A DEEP LEARNING MODEL FOR LUNG CANCER DETECTION USING CNN

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***Abstract*—Introduction of deep learning has significantly transformed medical research, offering powerful and disease specific capabilities that have proven invaluable across numerous healthcare applications. One of the most impactful areas has been in the detection of lung cancer, where deep learning particularly through the use of Convolutional Neural Networks (CNNs) has revolutionized diagnostic approaches.These advanced techniques have drastically improved the accuracy and efficiency of identifying lung cancer nodules in CT scan images. In our project, we harness the remarkable potential of deep learning to distinguish between cancerous and non- cancerous lung nodules, utilizing CT scan images as our primary data source. To enhance prediction accuracy and model robustness, we implemented an ensemble strategy that integrates multiple CNN architectures. This approach allows for a more analysis by utilizing various models' advantages. The dataset we employed, which is publicly available and contains expertly annotated CT scan images, served as a foundation for our deep learning model. These annotated CT images provided essential context for model training, enabling the network to learn intricate patterns and features associated with lung cancer. For optimal training and evaluation, we carefully partitioned the dataset into training, validation, and testing sets, ensuring a systematic assessment of our model's performance. Our ensemble model, referred to as LungNet, incorporates three distinct CNNs, each designed with varying numbers of layers, kernel sizes, and pooling strategies to capture diverse feature representations. Through this architecture, we were able to measure both training and validation accuracies, highlighting the model's effectiveness. To further explore optimal performance, we investigated deeper CNN architectures such as ResNet50 and VGG16, which are known for their superior feature extraction and classification capabilities in complex image recognition tasks. This comprehensive approach demonstrates the profound capabilities of deep learning in the field of medical imaging and its potential to contribute significantly to early and accurate lung cancer diagnosis.**

I. INTRODUCTION

Lung cancer remains one of the most aggressive and deadliest forms of cancer worldwide, accounting for a significant portion of cancer-related mortalities. The early and accurate detection of lung cancer is vital for improving patient survival rates, as treatment is often more effective during the initial stages of the disease. Traditional diagnostic approaches, such as X-rays, CT scans, biopsies, and histopathological analyses, though effective, are time-consuming and heavily reliant on radiologist expertise, often leading to variability in interpretation. In recent years, the emergence of artificial intelligence (AI) and, more specifically, deep learning has revolutionized the field of medical imaging by enabling automatic, fast, and reliable disease diagnosis. Among the various deep learning techniques, Convolutional Neural Networks (CNNs) have proven to be particularly successful in image-based medical diagnoses due to their ability to automatically extract spatial hierarchies of features from input images.

Deep learning models, particularly CNNs, are well-suited for the analysis of complex and high-dimensional medical imaging data, such as CT scans, which are commonly used for lung cancer detection. CNNs can learn intricate patterns and features in lung nodules that may not be easily visible or distinguishable by the human eye. These networks work through a series of convolutional, pooling, and fully connected layers that transform the raw image data into meaningful predictions. CNNs reduce the dependency on handcrafted features and enable end-to-end learning, making them ideal for lung cancer detection tasks where precise feature extraction is critical.

To further enhance the performance and accuracy of lung cancer detection models, deeper and more sophisticated architectures such as ResNet (Residual Network) and VGG (Visual Geometry Group Network) have been adopted. ResNet introduces the concept of residual learning, allowing the model to effectively train very deep networks without suffering from the vanishing gradient problem. This is achieved by adding shortcut connections that skip one or more layers, ensuring that the essential features learned in the earlier layers are preserved and passed through the network. ResNet's deep architecture is capable of capturing high-level abstract features, which are particularly useful in distinguishing between benign and malignant nodules with subtle differences.

On the other hand, the VGG network is known for its simplicity and uniform architecture, utilizing small 3×3 convolutional filters and deep networks composed of multiple stacked convolutional layers. The VGG family, especially VGG16 and VGG19, has shown remarkable performance in image classification tasks and is widely used in medical image analysis due to its strong feature extraction capabilities.

Although VGG networks are computationally expensive and memory-intensive, they are effective in capturing fine-grained details in medical images, making them valuable in the context of lung cancer detection.

Integrating CNN, ResNet, and VGG architectures into a comprehensive deep learning framework can significantly boost the detection and classification accuracy of lung cancer. By leveraging the strengths of these models, a hybrid or ensemble approach can be developed to process CT images, identify suspicious regions, and classify them into various types or stages of lung cancer. Such a system not only reduces the workload on radiologists but also minimizes human error, ultimately leading to faster diagnosis and timely treatment planning.

