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Research Paper

"An Explainable Hybrid 2D–3D Deep Learning Framework for Automated Lung Cancer Detection and Subtype Classification""

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***Abstract*— Lung cancer has a high mortality rate, largely due to late detection. Standard diagnostic tools, such as CT scans and X-rays, need radiologists to analyze them, which can be time-consuming and can have mistakes. This paper presents a deep learning system for the automated detection and classification of lung cancer using medical images. The system uses Convolutional Neural Networks (CNNs) and 3D-ResNet models to examine CT and X-ray images, learning about the characteristics of lung tissues. It classifies cancer into types like Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC) with good accuracy. The method involves a multi-stage process: data collection, image preparation, segmentation, feature extraction, and classification to get consistent results. Preparation steps, like noise reduction and normalization, make images clearer, and visualization tools, like heatmaps, show affected areas, which makes the system easier for doctors to understand and use. Tests showed that the model performs well in accuracy, precision, recall, and F1-score, cutting down diagnosis time and reducing the need for people to do the work. In conclusion, this system shows how artificial intelligence can change lung cancer screening by allowing for quicker, more accurate, and bigger diagnoses. In the future, it could be used for other respiratory diseases and added to real-time hospital systems for better healthcare.**

Keywords- Deep Learning, Convolutional Neural Network (CNN), 3D-ResNet, Lung Cancer Detection, Medical Imaging, Computer-Aided Diagnosis (CAD)

I. INTRODUCTION

Lung cancer is a major global health problem and causes many deaths. Often, it is found late because symptoms are not clear until the disease is advanced. Finding it early improves the chance of survival, but standard ways to diagnose it, like CT scans and biopsies, rely on radiologists to look at them, which takes time and can have mistakes, especially for small or hard-to-see tumors.

AI and deep learning have become useful in medical image analysis. They can learn to see details in images that people might miss. Using models like CNNs and 3D-ResNet, computers can find and classify lung tumors accurately.

This study aims to create a deep learning system to find and classify lung cancer types from CT and X-ray images. The system uses CNNs and 3D-ResNet models to tell the difference between Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC). This method can make diagnoses faster, reduce errors, and give radiologists AI tools to help them decide.

By combining image processing, segmentation, feature extraction, and classification, this system gives a faster and more dependable way to diagnose than older methods. The results are shown visually with heatmaps and confidence scores, which explain how the predictions are made and make them helpful for doctors.

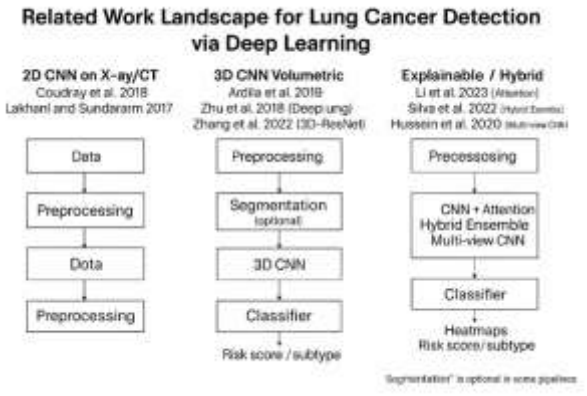
This study hopes to show how deep learning can change how lung cancer is found, allowing for earlier detection, better accuracy, and ability to be used widely. With work and adding it to hospitals, this technology could help doctors and

improve patient results.

II. RELATED WORK

Deep learning has become a leading technology in medical image analysis over the past ten years, especially for finding and diagnosing cancer. Various studies have looked into how AI models can make lung cancer detection quicker, more precise, and more dependable when compared to standard ways of doing things by hand.

Ardila et al. (2019) created a 3D deep learning model that looks at low-dose CT scans to check for lung cancer. Their method did about as well as skilled radiologists, suggesting that 3D CNNs can find early-stage lung cancer well by analyzing image volumes. Similarly, Coudray et al. (2018) made a CNN framework that sorted Non-Small Cell Lung Cancer (NSCLC) types and even predicted genetic changes straight from images of tissue samples. This research showed that deep learning can be useful for both figuring out what's wrong and planning treatments that are specific to each person.



The LUNA16 Challenge (Setio et al., 2017) set a standard in lung cancer research with a common data set for comparing different ways of finding nodules. Their results showed that CNN-based designs are better than standard image processing methods in how well they can find things and how accurate they are. Later, Zhu et al. (2018) came up with DeepLung, a 3D CNN system that can both find and sort lung nodules. This model was very accurate and greatly lowered the number of false positives.

Further progress was made by Kanavati et al. (2021), who made deep learning models for sorting lung cancer types like Adenocarcinoma and Squamous Cell Carcinoma with a high AUC of 0.99. Their study also showed ways to see AI predictions more clearly for medical experts. Hussein et al. (2020) created TumorNet, a CNN framework that looks at CT slices from different angles to improve how well things are sorted by using both spatial and contextual data.

More recently, Li et al. (2023) worked on AI that can be explained by including attention ways to CNN designs, which lets models point out the most important lung areas that affect their predictions. This move toward being able to understand things is key for building trust in AI-assisted diagnosis. Meanwhile, Silva et al. (2022) suggested a deep learning model that mixes CNNs with group methods to make things stronger and less sensitive to noise in CT images.

