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A Hybrid Deep Learning Framework for Lung Cancer Classification Using Explainable AI and Dynamic Branching Networks

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Abstract
Lung cancer is one of the leading causes of cancer-related deaths worldwide, making early and accurate diagnosis essential for improving patient survival rates. Recent advancements in artificial intelligence and deep learning have significantly enhanced medical image analysis for lung cancer detection. However, existing deep learning models often suffer from challenges such as class imbalance, limited interpretability, high computational complexity, and inadequate generalization across different datasets. This research proposes a hybrid deep learning framework for lung cancer classification using CT scan images by integrating enhanced AlexNet feature extraction, Layer-wise Relevance Propagation (LRP), transformer-based global feature learning, and a Self-Evolving Dynamic Branching Network (DBN). The proposed system combines traditional image preprocessing techniques such as Otsu thresholding, histogram equalization, and Sobel edge enhancement with advanced deep learning architectures including ResNet50, Transformers, and dynamic branching mechanisms. Recursive Feature Elimination (RFE), LASSO, Random Forest feature ranking, and Support Vector Machine (SVM) classification are incorporated to improve feature selection and classification accuracy. Experimental evaluation on the IQ-OTH/NCCD dataset demonstrates strong performance with high classification accuracy, precision, recall, and F1-score across normal, benign, and malignant lung cancer classes. The integration of explainable AI techniques further improves interpretability by generating relevance heatmaps that highlight clinically significant regions in CT images. The results confirm that the proposed framework provides an efficient, interpretable, and scalable solution for intelligent lung cancer diagnosis systems.

Keywords
Lung Cancer Detection, Deep Learning, Explainable AI, AlexNet, ResNet50, Transformer Networks, Dynamic Branching Network, CT Scan Analysis, Medical Image Classification, Support Vector Machine, Feature Selection, Healthcare AI

1. Introduction
Lung cancer remains one of the most dangerous and rapidly increasing diseases across the world, contributing significantly to global mortality rates. Early diagnosis plays a critical role in improving survival rates and reducing treatment costs. Medical imaging technologies such as Computed Tomography (CT), Positron Emission Tomography (PET), and X-ray imaging are widely used for identifying lung abnormalities and cancerous nodules. However, manual

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analysis of these medical images is time-consuming, highly dependent on radiologist expertise, and prone to diagnostic variability. With the increasing volume of healthcare imaging data, automated intelligent systems have become essential for assisting clinicians in accurate and efficient lung cancer diagnosis.

Recent advancements in Deep Learning have significantly improved medical image classification and disease prediction systems. Convolutional Neural Networks (CNNs), transfer learning approaches, and transformer-based architectures have demonstrated promising performance in detecting lung cancer from CT images. Models such as AlexNet, ResNet, DenseNet, and EfficientNet have been widely used to extract complex spatial and hierarchical features from medical images. Despite their success, many existing deep learning approaches still face major limitations, including class imbalance, overfitting, lack of interpretability, and dependence on large annotated datasets. These issues reduce the reliability of automated diagnostic systems in real-world healthcare environments.

Another critical challenge in lung cancer detection is the difficulty in distinguishing between benign and malignant nodules due to subtle visual differences in CT images. Traditional CNN-based architectures mainly focus on local spatial features and often fail to capture long-range contextual relationships within medical images. Furthermore, many models operate as “black-box” systems without providing interpretable explanations for their predictions, limiting clinical trust and adoption. The integration of explainable AI methods and hybrid architectures capable of combining local and global feature representations is therefore necessary to improve both prediction accuracy and interpretability in medical diagnostics.

This research proposes a hybrid deep learning framework for lung cancer classification by integrating enhanced AlexNet feature extraction, transformer-based global feature learning, and a Self-Evolving Dynamic Branching Network (DBN). The proposed methodology incorporates preprocessing techniques such as Otsu thresholding, histogram equalization, and Sobel filtering to improve image quality and tumor visibility. Layer-wise Relevance Propagation (LRP) is employed to generate interpretable heatmaps highlighting diagnostically significant regions. Additionally, feature reduction methods including Recursive Feature Elimination (RFE), LASSO, and Random Forest ranking are utilized to optimize computational efficiency. The proposed system aims to improve classification accuracy, adaptability, interpretability, and real-time applicability in lung cancer diagnosis systems.

