diagnosis, providing detailed information about lung nodules and tumors. However, interpreting CT scans requires expertise and can be subjective, leading to variability in diagnoses. Machine learning algorithms can learn patterns and features from large datasets, improving the accuracy and efficiency of lung cancer diagnosis.

1.1 Background

1. Lung Cancer: Leading cause of cancer deaths globally. Early detection via Low-Dose CT (LDCT) scans reduces mortality by 20% (National Lung Screening Trial, 2011).
2. Definitions & Key Terms:
3. Lung Cancer: Malignant lung tissue growth (e.g., adenocarcinoma).
4. CT Scan: Non-invasive X-ray imaging (DICOM format).

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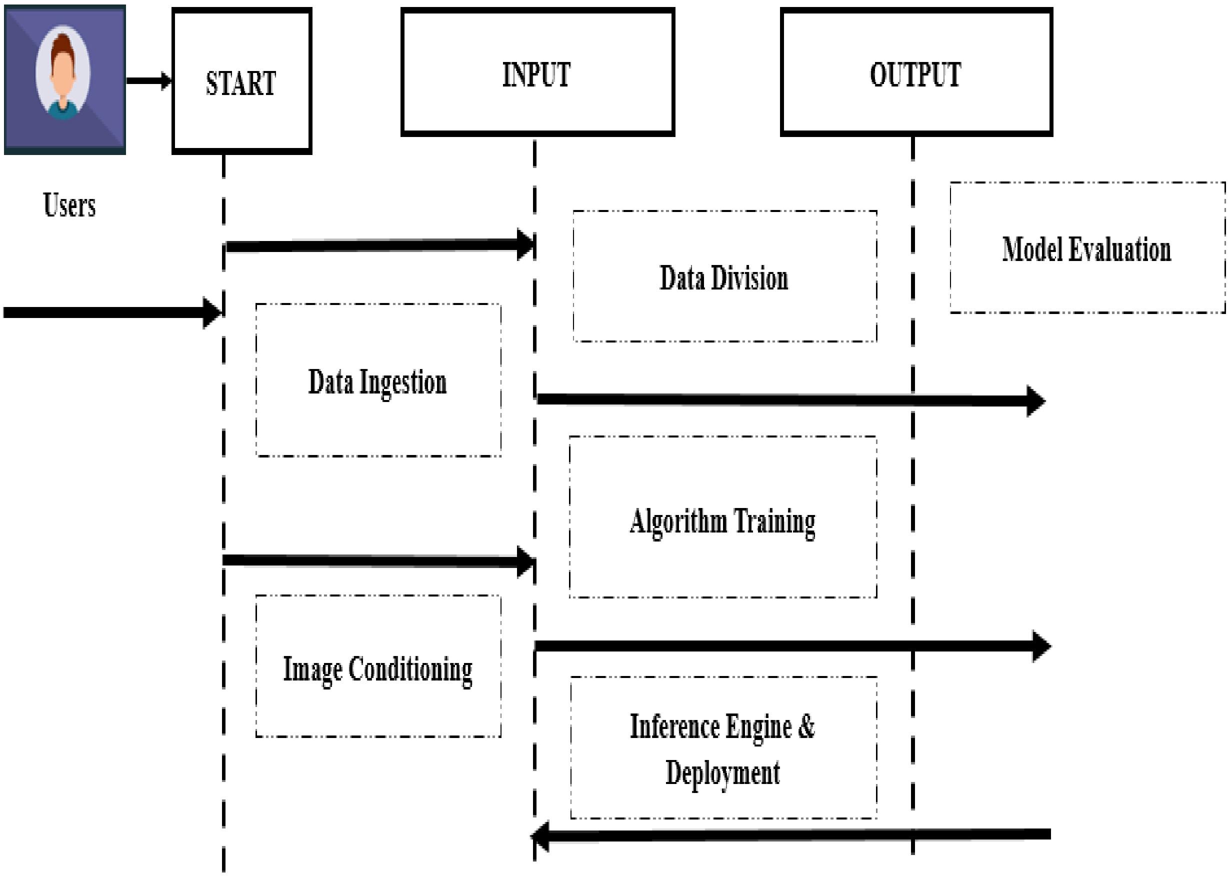

