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Deep Learning for Early Diagnosis of Lung Cancer

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ABSTRACT Early diagnosis of lung cancer is critical for improving patient prognosis. While Computer-Aided Diagnosis (CAD) systems leveraging deep learning have shown promise, the selection of an optimal model architecture remains a key challenge. This study presents a comparative analysis of three prominent Convolutional Neural Network (CNN) architectures InceptionV4, VGG-13, and ResNet-50 to determine their effectiveness in classifying lung cancer into benign, malignant, and normal categories from Computed Tomography (CT) images. Utilizing the publicly available IQ-OTH/NCCD dataset, a transfer learning approach was employed, where models pre-trained on ImageNet were fine-tuned for the specific classification task. To mitigate overfitting and enhance model generalization, a suite of data augmentation techniques was applied during training. It achieved an accuracy of 98.80%, with a precision of 98.97%, a recall of 96.30%, and an F1-score of 97.52%. Notably, the confusion matrix analysis revealed that InceptionV4 perfectly identified all malignant and normal cases in the test set, highlighting its clinical reliability. The study also evaluated the trade-off between diagnostic performance and computational efficiency, where InceptionV4 provided an optimal balance compared to the computationally intensive VGG-13 and the less accurate, albeit more efficient, ResNet-50. Our findings suggest that the architectural design of InceptionV4, with its multi-scale feature extraction, is exceptionally well-suited for the complexities of lung cancer diagnosis. This model stands out as a robust and highly accurate candidate for integration into clinical CAD systems, offering significant potential to assist radiologists and improve early detection outcomes.

KEYWORDS
Lung cancer
Deep learning
Convolutional neural networks
Image classification
Computed tomography (CT) images

INTRODUCTION

Lung cancer is a highly fatal malignancy, accounting for approximately one-fifth of all cancer-related deaths globally. The disease is characterized by the formation of solid tissue masses known as "pulmonary tumors" within and around the lungs (Monkam *et al.* 2019; Kumar and Bakariya 2021; Fontana *et al.* 1984). It stands as a significant cause of mortality for men, women, and transgender individuals worldwide, with an estimated five million fatalities annually. According to the World Health Organization (WHO), this figure represents a substantial global health burden. Unfortunately, the prognosis for lung cancer patients is often poor, as over 80% are diagnosed at an advanced stage, a point at which surgical intervention is frequently rendered ineffective (Blandin Knight *et al.* 2017; Siegel *et al.* 2024).

Early diagnosis of lung cancer is paramount for effective treatment and improving survival rates, as symptoms typically manifest only in advanced stages (Inage *et al.* 2018; Deepajothi *et al.* 2022). The manual interpretation of the vast number of medical images used in diagnosis is time-consuming, labor-intensive, and susceptible to human error. While various imaging modalities such as X-ray, CT (Computed Tomography), (Mohanapriya *et al.* 2019). MRI, and PET are utilized, CT imaging has become the preferred modality due to its ability to provide detailed information about the location and size of nodules (Li *et al.* 2020). Although low-dose CT scans have proven effective in detecting early-stage tumors, traditional computational approaches have inherent limitations. Early image processing techniques and machine learning algorithms have often relied on handcrafted features for analysis, a dependency that can limit accuracy and impede the optimal performance of computer-aided diagnosis (CAD) systems (Ozdemir *et al.* 2019). To overcome this challenge, researchers have proposed the use of Artificial Intelligence, particularly deep learning, which can automatically learn salient features from data during the training process, enabling end-to-end detection in CAD systems without manual feature engineering (Salama *et al.* 2022). In this context, Convolutional Neural Networks (CNNs) have demonstrated superior performance compared to other deep learning networks (Ahmed *et al.* 2022).

