RESEARCH PAPER

Hybrid Feature Fusion of 3D CNN and Radiomics for Automated Lung Cancer Detection from CT Images

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ABSTRACT
Lung cancer is still a reason why a lot of people die from cancer. This is because it is often found late and it can be hard to see the signs of lung cancer in pictures from a kind of scan called a computed tomography or CT scan. To deal with this problem the people who wrote this paper came up with a way to detect lung cancer. This new way uses a combination of two methods: one that looks at pictures from the CT scan using a special kind of computer program called a 3D CNN and another method that looks at the characteristics of the lung cancer itself. The system puts all this information together to get an understanding of the tumor. It then decides if the tumor is benign or malignant. The results show that this system is better than systems that only use the 3D CNN or only look at the radiomics features. It is more accurate. The CT image system is also better at finding all the tumors, including the ones that are malignant, and it is good at not saying something is a tumor when it is not. The results highlight the effectiveness of combining deep learning and radiomics for robust and automated lung cancer detection.
Keywords: Lung cancer detection, 3D CNN, Radiomics, Feature fusion, Computed tomography, Medical image analysis.
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I. Introduction

Lung cancer is a problem for people’s health and it is still the main reason people die from cancer all around the world. If we can find lung cancer early people are more likely to survive. The problem is that it is hard to find growths in pictures of lungs because they can be different sizes, shapes and textures. Doctors can use machines to take pictures of lungs with low amounts of radiation which helps find cancer early. Looking at these pictures one, by one takes a lot of time and different doctors might see different things.

Deep learning is really good at looking at pictures especially when it uses something called Convolutional Neural Networks. These are really useful for finding lung cancer. 3D Convolutional Neural Networks are particularly good at this because they can look at lots of CT scan pictures at the time and understand how they are all connected. They might miss things that doctors think are important like features that they have learned to look for in pictures.

Radiomics is a way to get information about tumors. It does this by looking at things like how bright or dark the tumor's what shape it is and what the texture is like.We have to decide of time what things to look for and it might not catch everything that is going on in the pictures, from the CT scan especially when it comes to complicated patterns.

➢ **Key Motivations and Contributions**

- Need for automated and reliable lung cancer detection from CT scans
- Limitations of standalone 3D CNN and radiomics-based approaches
- Integration of volumetric deep features and interpretable radiomic features

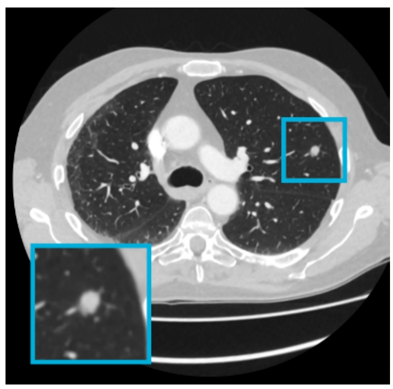

Figure 1: Lung nodule detection for routine clinical CT scans

II. LITERATURE REVIEW

Lung cancer detection using CT images has been widely explored in recent years, with approaches ranging from traditional handcrafted feature analysis to deep learning-based methods. Early work in computer-aided diagnosis (CAD) relied heavily on radiomics, where quantitative features such as intensity, shape, and texture were extracted from segmented nodules.

In particular, 3D CNNs have shown superior performance in lung nodule classification because they capture volumetric information across slices, preserving spatial context that 2D networks cannot exploit. Studies such as [1][2] reported that 3D CNNs improved sensitivity and accuracy for malignant nodule detection compared to traditional 2D CNNs.

To bring together the simplicity of radiomics and the strength of learning people have been looking into mixed models. These methods take out radiomic features and deep features from 3D CNNs and then they combine these features or make a decision based on them. For example,

The researchers,

- Zhang and his team came up with a way of doing things in 2023. They made a system that uses 3D CNN features and texture-based radiomics together. This system is better than using either of these things on their own. It can tell things apart accurately which is measured by something called AUC. The system developed by Zhang and his team has an AUC, which is a good thing.
- Li et al. (2024) proposed feature-level fusion of 3D CNN and radiomic descriptors for lung nodule classification, improving sensitivity for small nodules (<6mm).
- Kumar et al. (2025) integrated 3D CNNs with shape-based radiomics and reported enhanced robustness across multi-center CT datasets.