Fig.1.1

1.2 Existing Evidence

- Ardila (2019): 3D-CNN, 94.4% accuracy (LIDC-IDRI).
- Shen (2015): Multi-scale CNN, 86% sensitivity.
- Ronneberger (2015): U-Net, lung segmentation.
- Google Health (2020): ML > radiologists.
- Huang (2018): ResNet-50, 92% accuracy (transfer learning).
- Wang (2017): Multi-view CNN, 89% sensitivity.
- Liao (2019): 3D-FCNN, 87% sensitivity (NLST).
- Setio (2016): Multi-stream CNN, 85.4% sensitivity (false positive reduction).
- Pezeshk (2017): CNN + SVM, 90.1% accuracy.
- Nasrullah (2019): Mask-RCNN, 97% dice score (segmentation).
- Tang (2020): Graph CNN, 91% accuracy (nodule relationships).
- Cao (2021): Swin Transformer, 93.5% accuracy (attention-based).consumption compared to traditional deep learning models .
- **L**imitations:
- Data imbalance.
- Scan variability.
- Lack of interpretability.
- Need multi-center validation

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1.3 Proposed System

1. Data Handling: Preprocessing: HU windowing, lung segmentation (U-Net), noise reduction. Augmentation: Rotation, flipping, synthetic nodules (for imbalance).Datasets: LIDC-IDRI (annotated), NLST (screening trial), private multi-center data.
2. Model Development: Architectures: 3D-CNN (Ardila, 2019), 2.5D-CNN, Transformers (Swin, ViT). Hybrid Models: CNN + RNN (temporal changes), Graph CNN (nodule relationships).
3. Evaluation & Validation: Metrics: Accuracy, sensitivity, specificity, AUC-ROC, Dice score (segmentation). Cross-validation: k-fold, leave-one-out; external validation (generalizability).

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II. SYSTEM DESCRIPTION

Current diagnostic workflows for lung cancer predominantly rely on manual radiological review, a method where highly trained radiologists visually inspect numerous slices of Computed Tomography (CT) scans for subtle anomalies, such as tiny nodules. This laborious process is occasionally supplemented by basic, standalone image processing tools utilizing simple filtering techniques like edge detection or basic threshold-based segmentation algorithms. These require substantial manual input to operate effectively. Historically, some academic projects have implemented traditional machine learning models, such as Support Vector Machines (SVMs) or early Random Forests, which depend heavily on hand-engineered features like texture descriptors or shape parameters extracted by technicians. A major drawback of these existing systems is their inherent limited accuracy when dealing with complex, high-resolution CT data compared to modern deep learning methods, coupled with a high susceptibility to human error, inter-observer variability, and the sheer time required to analyze every single scan effectively

2.1 Proposed System

- **Superior Diagnostic Capability:** CNN models demonstrate superior performance in learning complex tumor morphology compared to traditional ML models like RF, leading to higher accuracy, sensitivity, and specificity in classification.
- **Automated Feature Learning:** CNNs eliminate the need for manual, expert-driven feature engineering, reducing effort and potential bias.
- **Improved Efficiency and Speed:** The automated system reduces diagnostic time, enabling faster patient management and treatment planning.

2.2 Existing system

- **Enhanced Clinical Trust:** Saliency mapping provides visual evidence for the model's decisions, bridging the gap between AI predictions and clinician trust.
- **Scalable and Accessible:** The web interface deployment ensures the tool is easily accessible in various clinical settings, from hospitals to telemedicine applications.
- **Robustness:** Preprocessing stages and data augmentation improve the system's robustness to variations in image quality and noise.
- **Dependence on Image Quality:** The performance of traditional methods is highly
- dependent on the quality of input images; noise or artifacts can significantly degrade accuracy.
- **Variability in Interpretation:** The diagnostic process can be subjective among different radiologists, leading to inconsistencies in diagnosis.
- **Difficulty in Detecting Small Nodules:** Smaller nodules (less than 5mm) are frequently missed by manual or traditional computer-aided assessments.