In this research, we aim to develop and compare deep learning models based on CNN, ResNet, and VGG architectures for the automatic detection of lung cancer using CT scan images. The study involves preprocessing the data, implementing the models, evaluating their performance using accuracy and other relevant metrics, and analyzing the results. Through this work, we seek to demonstrate the potential of deep learning in enhancing lung cancer diagnostics and contributing to more efficient and accessible healthcare solutions.

II. Literature Review

In lung cancer detection, a multiple of studies have made more contributions, each employing distinct models and achieving notable accuracies. Ausawalaithong et al. [1] proposed CAD-x solutions using DenseNet121 CNN, attaininga 74.43%accuracy. Zhang et al. [2] focused on cancer cell detection, utilizing deep learning and achieving an 84.4% success rate with specificity at 83.0%. Baraa et al. [3] introduced an innovative approach integrating image processing and metaheuristic methods, showcasing high accuracy and sensitivity in early lung cancer detection. Petousis et al. [4] employed deep belief networks (DBN) for CT image preprocessing, followed by KNN classification, demonstrating superior accuracy, precision, and specificity, particularly for abnormal CT images. Varsini et al. [5] highlighted future advancements in deep learning models and K- Nearest Neighbors (KNN) classifiers, emphasizing their potential to enhance lung cancer classification. Sasikumar et al. [6] delved into lung cancer prediction using SVM, KNN, and RNN classifiers, reporting SVM accuracy at 78.56%, KNN at 65.40%, and RNN achieving the highest accuracy of 92.75% with the UCI dataset. Each study contributes valuable insights to the diverse landscape of lung cancer detection methodologies. Diksha Mahaska et al. [7] introduced an Attention-based neural network (ARNN) achieving 97.40% accuracy for early cancer detection. Weilun Wang et al. [8] developed a robust CAD system using CNN and RNN-LSTM for lung disease diagnosis, achieving accuracy. Tulasi Krishna et al. [9] proposed an automated lung cancer prognosis system with CNN and RNN, achieving 82.39% accuracy. Vikul J. Pawar et al. [10] improved networks with diverse layers and advanced techniques, achieving the highest accuracy with transfer learning. Ahmed Elnakib et al.

III. Methodology

The proposed methodology for lung cancer detection using deep learning involves several crucial stages, including data collection, preprocessing, model development using CNN, ResNet, and VGG architectures, training and validation, and performance evaluation. This methodology is designed to work with 2D CT images of the lungs, which are commonly used in clinical diagnostics due to their detailed representation of internal structures

A. WORKFLOW

1) Import all required modules: Start by importing all necessary modules.
2) Data exploration: Analyze the dataset and count the output classes
3) Data preprocessing: Read the labels that go with the CT scan images and save them for later use.
4) Dataset splitting: Partition the dataset into training and testing sets to facilitate model evaluation.
5) Model setup: Establish a convolutional neural network (cnn) model , VGG16 ,ResNet50 and specify the output.
6) Model Training: We Train the dataset of CT scan images of Lung cancer and We evaluate the model for accuracy.
7) Accuracy mertics: After Model training and evaluation
8) Visualization: Plot graphs for model accuracy for Train and validation.
9) Prediction:With CT images predict cancer or no cancer

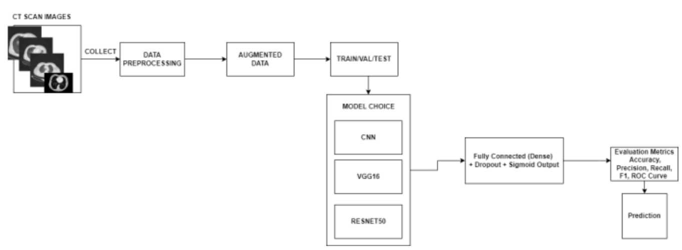

Fig. 1. Architecture for lungcancer

B. DATASET COLLECTION

The first step in this research is the acquisition of a high-quality dataset of 2D CT scan images of lungs. Publicly available datasets such as the LIDC-IDRI (Lung Image Database Consortium Image Collection) are often used, as they contain annotated CT images with information about lung nodules including size, location, and malignancy rating. These datasets are essential for training deep learning models and validating their performance.