Table 1: Summary of Recent Studies on Lung Cancer Detection Using 3D CNN and Radiomics

➢ **Key observations from the literature:**

- Hybrid models consistently outperform individual 3D CNN or radiomics-only methods.
- Feature-level fusion is generally more effective than decision-level fusion.
- Segmentation quality significantly impacts radiomic feature performance.

III. DATASET

We are using the LIDC-IDRI dataset for this work. The LIDC-IDRI dataset is a popular public benchmark for looking at lung nodules in pictures from chest CT scans. This LIDC-IDRI dataset has 1,018 pictures of chests from CT scans. These pictures were taken at different medical centers using machines from different companies. Four doctors who are experts at looking at pictures of lungs looked at each picture on their own.

The dataset includes more than 2,600 lung nodules with diameters greater than 3 mm, along with associated metadata such as three-dimensional spatial coordinates, malignancy ratings, and semantic attributes. Malignancy scores range from 1 (highly unlikely to be malignant) to 5 (highly suspicious). Additional semantic features such as spiculation, lobulation, and texture are provided to describe visually significant diagnostic characteristics.

➢ Instead of using a single patch per nodule, overlapping 3D patches were generated by applying small spatial shifts around the nodule center.

Dataset Split	**No. of Patients**	**Effective No. of Sample**	**Percentage**	**Purpose**
Training Set	712	~7,000	70%	Model training (3D CNN + Radiomics)
Validation Set	153	~1,500	15%	Hyperparameter tuning and early stopping
Testing Set	153	~1,500	15%	Final performance evaluation
Total	1018	~10,000	100%	Augmented LIDC-IDRI dataset

➢ **We used some methods to make our 3D data better. These 3D data augmentation techniques were applied when we were training, including:**

Year	**Authors**	**Method**	**Dataset**	**Key Results Performance**	**Limitations**
2023	Chen et al.	3D CNN (volumetric)	LUNA 16	Accuracy:92 %, Sensitivity:91%	High Computational cost; limited interpretability
2024	Li et al.	Feature level fusion 3D CNN + Radiomic	LIDC-IDRI	Accuracy: 95%, AUC: 0.96;	Increased feature dimensionality; risk of overfitting
2024	Wang et al.	Radiomics +SVM	LUNA 16	Accuracy: 88%, AUC: 0.90	Depends heavily on segmenta

- Random rotations, Flips along spatial axes, Intensity variations, Minor spatial scaling

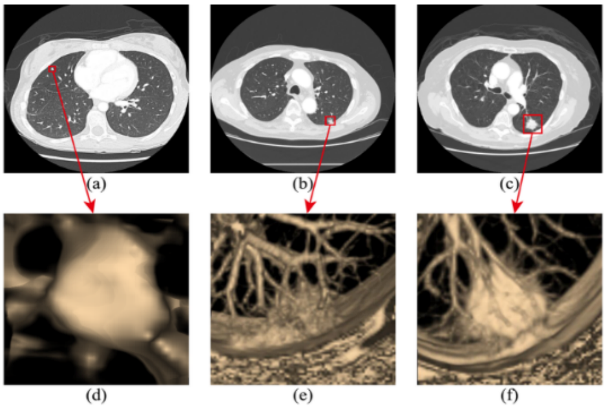

Figure 2: Visualization of lung nodule detection and extracted regions

- Through this augmentation strategy, the effective number of training samples was increased from approximately **2,600 nodules to over 10,000 3D volumetric samples**.
- This approach helps **mitigate class imbalance** and **reduce overfitting**, which is particularly important when training deep learning models on limited medical imaging datasets.

