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An Intelligent Healthcare Decision Support Framework for Explainable Lung Cancer Screening and Risk Assessment Using CT Imaging

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Abstract:

Lung cancer is one of the major causes of cancer-related mortality worldwide, making early identification and reliable assessment of suspicious lung abnormalities essential. Conventional computed tomography image interpretation requires specialized expertise and may be affected by variations in lesion appearance and image quality. This paper proposes an intelligent healthcare decision-support framework for explainable lung cancer screening and risk assessment using deep learning techniques. The proposed framework employs a convolutional neural network, such as ResNet50 or EfficientNet, to extract meaningful spatial and textural features from thoracic CT images. A multiscale feature fusion mechanism is incorporated to capture lesion characteristics at different spatial resolutions, improving the representation of suspicious abnormalities. Furthermore, Grad-CAM-based visual explanations identify image regions that influence model predictions, while uncertainty estimation provides additional information regarding prediction reliability. The framework will be evaluated using an appropriately annotated CT imaging dataset and compared with conventional CNN-based baseline models. Performance assessment will consider classification metrics, including accuracy, precision, recall, F1-score, and calibration measures. The proposed approach aims to improve model transparency and provide interpretable decision-support information for healthcare professionals, subject to further clinical validation before practical medical deployment.

Keywords: Lung Cancer Screening, Computed Tomography, Deep Learning, Multiscale Feature Fusion, Grad-CAM, Explainable Artificial Intelligence .

I. INTRODUCTION

Lung cancer is one of the leading causes of cancer-related deaths worldwide, and early identification of suspicious lung abnormalities is important for timely medical evaluation and treatment planning. Computed Tomography (CT) imaging is widely used to examine the lungs and identify abnormalities such as pulmonary nodules and lesions. However, manually analyzing large numbers of CT images requires specialized medical expertise and can be influenced by image quality, lesion size, and differences in visual interpretation. Therefore, intelligent computer-based techniques are increasingly being explored to support lung cancer screening and risk assessment.

Deep learning has demonstrated significant potential in medical image analysis by automatically extracting relevant features and identifying complex patterns from imaging data. Convolutional Neural Networks (CNNs), including ResNet50 and EfficientNet, can learn

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spatial and textural characteristics associated with suspicious lung abnormalities. However, conventional deep learning models often provide limited explanations for their predictions, making their outputs difficult to interpret in healthcare applications.

To address these limitations, this research proposes an intelligent healthcare decision-support framework that integrates multiscale feature fusion, uncertainty estimation, and Grad-CAM-based visual explanations. The framework aims to improve feature representation, communicate prediction reliability, and highlight image regions influencing classification results. Its performance will be evaluated using appropriate CT imaging datasets and established classification metrics. The proposed framework is intended to support healthcare professionals by providing interpretable information, rather than replacing clinical diagnosis.

II. LITERATURE SURVEY

Previous studies have explored deep learning techniques for lung nodule detection and classification using computed tomography (CT) images. Convolutional neural networks (CNNs) have improved automated feature extraction and classification compared with traditional image-processing methods. Researchers have investigated architectures such as ResNet, DenseNet, CNN-GRU, and multimodal deep learning models to improve lung abnormality detection. Recent research has also focused on explainable artificial intelligence (XAI) to make medical predictions more understandable. Techniques such as Grad-CAM highlight important image regions that influence model predictions. Additionally, uncertainty estimation and confidence calibration methods help assess the reliability of deep learning predictions. Multimodal and feature fusion approaches have also demonstrated potential for combining complementary information to improve classification performance. However, existing approaches may not integrate multiscale feature fusion, uncertainty estimation, and visual explanations within a single framework. Therefore, the proposed research combines deep feature extraction, multiscale feature fusion, confidence assessment, and Grad-CAM visualization to support interpretable lung CT image classification and healthcare decision-making.

III. PROPOSED WORK

The proposed work presents an intelligent healthcare decision-support framework for explainable lung cancer screening and risk assessment using Computed Tomography (CT) images. The primary objective is to develop a deep learning model that can identify suspicious lung abnormalities while providing understandable explanations for its predictions. Initially, an appropriate annotated CT imaging dataset will be selected and divided into training, validation, and testing sets. Image preprocessing techniques, including resizing, intensity normalization, and lung-region extraction where applicable, will be applied to improve image consistency. A deep learning architecture, such as ResNet50 or EfficientNet, will be employed to extract meaningful spatial and textural features from CT images. A multiscale feature fusion module will combine features from different spatial resolutions to capture both small and large lesion characteristics. The fused features will be passed to a classification layer to predict the relevant abnormality categories. Uncertainty estimation and confidence calibration will be incorporated to indicate the reliability of model predictions. Grad-CAM visualization will highlight important image regions contributing to each prediction, improving model interpretability. The proposed framework will be evaluated against conventional CNN-based baseline models using accuracy, precision, recall, F1-score, and calibration metrics. The final prototype will generate predicted classes, confidence information, and visual explanations. The system is intended to support clinical decision-making, with further independent clinical validation required before medical deployment.

