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Deep Learning-Based Lung Cancer Detection Using CT Scan Images: A Comparative Study of VGG16, ResNet50, and DenseNet121

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Abstract: ***Lung cancer is a major problem because it kills more people every year than any other type of cancer. If we can find the abnormal areas early, people are much more likely to recover. Doctors usually use a type of scan called a CT scan to look for these abnormal areas. The problem is that reviewing all the scan images is very tedious, and even experienced doctors can miss something. We wanted to see whether computers could help with this task. We tried using three kinds of computer programs, VGG16, ResNet50 and DenseNet121, to look at the pictures from the scan. We used a collection of pictures called the LIDC-IDRI collection to teach the computers what to look for. DenseNet121 performed best at identifying the regions. We think this is because it is good at using the information it has to make decisions. We also used a tool called Grad-CAM to see what the computers were actually looking at. It showed that the better programs focused on the abnormal areas, not just the normal tissue. Our results show that using computers to help with this task is promising, and it could help doctors make better decisions. We also know there is still a lot of work to do to make it perfect.***

Keywords**: *Lung Cancer Detection, CT Scan Analysis, Neural Network, Transfer Learning, VGG16, Resnet50, Densenet121, Grad-CAM, LIDC-IDRI Medical Image Classification***

Nomenclature:
CT: Computed Tomography
VGG16: Visual Geometry Group 16
LIDC: Lung Image Database Consortium
IDRI: Image Database Resource Initiative

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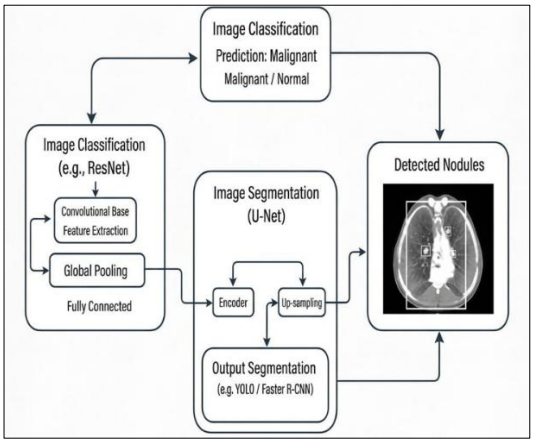
I. INTRODUCTION

Lung cancer is one of the leading causes of death from cancer every year. The reason people with lung cancer do not do well is really simple. By the time people feel sick, the lung cancer has usually spread to parts of the body. Some programs use CT scans to find small lung cancer nodules before people feel sick. These programs make a lot of work for the people who read the CT scans, and they are already very busy. It makes sense to use computers to help with some of this work. Computers can be trained to be as good as or even better than the people who read the CT scans. [1] To do this, the computers need to be trained on a lot of data. The problem is that it takes time and costs a lot of money to get the data ready for the computers to learn from. One way to solve this problem is to use something called transfer learning. This means the computer starts with some knowledge of what things look like and then learns what it needs to know about the specific task, like lung cancer. This approach is very common now. It is not always clear what kind of computer program to use.



[Fig.1: Deep Learning Architectures for Medical Image Analysis]

This is because different studies use different data sets, prepare the data differently, and evaluate the results differently. Lung cancer is what we are trying to find with these CT scans, and lung cancer is very hard to treat if it has spread. CT scans can help detect lung cancer, which is why CT screening programs are so important. We are trying to detect lung cancer, and computers can help us do that. Our work is simple: we

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compare three backbones. VGG16, ResNet50 and DenseNet121. To see which one is best at classifying CT nodule patches as benign or malignant. [2] We do this by having them compete against each other in a controlled test. We also use Grad-CAM to check if the models are paying attention to the parts of the images that make sense to doctors. We want to know whether VGG16, ResNet50, and DenseNet121 are looking at the same regions that doctors focus on when deciding whether a CT nodule patch is benign or malignant [3].