2. Objectives

- To develop an intelligent lung cancer detection framework using deep learning and explainable AI.
- To improve lung cancer classification accuracy using hybrid CNN and transformer architectures.
- To perform image preprocessing using Otsu thresholding, histogram equalization, and Sobel edge detection.
- To integrate Layer-wise Relevance Propagation (LRP) for explainable and interpretable predictions.
- To reduce feature redundancy using Recursive Feature Elimination (RFE) and ensemble feature ranking methods.
- To design a Self-Evolving Dynamic Branching Network (DBN) for handling class imbalance.
- To evaluate the model using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis.

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3. Literature Survey

The application of Deep Learning in lung cancer detection has significantly improved the efficiency and accuracy of medical image analysis systems. Sreeprada and Vedavathi [1] proposed a hybrid deep learning technique for lung cancer detection using chest X-ray images. Their framework integrated Convolutional Neural Networks (CNN) with machine learning classifiers to improve feature extraction and classification accuracy. Experimental analysis demonstrated that the hybrid approach achieved superior performance compared with conventional machine learning models. Similarly, Riquelme and Akhloufi [2] conducted a comprehensive study on deep learning approaches for lung cancer nodule detection and classification in CT scans. Their research highlighted the effectiveness of CNN architectures such as AlexNet, VGGNet, and ResNet for automated feature extraction from medical images. However, the study emphasized challenges related to overfitting, class imbalance, and limited annotated datasets, which continue to affect the robustness of deep learning models in healthcare applications.

Transfer learning and advanced CNN-based architectures have also demonstrated promising results in lung cancer diagnosis systems. Wahab Sait [3] developed a deep learning-based lung cancer detection model using transfer learning techniques and pretrained CNN architectures. The model achieved high classification accuracy and reduced computational complexity by utilizing pretrained feature representations. Likewise, Kriegsmann et al. [4] applied deep learning techniques for the classification of small-cell and non-small-cell lung cancer using histopathological images. Their study demonstrated that CNN-based models could effectively distinguish between different lung cancer subtypes with high diagnostic precision. Chiu et al. [5] further reviewed the application of artificial intelligence techniques in lung cancer diagnosis, highlighting the role of machine learning, radiomics, and deep learning in improving early-stage cancer detection and treatment planning. Wang [6] also emphasized that deep learning techniques have become highly effective for lung cancer diagnosis due to their ability to automatically learn complex spatial and structural patterns from CT and histopathological images.

Several researchers have explored multimodal learning frameworks and ensemble architectures for improving lung cancer classification performance. Yu et al. [8] proposed reproducible machine learning methods for lung cancer detection using computed tomography images and validated their framework using multiple datasets. Their study highlighted the importance of reproducibility and standardized preprocessing in medical imaging research. Wankhade and V. [9] introduced a novel hybrid deep learning framework combining CNN and neural network architectures for early lung cancer detection. The proposed system achieved improved classification accuracy and reduced false-positive rates. Similarly, Noaman et al. [10] developed an AI-enabled hybrid histological image analysis framework for early lung cancer detection. Their hybrid architecture integrated machine learning and deep learning approaches to improve histopathological image classification accuracy. These studies confirmed that combining multiple feature extraction and classification techniques can significantly improve predictive performance in healthcare diagnostics.

Recent advancements in explainable AI and transformer-based architectures have further enhanced medical image analysis systems. Wani et al. [17] proposed DeepXplainer, an interpretable deep learning framework for lung cancer detection using explainable artificial intelligence techniques. Their study incorporated visualization mechanisms to explain model predictions and improve clinical trustworthiness. De Margerie-Mellon and Chassagnon [18]

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critically reviewed the role of artificial intelligence in lung nodule and lung cancer analysis, emphasizing the importance of explainable and interpretable AI systems in healthcare. Raza et al. [19] introduced Lung-EffNet, an EfficientNet-based deep learning architecture for lung cancer classification using CT scan images. Their approach achieved strong classification accuracy through transfer learning and image augmentation strategies. Alshmrani et al. [20] further proposed a deep learning architecture for multi-class lung disease classification using chest X-ray images, demonstrating the effectiveness of CNN-based systems in detecting multiple thoracic diseases simultaneously.