Artificial Intelligence (AI) has been described as a system that mimics human cognition because it can learn from vast amounts of data has considerable promise across various healthcare applications, such as early diagnosis, monitoring, and assessing treatment (Puttagunta and Ravi 2021; Pacal 2025). The field of Machine Learning (ML), which is a sub-rule of AI, can use previous data to make predictions utilizing supervised learning, unsupervised learning, and semi-supervised learning (Cakmak *et al.* 2024; Cakmak and Pacal 2025; Zeynalov *et al.* 2025). Deep Learning (DL) is a sub-rule of ML, which employs structures called neural networks that are

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modeled after the human brain, to identify complex patterns in high-dimensional data (LeCun *et al.* 2015). The advantage of DL is that it can automatically identify relevant features from raw inputs and does not rely on manually created features as required by traditional ML algorithms (Liu *et al.* 2017). Thus, DL has become the preferred approach in many fields, and it has achieved higher performance than ML in many important areas including and admission not limited to image classification (Krizhevsky *et al.* 2017), speech recognition (Mikolov *et al.* 2011), and predicting the strength of potential drug molecules (Ma *et al.* 2015). As the previously mentioned recent rise in prominence of DL can be largely attributed to advancements in ways to only analyze images and accommodating automatic feature extraction methods, DL has become one of the most utilized AI-based systems in the area of decision support systems for early medical diagnosis (Sharif *et al.* 2022; Ozdemir *et al.* 2025).

Imaging modalities are now routinely employed in the identification of disease across medical specialties (Lubbad *et al.* 2024b; Kurtulus *et al.* 2024). Accordingly, we now see DL-based early diagnoses systems being built to identify various medical conditions from medical images (e.g., from retinal disease (Kayadibi and Güraksın 2023; Kayadibi *et al.* 2023), breast cancer (Coskun *et al.* 2023; Pacal 2022; Işık and Paçal 2024; Pacal and Attallah 2025), cervical cancer (Karaman *et al.* 2023b,a; Pacal 2024; Pacal and Kılıcarslan 2023; Lubbad *et al.* 2024a), and brain tumors (Pacal *et al.* 2025; İnce *et al.* 2025; Bayram *et al.* 2025). In our study, we use several widely-used CNNs (e.g., Inception-V4, ResNet-50, and VGG-13) to classify our dataset of CT images. This study presents a full classification analysis using the deep learning models. A comprehensive comparison of the results is then conducted based on a suite of success criteria, including performance and accuracy, to provide a multifaceted evaluation rather than a simple ranking of the models.

The early diagnosis of lung cancer through CAD systems has gained significant momentum with the advent of deep learning, particularly in the analysis of medical imagery. The literature extensively documents the efficacy of Convolutional Neural Network (CNN) based models and transfer learning for this task. Transfer learning is predominantly employed to leverage knowledge from models pre-trained on large-scale datasets (e.g., ImageNet), thereby enhancing feature extraction capabilities, especially when working with limited medical data. For instance, Kumar *et al.* (2025) demonstrated the power of this approach by using a VGG19 model as a feature extractor and feeding the resulting features into a Vision Transformer (ViT) for classification, achieving remarkable accuracies exceeding 99% on two distinct datasets. Similarly, Bagheri Tofighi *et al.* (2025) utilized the lightweight and efficient MobileNetV2 architecture for feature extraction, highlighting that such an approach not only yields high accuracy but also reduces computational overhead. In a more hybrid strategy, Taheri and Rahbar (2025) integrated multi-level semantic feature maps from a GoogleNet architecture, subsequently fusing these deep features with handcrafted texture and brightness attributes. Collectively, these studies establish that pre-trained CNN architectures have become a de facto standard for deriving rich and hierarchical feature representations from lung CT images.