II. LITERATURE REVIEW

The use of computers to look at chest CT scans has been around since the 1990s. Researchers then developed systems that used specialised computer tools, such as Gaussian filters and shape descriptors, to help identify features in the scans. These systems worked okay for the things they were designed to find, but they did not work well when scans differed or when the target features were not what they were trained to find. Then something big happened when people started using something called networks. At first, these networks looked at only one part of the scan at a time, called a 2D slice. This increased system efficiency, but they were still limited because they did not consider the entire scan. [4] Later, networks were developed that considered the entire scan, referred to as the 3D scan. The systems' accuracy improved when they could consider the entire scan. When these systems were applied to an application referred to as LIDC-IDRI, it emerged that 3D scans produce more errors than 2D scans and require much more computing power. Starting around 2015, transfer learning emerged. This process involves taking a pre-trained model and using it in other applications. [5] It worked well despite having insufficient training datasets. They used models pre-trained to recognise images of animals such as dogs and cats. They used them to look at medical scans. This made the systems work better than if they had been trained from scratch. Some people even made their own specialised systems trained specifically for medical scans, such as RadImageNet and MedMNIST, and these systems worked even better. People have also been trying ways to combine systems to improve performance. For example, they use one system to find the thing they are looking for. Then they use another system to look at it more closely. This helps the system make a decision. Some people have also used tools to explain how the systems make decisions, which is important because doctors want to know why the system is saying something. This has been a problem in the past because the systems were like a box, and nobody knew how they worked.

III. RESEARCH GAP

When we try to learn from what is already written, we have a problem. Published studies are often not similar enough to compare. Models are tested on parts of the LIDC–IDRI dataset, or they use completely different datasets. Data preparation also varies. Many papers focus only on model accuracy, which can be confusing if the dataset is imbalanced. For example, a model that says every single thing is benign might be 80 per cent accurate, but it would not be useful in a real medical setting. There is also a gap in understanding how the models work. Many studies that compare models only show how accurate they are. That is it. To understand whether a highly accurate model is actually paying attention to the right features, such as the nodule, or simply picking up on scanner artefacts that happen to match the label, we need to see what the model is doing. This is where visualisation tools come in. They are rarely used. This study tries to fix these two problems. We use the same method to prepare the data, split the dataset, and train the models for all three architectures. We also use images to help explain the numbers with Grad-CAM maps [6].

IV. PROBLEM STATEMENT

This study aims to determine whether a patch on a CT scan is abnormal. We examine a 224×224-pixel region of the scan that includes a spot a doctor thinks might be a problem. We want to know if this spot is malignant or benign. The problem is that we do not have much data, and most of the spots are not malignant. We also cannot start from scratch because we do not have enough data. We need to look at more than just whether our predictions are right or wrong. When screening for health problems, it is important to find all the spots, even if it means getting some false alarms. Missing a spot is much worse than a false alarm because a follow-up test can clear it up. This means we have to choose the way to measure how well our method is working, and we have to think carefully about what the results mean. Binary patch classification, like what we are doing, is about getting this right. We must be good at patch classification to ensure we do not miss any malignant spots [7].

V. OBJECTIVES

The key objectives for this study include:

- Comparing the accuracy with which models such as VGG16, ResNet50, and DenseNet121 perform when used on training methods to determine their accuracy in identifying whether or not the nodule is malignant.
- Evaluate the performance of the models based on several key factors, including their overall accuracy in correctly identifying malignancy, their ability to detect malignancies, their ability to identify non-malignant cases, etc. Use Grad-CAM maps to see whether the models are looking at the right parts of the lung when trying to find malignant nodules.
- Figure out which parts of the models are most important for finding nodules when there is not a lot of data to train them and when there are a lot more non-bad nodules than bad ones.
- Give some advice on which kind of model to use for projects that are trying to do similar things with medical pictures.