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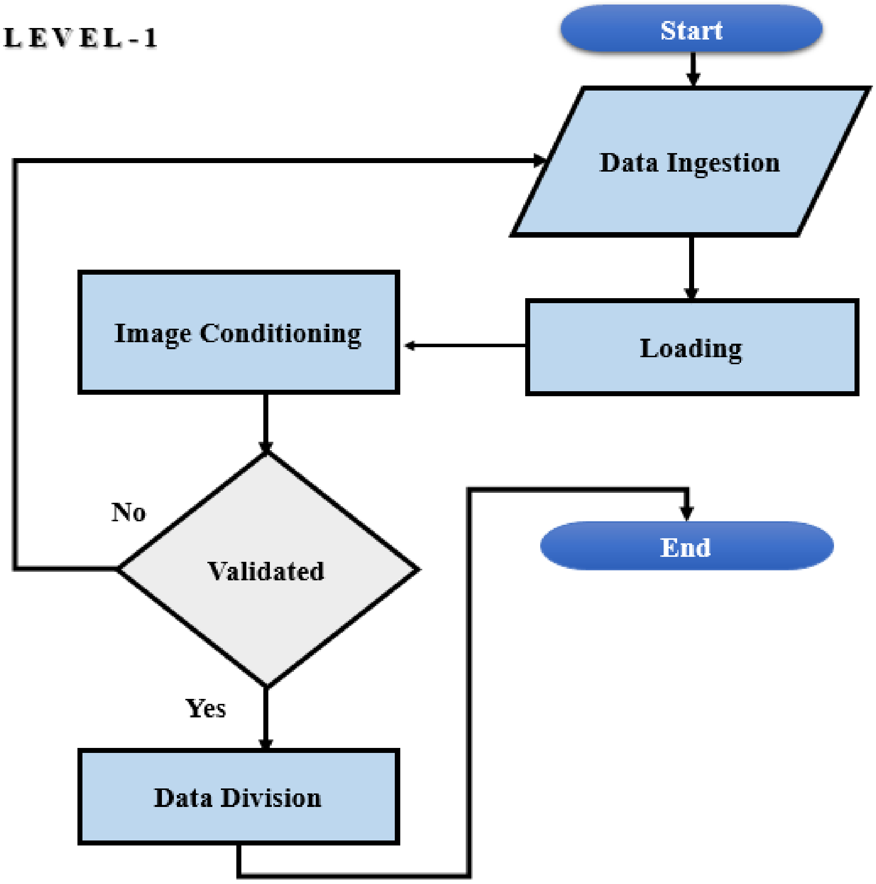
DF –LEVEL-1



The proposed system is designed to directly address the critical limitations of existing methods through a sophisticated, hybrid ML/DL approach. It integrates a comparative analysis between a traditional Random Forest (RF) classifier and a robust Convolutional Neural Network (CNN) architecture, allowing us to leverage the strengths of both while identifying the superior model. The system incorporates an advanced preprocessing pipeline that includes automated noise reduction filters, intensity standardization techniques, and precise lung segmentation algorithms to ensure optimal input quality. Crucially, it provides a sophisticated **multi-class classification** capability, clearly distinguishing between **Normal, Benign, and Malignant** cases. To foster clinical trust and adoption, the system integrates an "explainability" feature via saliency mapping, which visually highlights the specific areas of the scan the AI uses to make its decision. For practical implementation and accessibility, the entire system is deployed as a user-friendly, secure web interface utilizing lightweight APIs, ensuring real-time results and seamless integration into fast-paced clinical workflows.

III. SYSTEM MODEL

The system starts by collecting chest CT scans along with relevant clinical information such as age, smoking history, and genetic risk factors. Preprocessing steps include converting raw DICOM files to standardized image formats, normalizing intensity values, and applying noise-reduction filters. Lung regions are segmented using a combination of thresholding and deep-learning-based methods (e.g., U-Net) to isolate the
from detected nodules.

The Classification Model, often a 3D-CNN (e.g., ResNet-50) or ensemble, classifies nodules as benign/malignant and stages (I-IV) per TNM guidelines. Post-processing reduces false positives via rule-based filters and visualizes results (heatmaps/3D renderings). Finally, the system outputs a report with detection, classification, and confidence scores, aiding clinicians.