Transcending conventional CNNs, the research community has pivoted towards developing more sophisticated and bespoke architectures to further elevate classification performance and overcome the limitations of existing models. The adaptation of Transformer architectures, originally designed for natural language processing, to the computer vision domain represents one of the most innovative trajectories in this field. In addition to the work by Kumar *et al.* (2025) who used ViT as a classifier, Kavitha *et al.* (2025) advanced this trend by proposing a custom Multi-Head Attention-based Fused Depthwise CNN (MHA-DCNN), which extracts features using a Convolutional Vision Transformer (CViT). Such attention-based models possess the inherent potential to more effectively capture long-range dependencies within images, thereby enhancing model performance. Another hybrid approach is evident in the study by Bagheri Tofighi *et al.* (2025), where features extracted by MobileNetV2 were processed through Stacked Gated Recurrent Unit (SGRU) layers. This fusion of CNN and Recurrent Neural Network (RNN) components aims to enable the model to learn not only spatial features but also sequential and contextual information embedded within the images. These advanced frameworks promise superior accuracy and more robust performance by moving beyond standard architectural paradigms.

Achieving peak performance is contingent not only on architectural innovation but also on addressing critical challenges across the entire diagnostic pipeline, including data pre-processing, feature selection, model optimization, and data imbalance. Musthafa *et al.* (2024), while employing a CNN, critically addressed class imbalance by implementing the Synthetic Minority Over-sampling Technique (SMOTE). This data-centric intervention significantly improved the model's performance on underrepresented classes, contributing to an outstanding accuracy of 99.64%. Similarly, the comprehensive methodology of Kavitha *et al.* (2025) involved applying a Disperse Wiener filter for image quality enhancement, a sophisticated Enhanced Binary Black Widow Optimization (EBWO) algorithm for salient feature selection, and Adaptive Equilibrium Optimization (AEO) for hyperparameter tuning. To tackle the challenge of small datasets, Abe *et al.* (2025) proposed an ensemble of CNNs, which enhanced generalization and achieved over 98% accuracy. These works underscore the necessity of a holistic approach. Furthermore, the integration of explainable AI (XAI) techniques, such as Grad-CAM by Bagheri Tofighi *et al.* (2025), signifies a growing trend towards mitigating the "black box" nature of DL models, thereby fostering interpretability and trust for clinicians. Ultimately, these studies confirm that elements such as noise reduction, strategic feature engineering, data balancing, and meticulous optimization are as vital as the core model architecture for developing reliable and clinically translatable systems.

MATERIALS AND METHODS

Dataset

The publicly available Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset was used in the analysis of this study. The dataset was collected over a three-month duration in the fall of 2019 from the aforementioned specialist sites. The dataset includes CT images from 110 cases relating to lung cancer patients from various stages and with healthy patients. All CT slides were annotated by training oncologists and radiologists to ensure diagnostic quality ground truth labels. Each site's institutional review board approved the study protocol and all medical images were anonymized and deidentified for patient's privacy, the oversight board waived the need for written consent (Kareem *et al.* 2021).

CT imaging was performed on a Siemens SOMATOM scanner. The acquisition protocol was standardized to 120 kV, 1 mm slice thickness, and scanning kept during full-inspiration breath-holding. For this study, a total of 1097 CT slice images were selected and classified into three diagnostic classes: Benign (120 images), Malignant (561 images) and Normal (416 images). This dataset has a unique characteristic in that it has a significant class imbalance, where the Malignant class is the most represented, followed by Normal, while Benign is very much a minority. This class imbalance is an important consideration when training, and evaluating the performance of models, in particular for avoiding forming a bias regarding class predictions.

To ensure a robust and unbiased evaluation of the compared models, the dataset was partitioned into three independent subsets: training, validation, and testing. A stratified splitting method was employed to preserve the original class distribution across all subsets, which is crucial for developing a generalizable model. The data was divided following a 70% (767 images) for training, 15% (164 images) for validation, and 15% (166 images) for testing ratio. The precise distribution of images per class across these subsets is detailed in Table 1.

Table 1 Distribution of Images in the IQ-OTH/NCCD Dataset across Training, Validation, and Test Sets.