VI. METHODOLOGY

A. Dataset

We used part of the LIDC–IDRI dataset, a collection of chest CT scans that doctors reviewed and annotated. The

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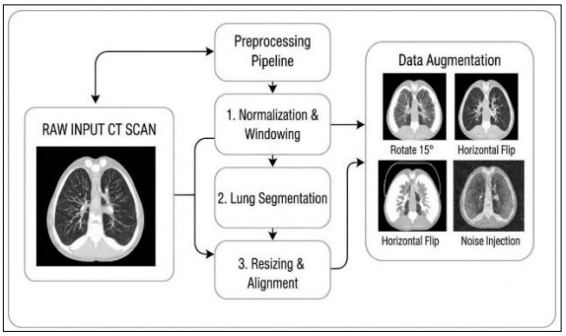
LIDC–IDRI dataset includes many chest CT scans. Each doctor looked at the chest CT scans from the LIDC–IDRI dataset. Marked the boundaries of nodules and said how likely they were to be bad. The doctors in the LIDC–IDRI dataset used a score from 1 to 5, where 1 meant the nodule was definitely not bad and 5 meant it was definitely bad. For our study, we defined nodules with a score above 3 in the LIDC–IDRI dataset as bad and those with a score below 3 as not bad. We did not use unclear cases. We split patients from the LIDC–IDRI dataset into training, validation, and testing groups. We used 70 per cent of the patients from the LIDC–IDRI dataset for training, 15 per cent for validation, and 15 per cent for testing. No patient from the LIDC–IDRI dataset was in more than one group.

B. Preprocessing

Raw CT scans were adjusted to focus on lung details ranging from -1000 to 400 HU. These values were then scaled down to a range of 0 to 1. We looked at each marked nodule. Took a 2D patch from the axial view, making sure to include a 64-pixel border around it. This border helped us see the lung tissue around the nodule. We then resized all patches to 224x224 so they could work with the pre-trained models.



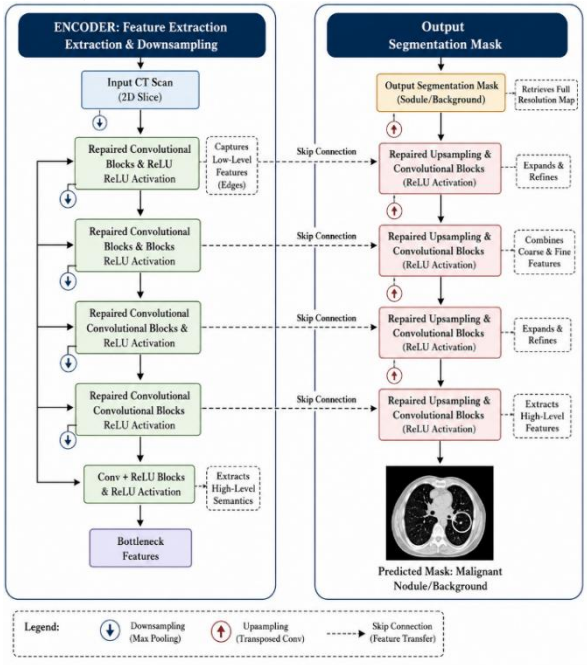
[Fig.2: Data Preprocessing and Augmentation pipeline for CT scan]

C. Data Augmentation

We used augmentation on the training patches when we loaded them. This included turning them up to 15 degrees and flipping them sideways or up and down. We also reduced the training patches (up to 10 per cent) and slightly adjusted the contrast. We applied these changes to the training patches. To ensure we had enough malignant patches, we used more of them to address the shortage. We left the validation and test sets unchanged; we did not change the number of each patch type in these sets. We left the validation and test sets unchanged, including the number of each patch type [8].