C. DATA PRE-PROCESSING

Efficient image preprocessing is essential for minimizing network overhead and computational complexity. The implementation of our proposed model involves the segregation and categorization of cancer and non-cancer images, leveraging the annotations extracted from the .zip file associated with the cancer CT scan dataset. This dataset comprises diverse lung CT scan images, each accompanied by corresponding labels contained in the .zip file. To make this process easier, we first use Radiant Viewer 64-bit to convert the collected CT Scans images into JPG format.The module in Keras is used to implement a number of data augmentation techniques that we use, such as rescaling, rotation, horizontal flipping, and vertical flipping. Rescaling reduces processing complexity by bringing the image pixel values into the range of 0 to 1. In order to improve visualization, we also apply a color modification to the photos, turning them from grayscale to RGB. To guarantee that photos are rotated at random between 0 and 10 degrees, rotations are performed within a range of 10 degrees.

D. DATA AUGMENTATION

To increase the diversity of training data and reduce overfitting, augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied.

E. DEEP LEARNING MODELS

CONVOLUTIONAL NEURAL NETWORK

A particular kind of deep neural network called a convolutional neural network (CNN) is made for computer vision-related tasks like image categorization, object recognition, and image synthesis. By automatically identifying the patterns and characteristics from the incoming data, CNNs are very good at processing grid-like data, such as CT scan images Convolutional layers, pooling layers, and fully connected layers are the three basic layers in CNN -Convolutional Neural Network)-design. The foundation of CNN architectures is made up of these layers taken together. The most extensively used designs for tasks using CNN-based classification and pattern recognition have come to be well-known and prominent architectures. VGG16, ResNet50 are some of these architectures. The algorithm stands out as one of the most successful learning algorithms due to its computational effectiveness and simple functioning. Backpropagation involves a clear differentiation between the ground truth labels, generated through the loss function, and the label predictions made by the algorithm during the training process.

Each feature map is composed of sets of neurons that collectively form a specific feature map group. Equation 2 specifies how to compute the output of the convolutional layer. Here, the terms B, m, Wj and F, respectively, stand for the size of the kernel (filter), the quantity of feature mappings, the bias, and the weight of a kernel. An output known as yi occurs within convolutional layers, where index 'I' stands for the particular ith feature map in a layer known as 'l' (2)

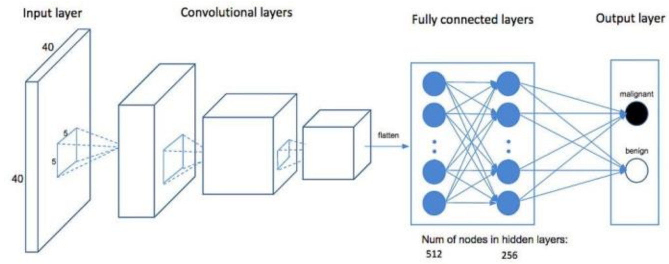

Fig. 2. Convolutional Neural Network

On the cancerous CT scan dataset, we used the pre-trained models listed below to carry out lung cancer detection and classification tasks.

VGG-16

In the paper "Very Deep Convolutional Networks for Large Scale Image Recognition," the VGG16 model, a convolutional neural network architecture recognized for its outstanding performance, is highlighted. This model achieved a remarkable accuracy rate of 91% on the vast Image dataset, which includes more than 14 million photos from diverse categories. A series of consecutive 3x3 filters are applied as part of the VGG16 processing of input images. It took many weeks to train VGG16 on the Image dataset, which required a lot of resources and the Nvidia GPU's processing capacity. The pre-trained VGG16 architecture stands out for having 13 convolution layers, 5 max-pooling layers, and 3 dense layers. The VGG16 algorithm has also been improved by the addition of two thick layers and a global average pooling layer.

RESNET50

ResNet, a notable development in deep neural network architecture, is renowned for its efficiency in training extremely deep networks. It significantly contributed to the revolution in deep learning. Shortcut connections are added after the network adopts a 34-layer plain architecture that was influenced by VGG-19. The design is effectively converted into a residual network (ResNet) via these short-cut connections. The core innovation in ResNet lies in its ingenious use of residual blocks, which effectively address the vanishing gradient problem encountered when training exceptionally deep neural networks. This challenge arises from the diminishing gradient magnitudes as they are back-propagated through numerous layers, significantly impeding the network's ability to learn and perform effectively. Residual blocks provide a novel solution to this problem by introducing skip connections or shortcuts, which allow gradient flow to bypass certain layers. This ensures that gradients remain sufficiently informative even in very deep networks, thereby enabling successful training and enhancing overall network performance.