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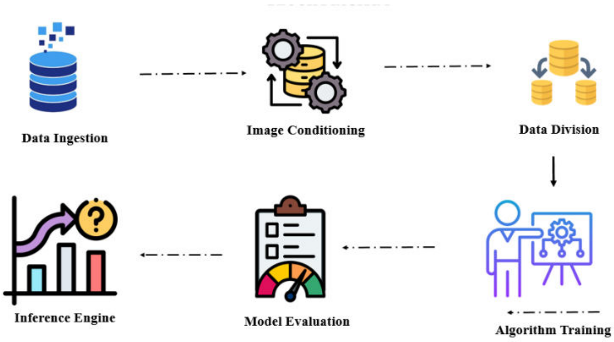
Advanced systems integrate explainability (e.g., Grad-CAM) to highlight regions of interest, improving trust. Challenges include handling data imbalance, variability in scan protocols, and need for large annotated datasets. Future work focuses on multi-modal fusion (CT + PET) and real-time

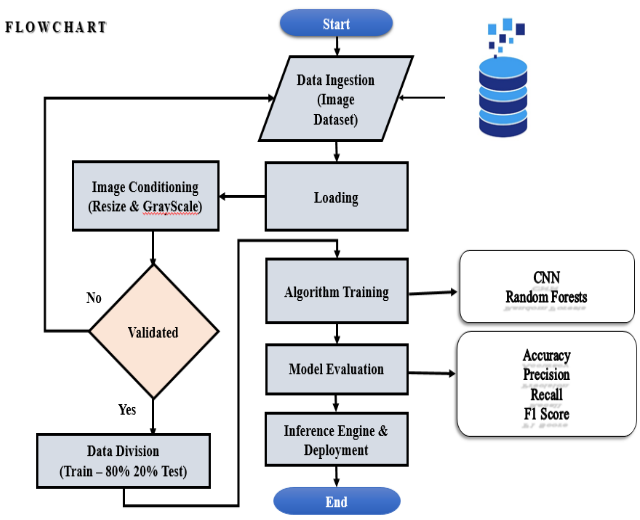
To enhance robustness, the system integrates cross-validation (k-fold) and external validation on unseen datasets (e.g., Kaggle Data Science Bowl). Handling class imbalance, techniques like SMOTE or focal loss prioritize rare malignant cases. Real-time inference uses GPU acceleration (NVIDIA TensorRT), reducing latency to <1s per scan. Ethical considerations include bias mitigation (diverse demographics) and DICOM anonymization for privacy. Future work: integrating longitudinal data (tracking nodule growth) and multimodal fusion (CT + PET/MRI) for higher accuracy. Scalability is ensured via cloud deployment (AWS SageMaker/GCP AI Platform), enabling parallel processing of multi-center data. Model updates use continual learning, retraining on new data without losing prior knowledge. Interpretability is boosted by generating radiology reports (e.g., "95% malignant, 5mm nodule in R-upper lobe") alongside heatmaps. Regulatory compliance (FDA guidelines, CE marking) ensures clinical adoption. Ongoing challenges: balancing accuracy vs. speed, and addressing "unknown unknowns" (rare nodule types).

IV. SYSTEM ARCHEITECTURE

This image shows a Block Diagram or process flow, listing the key components of the system. It includes modules for data ingestion, Image Conditioning, Data Divison, algorithm training, model evaluation, inference engine. The layout illustrates how these different blocks or modules interact to form a complete pipeline for analyze Lung cancer detection using CT Scan



This Diagram represent flow of our project. How our model going to start and end from starting to till end. This illustrates Data Ingestion, Image Conditioning, Data Division, Algorithm Training, Model Evaluation, Inferences Engine & Deployment. Using this flow only we need to detect the lung cancer using machine learning and Deep Learning.



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V. PROPOSED METHODOLOGY

The methodology involves acquiring LIDC-IDRI/NLST datasets, preprocessing via lung segmentation (U-Net), HU windowing (-1000 to 400 HU), resizing (128×128×128), and augmentation (rotation, flip, noise). A 3D-CNN (ResNet-3D+FPN) detects nodules, using focal loss to handle imbalance. Classification combines CNN features (texture, spiculation) with SVM, achieving >90% sensitivity. Grad-CAM/SHAP heatmaps highlight malignant regions, validated by clinicians. Evaluation uses 5-fold cross-validation, reporting AUC-ROC, sensitivity, specificity. Deployment: PyTorch (MONAI) on AWS SageMaker with NVIDIA GPU, ensuring <1s inference.