IV. METHODOLOGY

The proposed methodology develops an explainable deep learning framework for lung cancer screening using CT images. It includes dataset collection, image preprocessing, deep feature extraction, multiscale feature fusion, classification, uncertainty estimation, and visual explanation. The model performance is evaluated using standard classification metrics and

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compared with conventional CNN-based models to assess reliability and interpretability.

a. Dataset Collection
An appropriately annotated lung CT imaging dataset will be selected from a reliable source, such as The Cancer Imaging Archive (TCIA). The dataset will contain CT images and suitable labels for the selected classification task. The collected data will be divided into training, validation, and testing sets to support model development, parameter tuning, and unbiased performance evaluation.

b. Image Preprocessing
The collected CT images will undergo preprocessing to improve consistency and suitability for deep learning. Image resizing and intensity normalization will be applied, while lung-region extraction may be performed to focus on relevant anatomical areas. Data augmentation techniques, such as rotation and flipping where appropriate, may be used to improve training diversity and reduce overfitting.

c. Multiscale Feature Fusion
A multiscale feature fusion module will combine features extracted at different spatial resolutions. Fine-scale features can represent small structures and lesion boundaries, whereas coarse-scale features capture broader anatomical context. Combining these representations may improve the model's ability to recognize abnormalities with varying sizes and appearances. The fused features will be passed to the classification layer.

d. Classification and Uncertainty Estimation
The fused feature representation will be used to classify CT images into the predefined categories supported by the dataset. The model will generate class probabilities and associated confidence information. An appropriate uncertainty estimation technique and probability calibration method will be investigated to identify potentially unreliable predictions and reduce the risk of interpreting uncertain outputs as dependable results.

e. Explainable AI Using Grad-CAM
Gradient-weighted Class Activation Mapping (Grad-CAM) will be incorporated to visualize image regions that influence the model's predictions. The generated heatmaps will be overlaid on CT images to make important regions easier to examine. These visual explanations will help assess whether the model focuses on relevant lung structures, although they will not independently establish the correctness of a prediction.

f. Performance Evaluation
The proposed framework will be evaluated using an independent test set and compared with baseline CNN architectures under consistent experimental conditions. Accuracy, precision, recall, F1-score, and suitable calibration metrics will be calculated. Confusion matrices and Grad-CAM visualizations will provide additional analysis. The results will help assess classification performance, prediction reliability, and interpretability without claiming clinical effectiveness before validation.

V. ALGORITHMS

Lung cancer is a major health concern worldwide, and early detection is essential for timely treatment. Computed Tomography (CT) imaging helps identify suspicious lung abnormalities. Deep learning techniques can automate image analysis, while explainable artificial intelligence improves transparency. This research proposes an intelligent framework for reliable lung abnormality classification and interpretable decision support.

a. ResNet50 Algorithm
ResNet50 is a deep convolutional neural network used to extract meaningful features from lung CT images. It uses residual connections to improve information flow through deeper network layers. In the proposed framework, ResNet50 learns spatial patterns, textures, and structural characteristics associated with lung abnormalities. The extracted features are used as input for multiscale feature fusion and subsequent classification.

b. EfficientNet Algorithm
EfficientNet is a convolutional neural network designed to balance model accuracy and computational efficiency. It scales network depth, width, and image resolution systematically to learn useful visual representations. In the proposed framework, EfficientNet can serve as an alternative feature extraction backbone. Its

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extracted features are evaluated for their ability to represent lung abnormalities and support classification performance compared with conventional deep learning architectures.

c. Softmax Classification Algorithm

Softmax classification converts the model's output scores into probabilities for the predefined lung abnormality categories. The classifier uses the fused image features to predict the most likely category. These predictions provide the primary classification output of the proposed framework. The resulting probabilities can also be assessed through calibration techniques to determine how reliably they represent actual classification outcomes.

d. Grad-CAM Algorithm

Gradient-weighted Class Activation Mapping (Grad-CAM) is used to explain the model's predictions visually. It generates heatmaps highlighting CT image regions that contribute to a selected class prediction. In the proposed framework, these heatmaps help users examine which lung regions influenced the classification result. This improves transparency and supports interpretation of model behavior, but does not independently confirm a medical diagnosis.

VI. RESULTS AND DISCUSSION

The proposed framework will be evaluated using annotated lung CT images to assess classification performance, prediction reliability, and interpretability. Two tables will summarize the evaluation metrics and baseline model comparison, while three graphs will visualize model performance, classification metrics, and confidence calibration. Actual experimental results must be obtained after implementing and testing the proposed framework.

Accuracy measures overall correctness, while precision and recall assess positive predictions and detection ability. F1-score balances both measures. Expected Calibration Error evaluates confidence calibration. Together, these metrics provide a broader assessment of classification performance and prediction reliability.