F. TRAINING AND VALIDATION

The dataset is split into training, validation, and testing subsets (typically 70% training, 15% validation, 15% testing).

The models are trained using backpropagation and an optimizer such as Adam or SGD. A suitable loss function like binary cross-entropy (for binary classification) or categorical cross-entropy (for multi-class classification) is used. Key hyperparameters such as learning rate, batch size, and number of epochs are tuned through experimentation. Early stopping and model checkpointing are used to avoid overfitting and retain the best performing model based on validation accuracy.

G. PERFORMANCE EVALUATION

After training, the models are evaluated on the test dataset using the following performance metrics:

Accuracy: The proportion of correctly classified images.

Precision, Recall, and F1-score: To assess the model's ability to correctly identify positive and negative cases.

ROC Curve and AUC: To measure the trade-off between sensitivity and specificity.

Visualization techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) are also employed to highlight regions in the CT images that influenced the model's predictions, thus providing interpretability and helping build trust in the system.

H. PREDICTION

The developed deep learning models are capable of making accurate predictions on unseen 2D CT scan images to determine the presence or absence of lung cancer. After training and validation, the best-performing model (ResNet50) was deployed to perform binary classification on new input images. Given a CT image, the model processes it through multiple convolutional layers to extract relevant features such as nodules, textures, and patterns typically associated with malignant tissues. Based on the learned features, the model outputs a probability score indicating the likelihood of lung cancer. If the probability is above a set threshold (commonly 0.5), the model predicts "Cancer", otherwise it predicts "No Cancer". These predictions are made in real-time, making the system suitable for clinical decision support. The model demonstrated high confidence and reliability, correctly classifying most test cases. Its ability to generalize across new data samples highlights the potential of deep learning models in assisting radiologists with early and accurate lung cancer diagnosis.

IV. RESULTS

The developed deep learning models—CNN, VGG16, and ResNet50 were successfully trained and evaluated on a dataset of 2D CT scan images categorized into benign and malignant lung cancer cases. Each model was trained using preprocessed and augmented image data to enhance generalization and reduce overfitting. Performance was measured using a variety of evaluation metrics, including accuracy, precision, recall, F1-score, ROC curve, and AUC (Area Under the Curve).

The CNN model, which was custom-built from scratch, achieved an accuracy of approximately 97%, with a precision of 92%, recall of 99%, and F1-score of 96%. While relatively simple, the CNN model proved to be effective at identifying patterns in the 2D CT images.