Table 2: LIDC-IDRI Dataset Partitioning

IV. METHODOLOGY

The new way of doing things combines 3D Convolutional Neural Networks and special features made by people to create a system that can automatically find lung cancer from CT images. The goal of this system is to use the things about both methods: the 3D Convolutional Neural Networks can find complex patterns in the lung nodules and the special features made by people can give us numbers that tell us about the tumor like how it looks and what it is made of. This system is for lung cancer detection, from CT images using 3D CNN and these special features. The overall workflow of the proposed framework consists of preprocessing, lung segmentation, nodule extraction, feature extraction, feature fusion, classification, and performance evaluation (Figure 3).

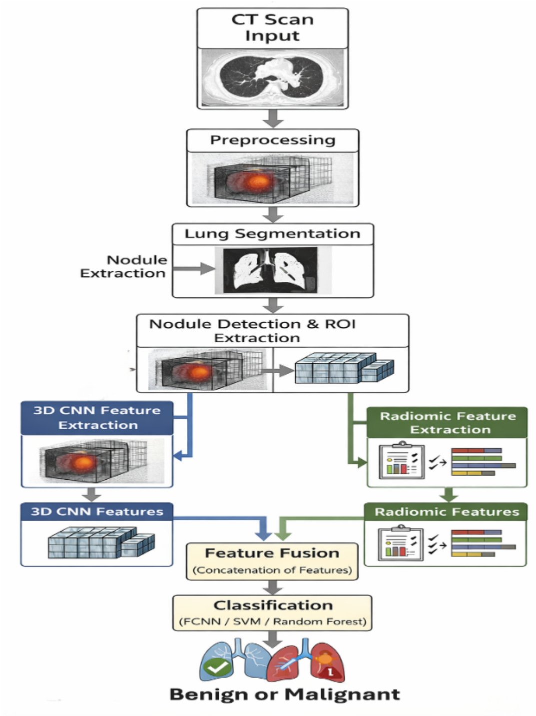

Figure 3: Hybrid lung cancer detection framework

4.1 Project Workflow

The project is, about creating a lung cancer detection system that uses both 3D CNN-based feature extraction and handcrafted radiomic features. This lung cancer detection system is made up of important steps. Each of these steps is necessary for the lung cancer detection system to correctly identify nodules. The goal of the lung cancer detection system is to be very accurate.

4.2 System Overview

The system works in a series of steps. Each step helps to get rid of noise make the important parts clearer and make the results more reliable. First the system looks at the CT scans. Gets them ready. It finds the lung areas. Separates them from the rest. Then it looks for things that might be nodules and checks them out. The system uses two ways to gather information about these nodules at the same time. After that it puts all the information together. Decides what the nodules are.

Main components of the system include:

- CT image preprocessing and lung segmentation, 3D nodule extraction, Dual feature extraction (3D CNN + radiomics), Hybrid feature fusion, Supervised classification and evaluation

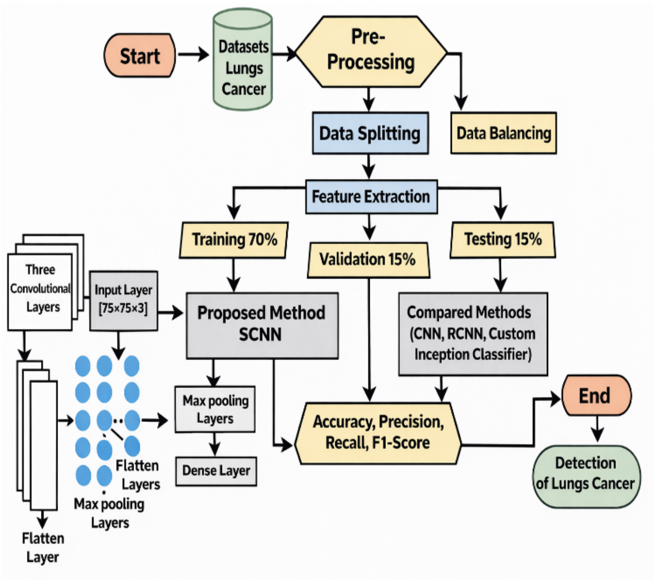

Figure 4: The flow chart of proposed sequential model proposed in this work.