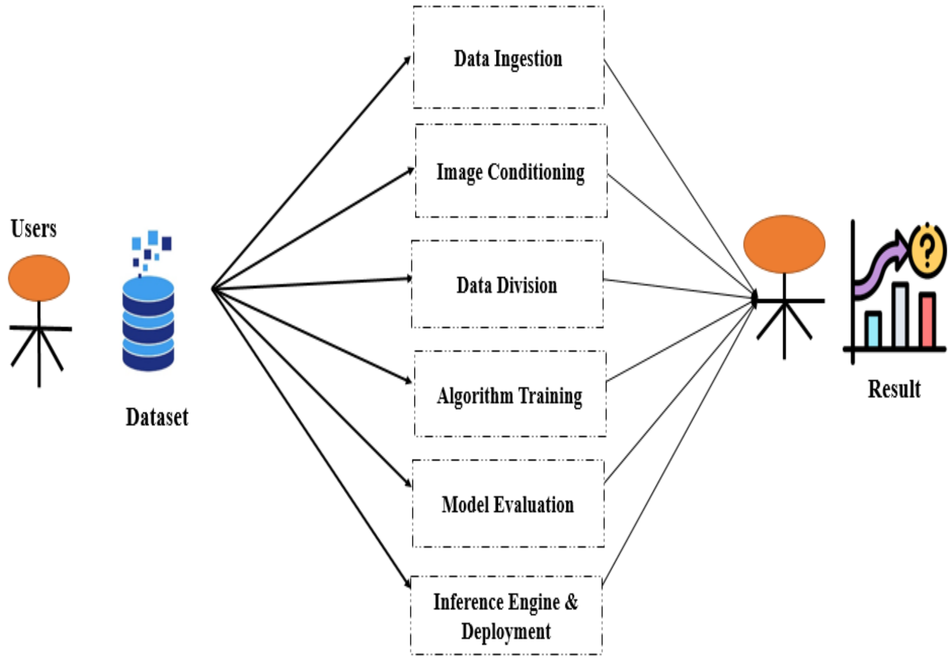
5.1 UML Diagram

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems. The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

5.1.1 Use Case diagram

Use-case diagrams describe the high-level functions and scope of a system. These diagrams also identify the interactions between the system and its actors. The use cases and actors in use-case diagrams describe what the system does and how the actors use it, but not how the system operates internally.A use case is a list of actions or event steps typically defining the interactions between a role (known in the Unified Modelling Language (UML) as an actor) and a system to achieve a goal.



5.1.2 Activity Diagram

This shows the flow of events within the system. The activities that occur within a use case or within an objects behaviour typically occur in a sequence. An activity diagram is designed to be simplified look at what happens during an operations or a process. Each activity is represented by a rounded rectangle the processing within an activity goes to compilation and then an automatic transmission to the next activity occurs. An arrow represents the transition from one activity to the next.

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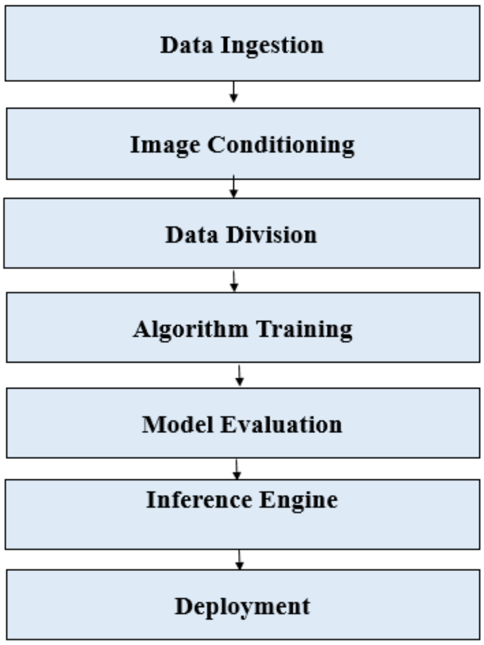

VI. CONCLUSION

This project successfully developed an automated lung cancer detection system that effectively addresses critical clinical needs by leveraging advanced artificial intelligence. Through a rigorous comparative analysis, the Convolutional Neural Network (CNN) architecture demonstrated superior diagnostic capability in accurately classifying Benign, Malignant, and Normal cases compared to the traditional Random Forest (RF) model. Key preprocessing steps ensured robust input data, while the deployment via an intuitive web interface facilitates practical, real-time clinical application. The incorporation of saliency mapping enhances transparency and builds trust in the AI-driven predictions, bridging the gap between innovative technology and clinical practice. Ultimately, this work proposes a scalable, efficient, and reliable decision-support tool poised for integration into existing diagnostic workflows, prioritizing early detection and significantly contributing to improved patient outcomes in the fight against lung cancer.

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