In general, current studies strongly support using deep learning in medical images. Studies often show that CNN-based and 3D designs can do better than standard diagnostic systems in how accurate, fast, and reliable they are. Still, we need systems that combine automatic detection, sorting, and visual understanding into one framework that can grow and be added to real clinical workflows — which is what this research is trying to do.

III. FRAMEWORK AND DESGIN PRINCIPLE

A. System Framework

The proposed system uses deep learning to automatically find and sort lung cancer types from CT and X-ray images. The design combines different parts, starting with getting data and ending with sorting and making reports. These parts work together to give correct, quick, and understandable results.

B. The system acts in these main steps:

Data Acquisition –

Big collections of labeled CT and X-ray lung images, like LIDC-IDRI and LUNA16, are the starting point. These collections have details like where nodules are, how big they are, and what type of cancer they might be. This information is important for training the system. The data is changed to make it look the same for the computer programs.

1. Image Preprocessing –

The images often have mistakes, bad contrast, or unnecessary parts. To fix this, actions like removing noise, making the images clearer, resizing, and adjusting contrast are done. For CT scans, the images are adjusted to keep the resolution steady across all images.

2. Lung Segmentation –

This isolates the lung area from the rest of the picture. The U-Net setup or a simple separation method is often applied here to take out the lungs. This process gets rid of bones and other tissues that could confuse the system, so it only focuses on the important parts of the medical images.

3. Feature Extraction –

After the lung area is separated, computer programs called Convolutional Neural Networks (CNNs) and 3D-ResNet take out special traits. CNNs find small details, and 3D-ResNet figures out how the CT slices relate to each other. This gives a more detailed sense of the tumor's shape and location.

4. Classification –

After the traits are taken out, the system uses fully connected layers and a Softmax sorter to put the nodules into groups, like Benign, Malignant, Small Cell Lung Cancer (SCLC), and Non-Small Cell Lung Cancer (NSCLC). The system gives a score for each guess, which tells how sure it is.

5. Result Visualization and Report Generation –

The system makes heatmaps (using Grad-CAM) to show which parts of the image were most important for its choice. This makes the process easier to see and understand. A summary report with the results, how sure the system was, and where the important spots are is made to help doctors make choices.

Overall, the system is made to make finding the problem faster, lower mistakes from people, and make things more correct with smart computerization. Using both 2D and 3D deep learning models makes sure the system sees the full lung structure, which helps give better medical information.

IV. APPENDIX

This part includes extra info, figures, and tech stuff that go with the main paper. It gives more info on the data, model setup, math stuff, and how we checked things in the “Lung Cancer and Its Types Using Deep Learning” project.

A. Data Info

- LIDC-IDRI Data –

A free set of lung CT scans marked by expert radiologists. It has labeled lumps with cancer ratings, which we used to train and test our models.

- LUNA16 Data –

A common data set taken from LIDC-IDRI, mostly used for finding and sorting lumps. It has ready-to-use CT images for deep learning work.

- Extra Data (Optional) –

A small group of open-source chest X-ray images was also used to check how well the model works with different image types.

B. Model and Math Detail

Deep Learning Models Used
Convolutional Neural Network (CNN): For pulling out 2D shapes from CT and X-ray images.
3D-ResNet Model: For learning sizes and shapes from 3D CT scan slices.
U-Net: For cutting out the lung area (ROI) before sorting.
Math Steps (Simple Version):
Image In (CT/X-ray)
Prep (Clean up noise, make things standard)
Cutting (U-Net)
Shape Pulling (CNN / 3D-ResNet)
Sorting (Softmax sorter)
Result (Cancer type + how sure + heatmap view)

C. Gear and Software Setup

Gear Used:
Processor: Intel Core i7 / AMD Ryzen 7
RAM: 16 GB (Good to have)
Storage: 100 GB SSD
GPU: NVIDIA RTX 3060 or better (for training)

Software:
Language: Python 3.9
Libraries: TensorFlow / PyTorch, OpenCV, NumPy, Pandas, Matplotlib
Tools: Jupyter Notebook, Google Colab, VS Code
Views: Grad-CAM for heatmaps, Matplotlib for graph

D. How We Measured Performance

We checked the model using normal ways in medical image sorting
Accuracy (ACC): How many right answers as a percent.
Precision: How many of the positive predictions were actually positive.
Recall (Sensitivity): How well it finds the actual positives.
F1-Score: A mix of precision and recall scores.
AUC (Area Under Curve): How well it sorts across different levels.

E. Example Result

Heatmap views showing important spots in CT images.
Sorting reports showing what kind of cancer (SCLC or NSCLC).
Graphs showing model training getting better or worse over time.

F. What's Next

Using PET scan data together for better cancer finding.
A cloud-based tool for hospitals and clinics far away.
AI working right away on devices for faster results.

G. Data Sources and Links

LIDC-IDRI Data: https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI
LUNA16 Challenge Data: https://luna16.grand-challenge.org
More Info: IEEE Xplore, SpringerLink, and Nature Medicine articles about lung cancer finding using deep learning.
This part gives extra tech info to go with the main paper, making sure it can be copied, is open, and easy to get for other researchers working on AI in medical finding systems.

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