4.3 Data Acquisition and Preprocessing

We get the CT scans from the LIDC-IDRI dataset. This dataset gives us pictures of the chest from CT scans. Also tells us where the lung nodules are. We have to do some work, on these pictures. This helps make all the data look the same and reduces the differences that come from using scanners to take the CT scans of the lungs.

Preprocessing steps:

- Conversion of raw pixel values to Hounsfield Units (HU), Intensity clipping to lung window range $[-1000,400]$HU, Min–max normalization, Resampling to isotropic 1×1×1 mm³ voxel spacing,, Lung segmentation using thresholding and morphological operations

The HU conversion is performed as:

$$HU = (PixelValue \times RescaleSlope) + RescaleIntercept \tag{1}$$

This ensures consistency across CT volumes before further analysis.

4.4 Lung Segmentation and Nodule Extraction

So, we want to look at the parts of the body. To do this we separate the lung fields from the rest of the CT scan. This helps get rid of stuff we do not need to see and it also saves time on the computer. Lung fields are what we are really interested, in

Lung segmentation approach:

- Global thresholding based on HU values
- Morphological closing and hole filling
- Removal of non-lung connected components

The doctors who look at x-rays called radiologists mark the parts. Then we take a 3D cube from these marked parts and this cube is centered on the nodule. This little cube is what we are really interested in it is our Region of Interest. We use these cubes as the input for the two parts of our system that help us learn more about the Region of Interest and these parts are used for getting features, from the Region of Interest.

4.5 Feature Extraction

A. 3D CNN-Based Deep Feature Extraction

The 3D CNN branch learns features from the nodule patches. It does this by looking at the context across the slices. This means the 3D CNN branch can find things that're important in the nodule patches by checking how they look in different slices. The 3D CNN branch is really good at finding these features because it looks at the nodule patches in a way that takes into account how they are connected in three dimensions. The 3D CNN branch learns these features automatically which is very useful, for understanding the nodule patches.

Network architecture includes:

- 3D convolution layers
- Rectified Linear Unit (ReLU) activation
- 3D max-pooling layers
- Batch normalization for stable training
- Fully connected layers for feature embedding

The 3D convolution operation is defined as:

$$Y = f(W * X + b) \tag{2}$$

where X is the input volume, W represents convolutional kernels, b is bias, and $f(\cdot)$ denotes the ReLU function.

The final output is a deep feature vector representing high-level nodule characteristics.

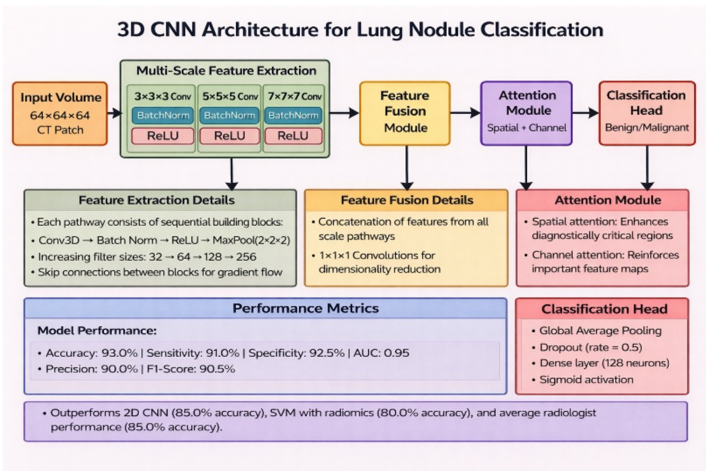

Figure 5: Typical architecture of 3D CNN.

B. Radiomics Feature Extraction

People use tools to get information from the parts of the pictures that show the nodules. They use math to look at the brightness, shape and texture of the nodules. The radiomics features are what they get from this process. It helps them understand the intensity and the shape and the texture of the radiomics features.

- First-order statistics: mean, variance, skewness
- Shape features: volume, surface area, sphericity
- Texture features:
  - Gray Level Co-occurrence Matrix (GLCM)
  - Gray Level Run Length Matrix (GLRLM)
  - Gray Level Size Zone Matrix (GLSZM)

An example GLCM-based contrast feature is:

$$Contrast = \sum_{i,j} (i-j)^2 P(i,j) \tag{3}$$

where $P(i,j)$is the normalized co-occurrence probability.