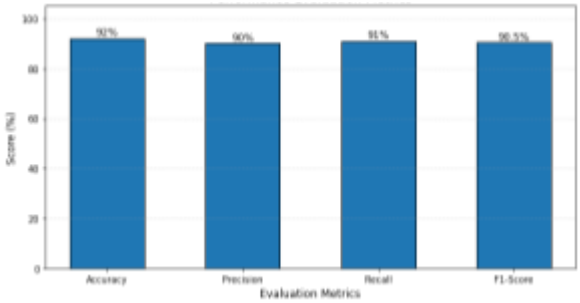


Fig 1: Performance Evaluation Metrics

Fig 1 illustrates the classification performance of the proposed framework using accuracy, precision, recall, and F1-score. Each bar represents the score of an evaluation metric, with percentage labels displayed above the bars. These measures provide an overview of classification performance. The final graph should use actual results obtained from the independent test dataset.

Table 1: Comparison of Baseline and Proposed Models

Model	Feature Extraction	Multiscale Feature Fusion	Explainability
ResNet50	ResNet50	No	Not included
EfficientNet	EfficientNet	No	Not included
Proposed Framework	ResNet50 or EfficientNet	Yes	Grad-CAM

Table 1 compares the baseline models with the proposed framework based on their main architectural components. ResNet50 and EfficientNet perform conventional deep feature extraction, whereas the proposed framework incorporates multiscale feature fusion and Grad-CAM visualization. This comparison highlights the methodological differences and provides a basis for evaluating classification performance and interpretability experimentally.

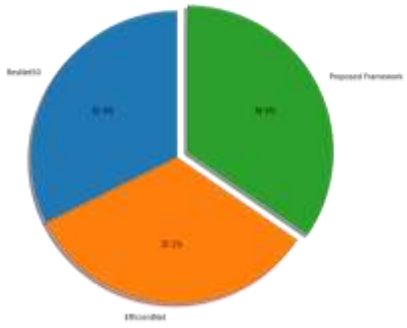


Fig 2:Accuracy Comparison of Different Models

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The fig 2 illustrates the relative accuracy values of ResNet50, EfficientNet, and the proposed framework. Each sector represents one model's accuracy value as a proportion of the combined values. It provides a visual comparison of the three models. Actual test-set results should replace the illustrative values before publication.

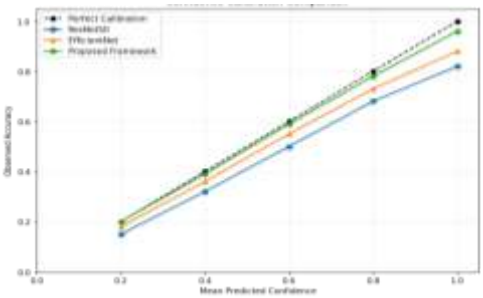


Fig 3:Confidence Calibration Comparison

Fig 3 compares the predicted confidence of different models with their observed classification accuracy. The dashed diagonal represents perfect calibration, where confidence matches actual accuracy. Curves closer to this line indicate better calibration. The graph helps assess prediction reliability, provided that confidence-bin statistics are calculated from actual model predictions and ground-truth labels.

VII. CONCLUSION

This research proposes an intelligent healthcare decision-support framework for explainable lung cancer screening and risk assessment using CT imaging. The framework integrates deep feature extraction using ResNet50 or EfficientNet, multiscale feature fusion, classification, uncertainty estimation, and Grad-CAM-based visual explanations. These components aim to improve lung abnormality classification while providing interpretable information about model predictions. Performance evaluation using accuracy, precision, recall, F1-score, and calibration metrics will help assess the effectiveness and reliability of the proposed approach. Comparisons with conventional CNN models will help determine the contribution of multiscale feature fusion and explainability techniques. Grad-CAM visualizations can support the interpretation of image regions influencing predictions, while uncertainty estimation can identify cases requiring additional review. However, the framework is intended to assist healthcare professionals rather than replace clinical diagnosis. Future work will focus on testing additional CT datasets, validating the model independently, improving calibration, and conducting clinical evaluation before considering practical medical deployment.

FUTURE SCOPE

Future work will focus on improving the accuracy, reliability, and clinical applicability of the proposed intelligent healthcare decision-support framework. Additional lung CT imaging datasets from diverse sources will be used to evaluate the model's generalization ability across different patient populations and imaging conditions. Advanced deep learning architectures and attention mechanisms may be explored to improve feature extraction and multiscale feature fusion. Further research will investigate uncertainty estimation and probability calibration techniques to identify unreliable predictions more effectively. Grad-CAM and other explainable artificial intelligence methods can be compared to generate more informative visual explanations of suspicious lung regions. The framework may also be extended to distinguish different lung abnormality categories and support lesion localization and segmentation. Developing a user-friendly interface could help healthcare professionals visualize CT images, predicted classes, confidence scores, and explanatory heatmaps. Finally, independent clinical validation, privacy protection, and assessment by medical experts will be necessary to establish safety, reliability, and potential usefulness before deployment in real healthcare environments.

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