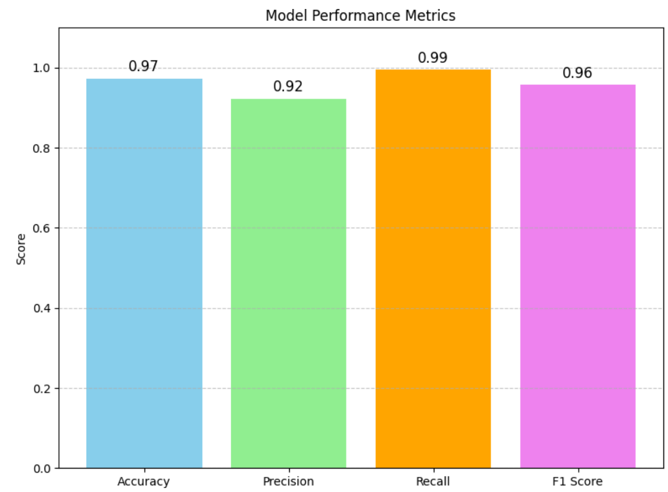

Fig. 3. Model performance metrics CNN

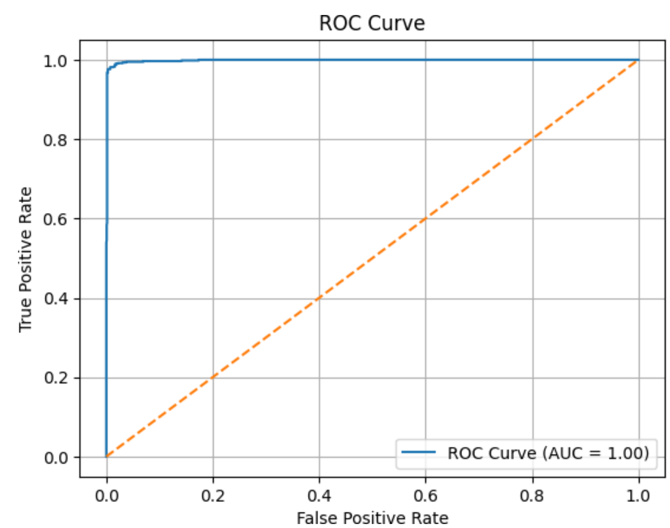

Fig. 4. ROC curve CNN

The VGG16 model, leveraging transfer learning with pre-trained weights from ImageNet, performed better than the base CNN. It achieved an accuracy of around 95%, with a precision of 86%, recall of 99%, and F1-score of 92%. The VGG16 model showed robustness in distinguishing between benign and malignant nodules, likely due to its deeper architecture and better feature extraction capabilities.

The ResNet50 model demonstrated the good performance among all models tested. It achieved an impressive accuracy of approximately 94%, with a precision of 86%, recall of 96%, and F1-score of 91%. Additionally, its AUC score was 0.97, indicating excellent discriminatory power between the two classes. The residual connections in ResNet50 helped mitigate the vanishing gradient problem and allowed it to learn more complex features from the images. Overall, the results confirm