Class	Training	Validation	Test	Total
Benign	84	18	18	120
Malignant	392	84	85	561
Normal	291	62	63	416
Total	**767**	**164**	**166**	**1097**

The Figure 1 displays a selection of axial CT scan slices for the three diagnostic classes used in this study. The top row presents cases classified as Benign, the middle row shows Malignant tumors, and the bottom row illustrates Normal lung scans. These images highlight the visual diversity within each category and the subtle differences that diagnostic models must learn to distinguish, showcasing the complexity of the classification task.

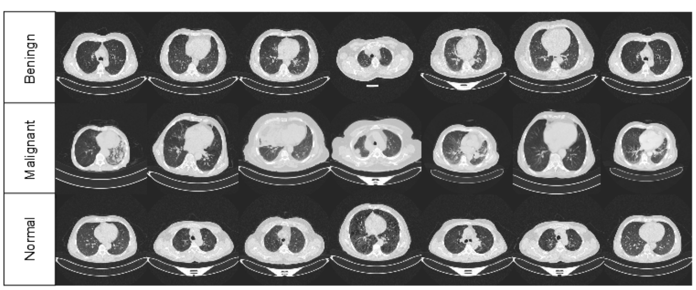

Figure 1 Representative sample images from the IQ-OTH/NCCD dataset.

Data Augmentation

To address the common issue of overfitting and enhance the generalization capabilities of our DL models, particularly on a limited medical imaging dataset, a suite of data augmentation techniques was applied dynamically during training. Prior to training, the dataset was streamlined for our classification task by excluding the segmentation masks (mask.png files). The augmentation pipeline applied to each training image included a RandomResizedCrop operation, which randomly selected a portion of the image (scaling between 8% and 100% of the original area with an aspect ratio of 0.75 to 1.33) before resizing it to a standard 224x224 pixel dimension using random interpolation. This was complemented by random horizontal flipping (with a 50% probability) and color jittering, which altered the brightness, contrast, saturation, and hue by a factor of 0.4. Notably, vertical flipping was deliberately omitted. This on-the-fly augmentation strategy ensures that the model is exposed to a diverse range of transformed data in each training epoch, fostering the development of more robust and generalizable features (Wang *et al.* 2024; Mumuni *et al.* 2024).

Model Architectures

For the task of lung cancer detection from CT images, this study compares three widely known Convolutional Neural Network (CNN) architectures based on three different architectural strategies: InceptionV4, ResNet-50 and VGG-13. The three models were selected in order to consider the various trade-offs associated with depth of the network, compute resources, and feature extraction. All three models used a transfer learning protocol where the models weights were first pre-trained using ImageNet and then fine-tuned using our specific lung cancer data set. This approach utilizes the powerful and generalized features learned from a large-scale, general image dataset, and applies them to a more focused medical imaging application. The main aim is to assess the impact of the architectural differences from the efficient multi-scale processing of InceptionV4 to the deep residual learning of ResNet-50 and the baseline VGG-13 on diagnostic accuracy in a clinical task.

Delving into their specific architectures reveals their unique approaches to feature learning. InceptionV4, an advancement in Google's Inception series, is engineered to balance computational cost with the ability to capture features at multiple scales. This is achieved through its "Inception module," which concurrently deploys convolutional filters of varying sizes (1x1, 3x3, 5x5) to analyze visual information in parallel, making it a powerful and efficient feature extractor (Szegedy *et al.* 2016). In contrast, ResNet-50 addresses the challenge of training exceptionally deep networks by introducing "skip connections" within its "residual blocks." This revolutionary mechanism mitigates the vanishing gradient problem, allowing the 50-layer network to be trained effectively and learn highly complex, hierarchical features without performance degradation (He *et al.* 2016). Lastly, the VGG-13 model serves as a crucial baseline, characterized by its straightforward and uniform structure of stacked 3x3 convolutional layers. Despite being shallower than its counterparts, its design demonstrates the efficacy of fundamental CNN principles and provides a valuable reference point for assessing the advancements offered by the more intricate architectures (Simonyan and Zisserman 2014).