D. Model Architectures

The VGG16 model uses thirteen layers in a straightforward sequence with no connections that skip other layers. This model has 138 million parameters, which makes it expensive to store and more likely to overfit when trained on small datasets. ResNet50 differs in that it uses connections that allow shortcut paths. These connections allow a block's input to be added to its output. This enables gradient flow across the fifty layers. This is critical because it lets the network learn discriminative features without suffering from vanishing gradients. DenseNet121 takes the idea a step further by having each layer use the feature maps from all previous layers. This feature reuse is pretty efficient. It uses far fewer parameters than ResNet50, which helps when you do not have much data to train on. For each backbone model, we removed the classification part and added a few new components. We added a way to average the output of a layer that drops out half the connections, and a single output neuron with a sigmoid activation. We froze the convolutional layers and fine-tuned the upper layers. We did this for VGG16, ResNet50, and DenseNet121.

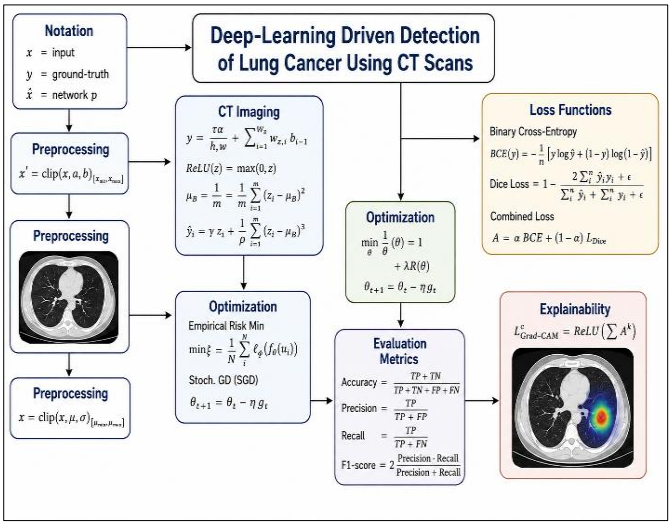


[Fig.3: Deep Learning Network Architecture: Encoder–Decoder]

E. Training Configuration

All three models were trained under identical settings: Adam optimiser (lr = 0.0001), binary cross-entropy loss with class weights inversely proportional to class frequency, batch size 16, maximum 30 epochs, and early stopping with patience 5 based on validation loss. A learning-rate reducer halved the rate after 3 epochs of plateau.

VII. KEY MATHEMATICAL FORMULATIONS



[Fig.4: Mathematical Framework for Deep-Learning-Driven Lung Cancer Detection]

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A. Hounsfield Normalisation

CT scanners report tissue density in Hounsfield Units:

$$HU = 1000\frac{(\mu - \mu_{water})}{\mu_water}$$

After windowing to [−1000, +400] HU, values are rescaled to [0, 1] using training-set statistics.

B. 2D Convolution and Feature Map Size

$$y = Wx + b$$

$$S_{out} = floor\,\frac{(S_{in} + 2p - K)}{s} + 1$$

C. Residual Link (ResNet)

$$H(x) = F(x, W) + x$$

Using an identity link enables gradient flow through convolution blocks during backpropagation.

D. Dense Link (DenseNet)

$$x_l = H_l([x_0, x_1, \ldots, x_\{l-1\}])$$

Each block takes input feature maps from all previous blocks, ensuring efficient feature reuse.

E. Binary Cross-Entropy Loss

$$L = -[y \cdot \log(p) + (1-y) \cdot \log(1-p)]$$

Weights for each class are computed using the inverse proportion of the class frequencies.