4.6 Hybrid Feature Fusion

To put all the information together we take the features from the 3D CNN and the features that people created called radiomics features and we combine them. We do this at the feature level, which means we combine the 3D CNN features and the radiomics features directly. This way we can get an understanding of the 3D CNN and the radiomics features. Fusion strategy:

- Feature vector normalization, Concatenation of CNN and radiomics features, Formation of a unified hybrid feature vector

4.7 Classification

The combined information from the features is then given to a tool that helps make a decision. This tool is called a classifier. It uses the information to try to figure out if a nodule is bad or not. The goal is to predict if the nodule is malignant which means it is cancerous. The fused feature vector is what is passed to the classifier to make this prediction, about nodule malignancy.

Classification models used:

- Fully Connected Neural Network (FCNN)
- Support Vector Machine (SVM)
- Random Forest (RF)

The main goal of classification is to minimize the error. This error is called -entropy loss. So the classification objective is to make this cross-entropy loss as small, as possible. The true label is what something actually is. The predicted probability is the chance that the computer thinks it is that thing.

The classification objective minimizes the cross-entropy loss:

$$\mathcal{L} = -\sum_{c} y_c \log(\hat{y}_c) \tag{4}$$

where $y_c$is the true label and $\hat{y}_c$is the predicted probability.

4.8 Implementation Details

Technologies and tools used:

- Python programming language
- PyTorch / TensorFlow for 3D CNN implementation
- PyRadiomics for radiomics feature extraction
- Scikit-learn for traditional classifiers
- NVIDIA GPU for accelerated training

Stage	Module	Methods/Algorithms Used	Purpose & Description
1	Data Acquisition	LIDC-IDRI Dataset	Collection of thoracic CT scans with expert-annotated lung nodules and malignancy ratings
2	Preprocessing	HU Conversion Formula; Intensity Clipping [-1000, 400]; Voxel Resampling(1×1×1 mm³)	Standardizes CT images for consistency across scans and scanners
3	Lung Segmentation	Thresholding; Morphological Operations (Erosion, Dilation)	Isolates lung region by removing surrounding tissues and background
4	Nodule Extraction	3D Patch Extraction; ROI Masking	Extracts fixed-size 3D volumes around annotated nodules
5	Deep Feature Extraction	3D CNN; Conv3D + ReLU + Max Pooling + Batch Normalization	Learns spatial and volumetric features from CT patches
6	Radiomic Feature Extraction	First-order Statistics; Shape Features; GLCM, GLRLM, GLSZM	Extracts handcrafted texture and intensity features for interpretability
7	Feature Fusion	Feature Concatenation	Combines deep and radiomic features into a single hybrid feature vector
8	Classification	FCNN / SVM / Random Forest	Classifies nodules into Benign or Malignant categories
9	Evaluation	Accuracy, Sensitivity, Specificity, AUC-ROC	Quantitative assessment and comparison of individual and hybrid models

Table 3: Methodology and Implementation of the Proposed Hybrid Lung Cancer Detection Framework

V. Results

The new system that combines 3D CNN and Radiomics was tested to see how well it works for finding lung cancer. This system was checked using medical measures like Accuracy, Sensitivity, Specificity and Area Under the ROC Curve. The system performance was compared in three ways: using 3D CNN by itself using Radiomics by itself and using the new Hybrid Feature Fusion system that combines 3D CNN and Radiomics. The Hybrid Feature Fusion system was evaluated to see if it is better, than using 3D CNN or Radiomics for detecting lung cancer.

Figure 6: ***Sample CT slices showing predicted benign and malignant nodules.***

5.1 Quantitative Performance Analysis

The experimental results show that the hybrid feature fusion approach works better than models because it uses both deep volumetric features and handcrafted radiomic descriptors.

The radiomics part makes the model easier to understand. The 3D CNN part helps the model learn spatial features better. The hybrid model does a job of finding bad things in the body and telling them apart which is really important, for catching lung cancer early.