Evaluation Metrics

The rigorous evaluation of DL models is an indispensable process, crucial for ascertaining their practical utility, substantiating pertinent design decisions, and fostering data-driven advancements. Performance assessment criteria play a pivotal role in this endeavor, serving to gauge the efficacy of classification models, facilitate their optimization, reveal inherent errors or biases within the dataset, enable objective comparisons between different models, and crucially, identify instances of overfitting. While the specific application domain of this paper pertains to performance metrics for lung cancer classification, our approach relies on the adoption of standard evaluation benchmarks that are firmly established within the academic sphere. The fundamental metrics utilized in this project namely accuracy, precision, recall, and the

F1-score hold significance not only within the realm of DL but also extend to broader analytical contexts. Accuracy provides an overarching measure of a model's performance by quantifying the proportion of correctly classified instances against the total. Precision, defined as the ratio of true positives to the sum of true positives and false positives, reflects the model's reliability in its positive predictions, with high precision signifying a minimal rate of false positives. Recall, on the other hand, measures the proportion of actual positives that are correctly identified, thereby indicating the model's completeness in capturing true positive cases. The F1-score, calculated as the harmonic mean of precision and recall, offers a consolidated performance indicator that judiciously balances the trade-off between minimizing false positives and false negatives. Although these metrics can be described conceptually, each is also defined by precise mathematical expressions.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Number of total predictions}} \tag{1}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{2}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{3}$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

RESULTS AND DISCUSSION

The comparative performance evaluation of the three selected CNN architectures InceptionV4, VGG-13, and ResNet-50 yielded significant insights into their suitability for lung cancer classification from CT images. The comprehensive results, encompassing both classification accuracy and computational efficiency metrics, are detailed in Table 2. The findings clearly indicate that InceptionV4 emerged as the superior model, achieving the highest performance across all key metrics. It recorded a remarkable accuracy of 98.80%, precision of 98.97%, recall of 96.30%, and an F1-score of 97.52%. This outstanding performance can be attributed to its sophisticated architecture, which leverages multi-scale feature extraction to effectively capture both fine-grained details and broader contextual patterns within the CT scans, a critical capability for distinguishing between benign, malignant, and normal tissue.

Table 2 Comparative Performance and Computational Efficiency of Evaluated CNN Models on the Test Set

Models	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Params (M)	GFLOPs
Inception V4	98.80	98.97	96.30	97.52	41.15	12.2450
VGG 13	97.59	95.24	95.24	95.24	128.96	22.6088
ResNet 50	94.58	90.05	89.95	90.00	23.51	8.2634

While InceptionV4 demonstrated the best classification performance, the other models also provided valuable comparative data. VGG-13 delivered a strong, competitive performance with an accuracy of 97.59% and a balanced F1-score of 95.24%. However, its primary drawback lies in its computational inefficiency. With 128.96 million parameters and 22.6 GFLOPs, VGG-13 is significantly more demanding than the other models, making it less practical for deployment in resource-constrained clinical environments. Conversely, ResNet-50, despite being the most computationally efficient model with only 23.51 million parameters and 8.26 GFLOPs, exhibited the lowest classification performance, achieving an accuracy of 94.58% and an F1-score of 90.00%. This suggests that while its deep residual architecture is highly efficient, it may not have captured the most salient diagnostic features in this specific dataset as effectively as the other models. This outcome underscores a critical trade-off in model selection: the most computationally "lightweight" model is not always the most diagnostically accurate.

Thus, the results of this study strongly advocate for the use of InceptionV4 for this specific task. It not only achieves state-of-the-art accuracy but also maintains a reasonable computational footprint (41.15M parameters and 12.24 GFLOPs), striking an optimal balance between diagnostic performance and practical deploy ability. The comparison highlights that architectural design plays a more significant role in classification success than mere network depth or parameter count. For sensitive medical applications like lung cancer diagnosis, the ability of a model like InceptionV4 to discern features at multiple resolutions is evidently more beneficial than the straightforward depth of VGG-13 or the lean structure of ResNet-50.