F. Adam Optimiser

$$m_t = \beta_1 m_\{t-1\} + (1-\beta_1) g_t$$

$$v_t = \beta_2 v_\{t-1\} + (1-\beta_2) g^2_t$$

$$\theta_t = \theta_\{t-1\} - \frac{\eta \cdot \hat{m}_t}{(\sqrt{\hat{v}_t} + \varepsilon)}$$

[β_1=0.9, β_2=0.999, η=0.0001]

G. Grad-CAM Explainability

$$\alpha_k^c = \frac{1}{Z}\frac{\Sigma_i \Sigma_j \partial y^c}{\partial A^k_ij}, \quad L^c = ReLU(\Sigma_k \alpha_k^c A^k)$$

H. Evaluation Metrics

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Recall = \frac{TP}{TP + FN}; \quad Specificity = \frac{TN}{TN + FP}$$

$$F1 = \frac{2.Precision \cdot Recall}{Precision + Recall}$$

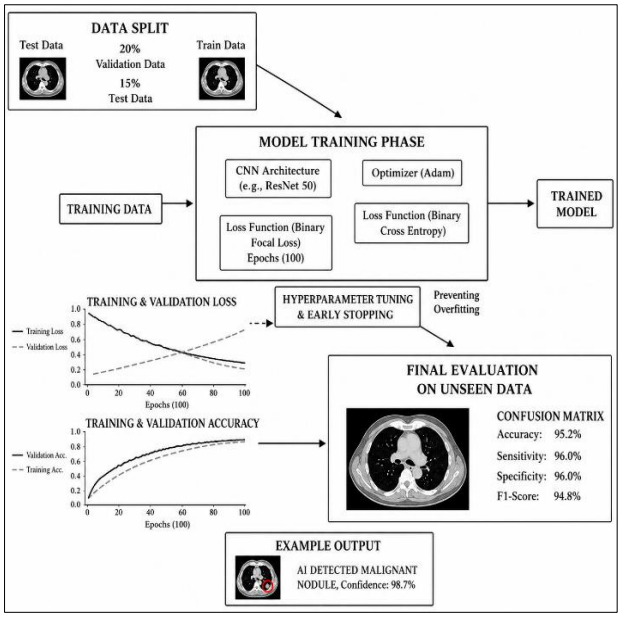
Recall (sensitivity) is the primary clinical metric — a missed malignant nodule carries far greater risk than a false alarm.

VIII. DATASET AND DATA COLLECTION

The LIDC–IDRI includes many thoracic CT studies from different sites, which means it includes many different scanner hardware types, slice thicknesses, and reconstruction kernels. This makes the LIDC–IDRI more realistic. The LIDC–IDRI also includes reader annotations, meaning several radiologists review each nodule and assign a score. We use the average of these scores to label the nodules. This helps reduce bias because one person might see something another person does not. We did not include nodules smaller than 3 mm in the LIDC–IDRI because they are very hard to see, and most scanners cannot detect them well. [9] Also, when we try to agree on what these small nodules are, we often disagree. The LIDC–IDRI includes a range of nodules, including large and small ones, as well as nodules that are somewhat translucent and solid. The LIDC–IDRI also includes nodules with spiculated margins, meaning they have pointed margins. We had to be careful when creating the LIDC–IDRI because we did not want the model to learn patient-specific patterns. If the model learns these patterns, it will not generalise well to other patients. So, we separated the patients so the model would perform better on many patients.

IX. MODEL DEVELOPMENT

Training proceeded in two phases for each backbone. In the first phase, we trained only the newly added classification head for five epochs to stabilise its weights before unfrozen the backbone layers. In the second phase, the upper convolutional blocks were fine-tuned alongside the head, while the lower blocks remained frozen. This two-phase approach reduced the risk of overwriting the pre-trained representations early in training, when head gradients are largest. We monitored training and validation loss after each epoch. If validation loss did not decrease for five successive epochs, we halted training and reloaded the weights from the best epoch. As expected, DenseNet121 converged early (epoch 22), followed by ResNet50 (epoch 26) and, lastly, VGG16 (epoch 28) [10]. This finding supports the belief that dense connections help in optimisation when data is scarce. We produced Grad-CAM activation maps after training using samples from both categories. We upscaled these activation maps to 224×224 and superimposed them on their original patches.