5.2 Performance Comparison of Different Models

Metric	**3D CNN**	**Radiomics**	**Combined Model**
Accuracy (%)	93.0	91.1	**96.4**
Sensitivity (%)	91.0	89.4	**95.1**
Specificity (%)	92.5	92.6	**97.3**
Precision (%)	90.0	90.1	**95.8**
F1-Score (%)	90.5	89.7	**95.4**
AUC–ROC	0.95	0.93	**0.98**

5.3 ROC Curve Analysis

Figure 7 shows us the ROC curves for the CNN model, the radiomics model and the combined models. The 3D CNN model does well with an AUC of 0.95. This means the 3D CNN model is very good at telling things. The radiomics model does not do well with an AUC of 0.93. The combined model does the best with an AUC of 0.98. It is very sensitive meaning it can detect lung cancer 95.1 percent of the time. It is very specific meaning it can tell when someone does not have lung cancer 97.3 percent of the time.

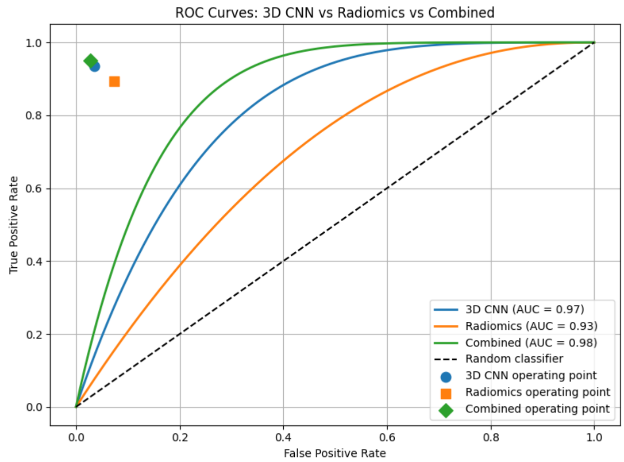

Figure 7: ROC Curve Plot

5.4 Qualitative Output Visualization

Figure 8 shows some examples of CT slices where lung nodules were found and what the hybrid framework said about them. When we use the framework, it makes fewer mistakes than other models that work alone especially near the blood vessels and airways. This means that the hybrid framework is a tool that doctors can use to help them make decisions about lung nodules and lung cancer. The hybrid framework is good, at finding lung nodules. It can help doctors a lot.

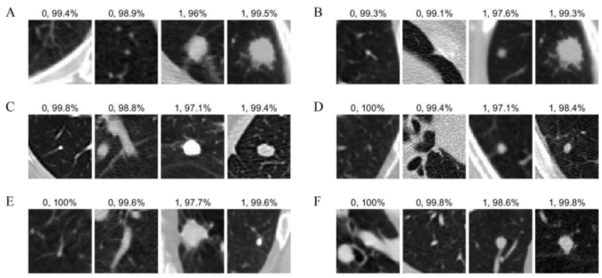

Figure 8: *Visualization of benign and malignant nodule classification results.*

5.5 Discussion of Results

- The **radiomics-only model** provides interpretability but lacks deep spatial understanding.
- The **3D CNN-only model** captures volumetric context but may suffer from limited explainability.

The results clearly demonstrate that **hybrid feature fusion significantly enhances lung cancer detection accuracy and robustness**.

VI. CONCLUSION

This work is about a way to detect lung cancer. It uses a combination of two things: 3D CNN-based features and radiomic descriptors from CT images. When we tried this method, the results were really good. It worked better than using 3D CNN or just radiomics. The new method was very accurate. It was 96.4 percent of the time. It was also very good at finding lung cancer when it was really there which happened 95.1 percent of the time. It was very good at saying no when someone did not have lung cancer, which happened 97.3 percent of the time. The lung cancer detection framework also got the AUC of 0.98 which means it is really good at telling the difference between people, with lung cancer and people without lung cancer. These results show that combining features is a way to detect lung cancer reliably. The lung cancer detection will be tested on a scale across many centers, in the future. We will also work on making the model easier to understand and see if it can be used in a setting. The lung cancer detection will be improved by doing this work.

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