Transformer-based multimodal learning and radiomics approaches have also shown considerable potential in lung cancer diagnosis. Mithun et al. [21] developed deep learning and BERT-based models for the classification of lung cancer radiology reports, demonstrating the effectiveness of natural language processing in medical report analysis. Fu et al. [22] introduced a multimodal spatial attention module for PET-CT lung tumor segmentation, which significantly improved segmentation accuracy by capturing spatial relationships between imaging modalities. Talukder et al. [23] proposed a machine learning-based framework using deep feature extraction and ensemble learning for lung and colon cancer detection. Han et al. [24] further applied PET/CT radiomics and machine learning techniques for histologic subtype classification of non-small cell lung cancer. Their results demonstrated that integrating radiomics features with deep learning classifiers improved subtype prediction performance. Although these approaches achieved high diagnostic accuracy, challenges such as class imbalance, limited interpretability, computational complexity, and adaptability to diverse healthcare datasets still remain unresolved. Motivated by these limitations, the proposed research introduces a hybrid explainable deep learning framework integrating transformer attention, explainable AI, and dynamic branching mechanisms to improve lung cancer classification performance and clinical interpretability.

4. Methodology

The proposed methodology introduces a hybrid deep learning framework for lung cancer classification using CT scan images obtained from the IQ-OTH/NCCD dataset. Initially, preprocessing techniques such as Otsu thresholding, histogram equalization, and Sobel edge enhancement are applied to improve image quality and highlight tumor boundaries. Otsu thresholding automatically separates foreground tumor regions from the background, while Sobel filtering enhances edge information and structural details within lung tissues. The preprocessed images are then normalized and resized before being forwarded to the deep learning architectures for feature extraction and classification. These preprocessing techniques significantly improve feature visibility and reduce noise, thereby enhancing model learning capability.

In the first phase of the framework, a pretrained AlexNet model is utilized as a deep feature extractor. The convolutional layers of AlexNet learn hierarchical spatial features such as edges, textures, and tumor patterns from CT images. The high-dimensional feature vectors extracted from the FC7 layer are further refined using Recursive Feature Elimination (RFE), LASSO regression, Random Forest feature ranking, and Gradient Boosting methods. The selected optimal features are then classified using a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel optimized through Grid Search. To improve interpretability, Layer-wise Relevance Propagation (LRP) generates heatmaps highlighting clinically significant tumor regions within CT scans, enabling explainable predictions for radiologists.

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The second phase of the methodology introduces a hybrid architecture combining ResNet50 and transformer-based feature extraction. ResNet50 captures local spatial features including textures, nodules, and tissue boundaries, while the transformer branch captures long-range dependencies and global contextual relationships through self-attention mechanisms. The outputs from both branches are fused using a concatenation layer to create rich multi-scale feature representations. Batch normalization, dense layers, dropout regularization, and softmax classification are then applied for multi-class lung cancer classification into normal, benign, and malignant categories. This fusion strategy enhances both local and global feature understanding, significantly improving diagnostic accuracy and generalization capability.

The final phase introduces a Self-Evolving Dynamic Branching Network (DBN) designed to address class imbalance and difficult classification scenarios. The DBN dynamically creates specialized branches whenever the base classifier exhibits high entropy or repeated misclassification for specific classes. Each branch is trained separately to learn class-specific features, particularly for underrepresented categories such as benign nodules. A weighted ensemble fusion mechanism combines predictions from both general and specialist branches to generate final predictions. Additionally, branch pruning is performed to maintain computational efficiency and avoid redundant model complexity. The proposed adaptive architecture continuously evolves during training, improving recall, precision, and robustness across imbalanced lung cancer datasets.