[Fig.5: Training and Validation Pipeline for Deep Learning-Based Lung Cancer Detection]

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X. RESULTS AND DISCUSSION

Table I summarises the test-set performance of all three architectures across six metrics.

Table I: Performance Comparison on LIDC–IDRI Test Set

Metric	VGG16	ResNet50	DenseNet121
Accuracy	82.4%	87.6%	91.3%
Precision	79.8%	85.2%	90.1%
Recall	76.3%	86.9%	89.7%
F1-Score	78.0%	86.0%	89.9%
Specificity	84.1%	88.4%	92.5%
AUC-ROC	0.857	0.903	0.937

A. DenseNet121

DenseNet121 achieved the best results across every metric: 91.3% accuracy, 89.7% recall, and an AUC of 0.937. The recall figure is the one we care most about clinically — missing roughly one in ten malignant nodules is not ideal, but it compares favourably with published inter-radiologist agreement rates and improves considerably over the baseline architectures. Grad-CAM maps for DenseNet121 were consistently tight and well-centred on the nodule boundary, even for sub-centimetre cases that caused the most confusion. We attribute DenseNet121's advantage primarily to its feature reuse mechanism. When training data are limited, repurposing feature representations from earlier layers without relearning them effectively increases the model's expressive capacity for a given dataset size.

B. ResNet50

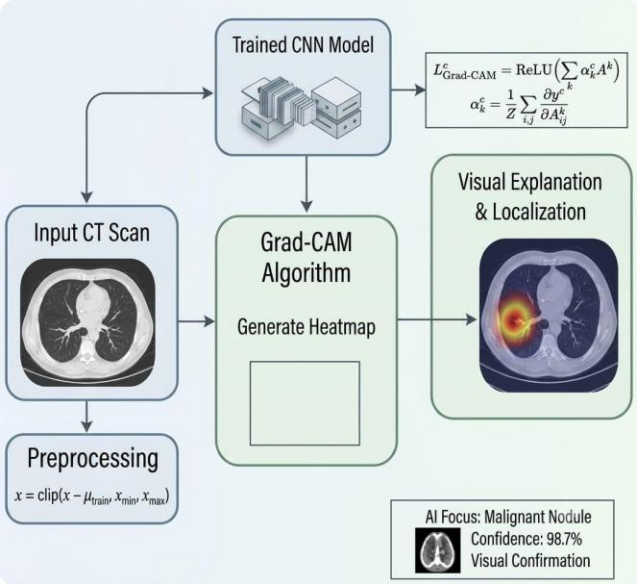
ResNet50 was a solid second, reaching 87.6% accuracy and an AUC of 0.903. Its recall of 86.9% was notably higher than VGG16's, indicating that residual connections genuinely help with the subtle contrast patterns of early-stage malignant nodules. The model showed a slight bias toward the positive class—its specificity (88.4%) was lower than its sensitivity—which might be desirable in a first-pass screening tool where false negatives are more costly than false positives.

C. VGG16

VGG16 performed the least well, with 82.4% accuracy and recall of only 76.3%. One in four malignant test nodules was missed, which is too high for a screening application. The model's Grad-CAM maps were the most diffuse, sometimes highlighting broad lung parenchyma regions rather than the nodule itself. VGG16's large parameter count leads to more overfitting even with dropout and augmentation, and the lack of skip connections means it cannot effectively recover information from early feature maps.

D. Grad-CAM Visualisation

Beyond raw classification metrics, we applied Grad-CAM to see where each model looked when making its predictions. The visualisation confirms that DenseNet121 and ResNet50 consistently focused on nodule-containing regions, while VGG16 often activated on surrounding parenchyma or pleural surfaces.



[Fig.6: Grad-CAM Explainability for Lung Cancer Detection]

E. General Observations

All three models struggled most with sub-6mm nodules with smooth, well-defined margins and low attenuation — consistent with the wider literature. The false-negative cases for all architectures clustered in this morphological category, suggesting the next logical step is not simply a better 2D backbone but a model that can integrate cross-slice context.