Figure 2 presents the confusion matrix for the top-performing InceptionV4 model, offering a detailed, class-specific breakdown of its predictions on the test set. The strong diagonal values (16, 85, and 63) visually confirm the model's high accuracy. Most notably, the model demonstrates flawless performance for the Malignant and Normal classes, correctly identifying all 85 malignant cases and all 63 normal cases without a single misclassification. This is a clinically significant achievement, as it indicates a 100% recall for malignant tumors (zero false negatives) and ensures that no healthy subjects were incorrectly flagged. The model's only confusion occurred in the Benign class, where 2 out of 18 benign cases were misclassified as Normal. This suggests a minor difficulty in distinguishing some benign nodules from normal lung tissue, a less critical error compared to misclassifying a malignant case. Taken as a whole, the confusion matrix powerfully validates the quantitative metrics in Table 2, underscoring the model's exceptional reliability and robustness, particularly for the critical task of identifying malignancy.

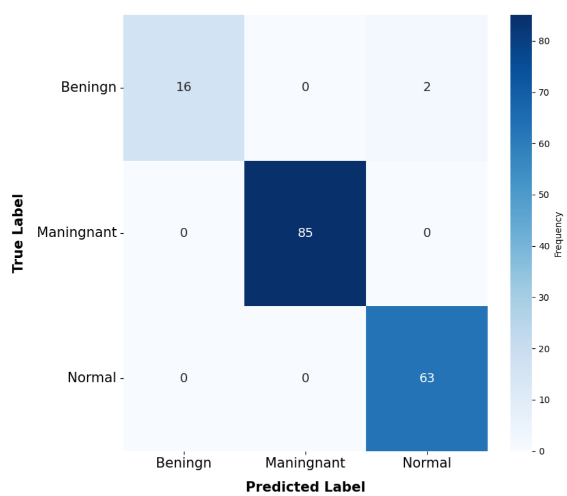

Figure 2 Confusion Matrix of the InceptionV4 Model for Lung BT Image Classification.

CONCLUSION

This study compared the three different CNN architectures InceptionV4, VGG-13, and ResNet-50, for classifying lung cancer from CT images using a transfer learning approach. The results clearly show that InceptionV4 provided the highest results with an accuracy of 98.80%. The strength of InceptionV4 lies within its ability to create model features that can extract many multi-scale features and patterns that can discern all layers of distinguishing patterns of benign, malignant, and normal lung tissue. The analysis of results was the blend of diagnostic performance and computational efficiency. Although VGG-13 showed accuracy that could compete with InceptionV4, it stands-in excellence by the sheer number of parameters that would lose practical appearance for purposeful clinical use. ResNet-50 was very computationally efficient but did not hold diagnostic accuracy. The findings identify InceptionV4 as the superior architecture, offering an optimal balance between efficiency and accuracy that results in state-of-the-art operational performance. This makes it the most suitable model for this clinical application.

This research project is highly relevant for the future development of CAD systems for oncology. The InceptionV4 model in this research correctly detected all malignant cases in the test set. This indicates that InceptionV4 potentially offers a strong resource to assist radiologists, which may ultimately help reduce the number of misdiagnosed cancers, facilitate the diagnosis of cancers at earlier stages, and support timely interventions. At the same time, this study acknowledged some limitations in this research including that the dataset came from a single source, and there was slight confusion between benign and normal cases. Therefore, we strongly recommend as a continuation of the research looking to validate this models performance on larger, multi-institutional datasets to confirm that the model is truly generalizable. Future work could also investigate combining the InceptionV4 model with another model or or explore different attention mechanisms to further distinguish benign and normal cases bringing us closer to being able to incorporate these powerful DL based tools into clinical practices in a way that improves patient outcomes.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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