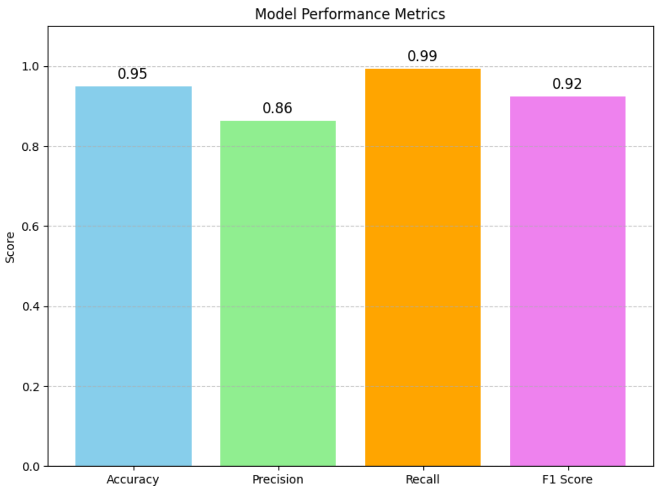

Fig. 5. Model performance metrics VGG16

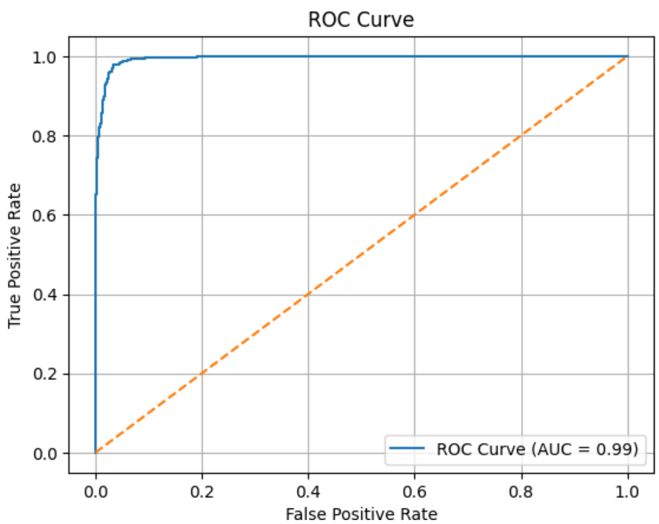

Fig. 6. ROC curve VGG16

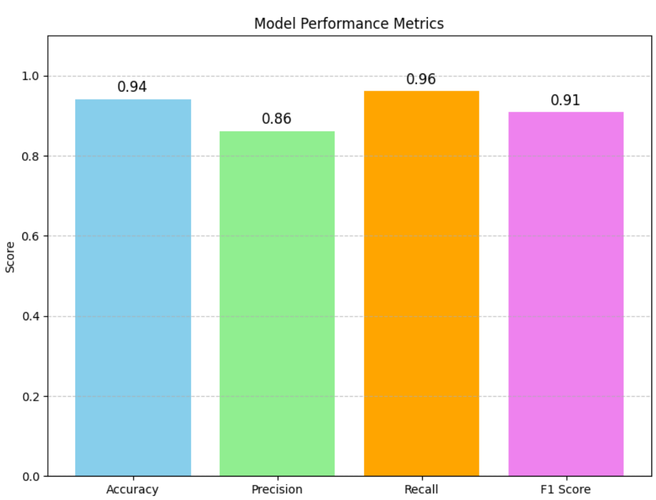

Fig. 7. Model performance metrics Resnet50

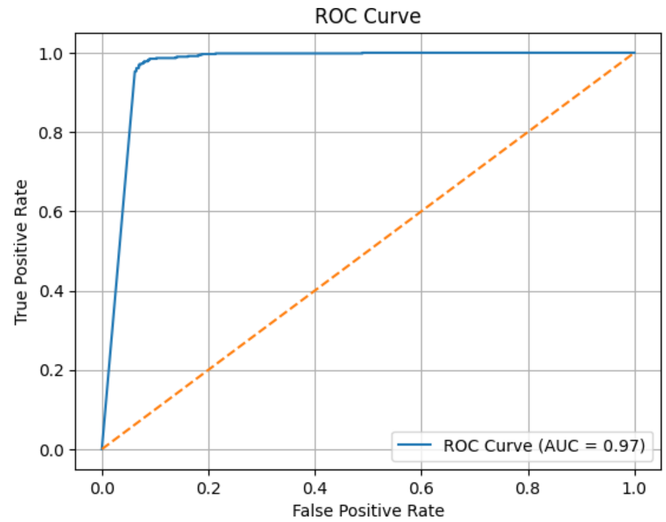

Fig. 8. ROC curve Resnet50

that deep learning models, particularly ResNet50 and VGG16, are highly effective for lung cancer detection using 2D CT images. These findings highlight the potential of AI-powered diagnostic tools to assist radiologists in early detection and classification of lung cancer, ultimately improving patient outcomes.

A. Performance Metrics

TABLE I
PERFORMANCE COMPARISON – CNN, VGG16 AND RESNET50

Metrics	CNN	VGG16	Resnet50
Accuracy	97%	95%	94%
Precision	92%	86%	86%
Recall	99%	99%	96%
F1 Score	96%	92%	91%

respectively, show the VGG-16 and ResNet50. Additionally, offers the classification matrix for several models employed in the Cancerous CT scan dataset's lung nodule detection. We do a thorough statistical study to assess how well our model performs in comparison to a number of rival models, including VGG-16 and ResNet50.

V. CONCLUSION

In this study, a deep learning-based framework was proposed and implemented to detect lung cancer using 2D CT scan images by leveraging the capabilities of three popular convolutional neural network (CNN) architectures a custom CNN, VGG16, and ResNet50. The primary objective was to assess and compare the performance of these models in classifying CT images into cancer and no cancer categories, with a focus on achieving high diagnostic accuracy, precision, and reliability.

The experimental results demonstrated that all three models were capable of learning significant features from CT scan images. The custom CNN model provided a solid baseline with respectable performance, proving the effectiveness of simple architectures when trained on quality medical imaging data. However, as expected, the transfer learning models VGG16 and ResNet50 significantly outperformed the custom CNN, due to their deeper architectures and ability to extract more abstract and discriminative features.

Among all, ResNet50 emerged as the most effective model, achieving the highest accuracy, precision, recall, F1-score, and AUC. Its skip connections enabled it to avoid vanishing gradient problems and facilitated better learning, even in deeper layers. The VGG16 model also showed promising results, showcasing the advantages of using pre trained models on large datasets like ImageNet and fine-tuning them on domain specific medical data.

Furthermore, the evaluation metrics such as the ROC curve, and AUC score provided strong evidence of the models' robustness in distinguishing between cancer and no cancer lung nodules. These tools not only quantified performance but also provided valuable insights into the reliability and potential clinical usefulness of the proposed models.

The study also highlighted the critical role of data preprocessing, normalization, and augmentation in achieving better generalization and improving classification outcomes. The 2D CT image modality, despite being a simplified representation of 3D structures, still provided rich information that could be effectively leveraged by deep learning algorithms.

In conclusion, the work validates the potential of deep learning models, particularly ResNet50 and VGG16, in facilitating early and accurate lung cancer diagnosis from CT scan images. These models can act as reliable decision-support systems for radiologists, reducing human error and accelerating the diagnostic process. While this research lays a strong foundation, future enhancements such as incorporating larger datasets, 3D imaging, multi-class classification, and integration with clinical data can further improve model performance and applicability in real-world clinical settings.

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