XI. CONCLUSION

In this experiment, three transfer learning architectures were evaluated in their ability to classify lung nodules in CT image patches, using criteria that simulate the data limitations found in a realistic academic environment. Clearly, DenseNet121 won hands down – it has superior sensitivity and specificity, and is more interpretable. This may be due to its characteristic dense network topology, which seems ideally suited to small datasets. ResNet50 is an acceptable compromise when computational power is limited and tolerable levels of false positives are acceptable. VGG16 is no longer recommended unless there is some specific reason to favour its less sophisticated topology. Future research areas might include: application of the method to 3D CT volume inputs to take into account inter-slice features of the nodules; application of medical image transformer networks; implementation of a pipeline combining detection, segmentation, and malignancy classification stages; and finally, federated learning to enable training on multiple institution data without sharing patient records. Proper clinical validation must always follow, but it is a critical missing step before any of these systems can be considered for actual deployment.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of interest:** The authors declare no competing interests.

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- **Author's Contribution:** The authorship of this article is contributed equally to all participating individuals.

REFERENCES

1. Geppert J, Asgharzadeh A, Brown A, et al. Software using artificial intelligence for nodule and cancer detection in CT lung cancer screening: systematic review of test accuracy studies. Thorax. 2024;79(11):1040–1049. DOI: 10.1136/thorax-2024-221662
2. Gao J, Jiang Q, Zhou B, Chen D. Lung Nodule Detection using Convolutional Neural Networks with Transfer Learning on CT Images. Current Medical Imaging Reviews. 2021;17(6):814–824. DOI: 10.2174/1386207323666200714002459
3. Kumaran, Y. S., et al. (2024). Explainable lung cancer classification with ensemble transfer learning of VGG16, ResNet50 and InceptionV3 using Grad-CAM. BMC Medical Imaging, 24, 176. DOI: 10.1186/s12880-024-01345-x
4. Gao C, Wu L, Wu W, et al. Deep learning in pulmonary nodule detection and segmentation: a systematic review. European Radiology. 2025; 35:255–266. DOI: 10.1007/s00330-024-10907-0
5. Gao J, Jiang Q, Zhou B, Chen D. Lung Nodule Detection using Convolutional Neural Networks with Transfer Learning on CT Images. Current Medical Imaging Reviews. 2021;17(6):814–824. DOI: 10.2174/1386207323666200714002459
6. Zafaranchi A, Lizzi F, Retico A, Scapicchio C, Fantacci ME. Explainability Applied to a Deep-Learning-Based Algorithm for Lung Nodule Segmentation. Proceedings of the International Conference on Pattern Recognition Applications and Methods (ICPRAM). 2024. DOI: 10.5220/0013014600003837
7. Wulaningsih W, Villamaria C, Akram A, et al. Deep Learning Models for Predicting Malignancy Risk in CT-Detected Pulmonary Nodules: A Systematic Review and Meta-analysis. Lung. 2024; 202:625–636. DOI: 10.1007/s00408-024-00706-1
8. Saied M, Raafat M, Yehia S, Khalil MM. Efficient pulmonary nodule classification using radiomics and different artificial intelligence strategies. Insights into Imaging. 2023; 14:91. DOI: 10.1186/s13244-023-01441-6
9. Dai, Y., et al. (2023). MS-Net: Learning to assess the malignant status of a lung nodule by a radiologist and her peers. Journal of Applied Clinical Medical Physics. DOI: 10.1002/acm2.13964
10. Eliwa, A. A., et al. (2025). Enhancing Skin Cancer Diagnosis Through Fine-Tuning of Pretrained Models: A Two-Phase Transfer Learning Approach. International Journal of Breast Cancer. DOI: 10.1155/ijbc/4362941

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