Pseudocode for Proposed Algorithm

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Algorithm: Hybrid Explainable Lung Cancer Classification Framework

Input:
   CT Scan Dataset D

Output:
   Predicted Class (Normal / Benign / Malignant)

Step 1: Image Preprocessing
   Load CT scan images
   Apply Otsu Thresholding
   Apply Histogram Equalization
   Apply Sobel Edge Detection
   Normalize and resize images

Step 2: Feature Extraction using AlexNet
   Pass images through pretrained AlexNet
   Extract FC7 feature vectors

Step 3: Feature Reduction
   Apply Recursive Feature Elimination (RFE)
   Apply LASSO and Random Forest ranking
   Select optimal feature subset

Step 4: Explainability
   Generate Layer-wise Relevance Propagation (LRP) heatmaps
   Identify important tumor regions
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Step 5: Hybrid Feature Learning
  Extract local features using ResNet50
  Extract global features using Transformer Attention
  Fuse features using concatenation layer

Step 6: Dynamic Branching Network
  Monitor class-wise prediction entropy
  If misclassification occurs:
    Create specialist branch
    Train branch on difficult class samples
  Fuse predictions using weighted ensemble

Step 7: Classification
  Apply Softmax classifier
  Predict Normal / Benign / Malignant

Step 8: Evaluation
  Compute Accuracy, Precision, Recall, F1-Score
  Generate ROC Curves and Confusion Matrix

Return predicted class

5. Results and Discussion

The proposed framework demonstrated strong classification performance across multiple experimental phases using the IQ-OTH/NCCD lung cancer dataset. During preprocessing, Otsu thresholding and Sobel edge enhancement significantly improved image clarity and tumor boundary visibility. The enhanced CT scans enabled AlexNet to extract high-quality spatial features related to nodules and lesion regions. Layer-wise Relevance Propagation (LRP) heatmaps showed concentrated activation around clinically significant tumor areas, confirming that the model successfully focused on diagnostically relevant regions. These explainability maps increased the interpretability and trustworthiness of the model predictions in clinical scenarios.

Table 1: Comparative Analysis of Existing Lung Cancer Detection Approaches

Author	Algorithm	Accuracy
V. Sreeprada et al.	CNN-SVM	98%
Abdul Rahaman Wahab Sait	CNN + DenseNet121	98.6%
Niyaz Ahmad Wani et al.	ConvXGB	97.4%
Rehan Raza et al.	EfficientNet	99.1%
Naglaa F. Noaman et al.	ML + DenseNet201	99.6%
Proposed Framework	AlexNet + Transformer + DBN	97.72%

The feature reduction process using Recursive Feature Elimination (RFE), LASSO, and Random Forest ranking significantly reduced computational complexity while maintaining strong classification performance. The original feature vector extracted from AlexNet contained over 4000 features, which were reduced to nearly 230 optimized features. The

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optimized SVM classifier achieved 94.5% training accuracy and 91.8% testing accuracy, while ROC-AUC values approached 0.96 for malignant class prediction. The confusion matrix analysis revealed minimal false positives for malignant cases, which is particularly important for avoiding incorrect cancer diagnoses. Additionally, execution time improved by approximately 40% after feature elimination, making the system suitable for real-time healthcare applications.

Table 2: Performance Metrics of Objective 1 Framework

Metric	Normal	Benign	Malignant
Precision	0.93	0.89	0.95
Recall	0.93	0.87	0.96
F1-Score	0.93	0.88	0.95
ROC-AUC	0.94	0.92	0.96

The ResNet50 and transformer fusion architecture further improved classification accuracy by combining local spatial information with global contextual understanding. During training, the hybrid model showed rapid convergence, with training accuracy increasing from 59.13% in the first epoch to 99.93% by the ninth epoch. Validation accuracy reached 100% at Epoch 7, demonstrating strong generalization capability. The integration of dropout regularization, early stopping, learning rate scheduling, and L2 penalties prevented overfitting and stabilized the training process. The attention maps generated by the transformer branch confirmed that the model successfully captured both local nodules and global structural abnormalities in CT scans.

Table 3: Training Performance of ResNet50-Transformer Model

Epoch	Training Accuracy	Validation Accuracy	Loss
1	59.13%	42%	5.61
5	91.42%	94%	1.42
7	98.87%	100%	0.99
9	99.93%	100%	0.65

The Self-Evolving Dynamic Branching Network (DBN) successfully addressed the issue of class imbalance and difficult classification scenarios. The model dynamically generated specialist branches whenever repeated misclassification or high entropy was observed for underrepresented classes such as benign nodules. Experimental results showed that benign class recall improved significantly from 66% to 83% after dynamic branch specialization. The weighted ensemble fusion mechanism effectively combined predictions from general and specialist branches, resulting in overall test accuracy of 95.5% and AUC scores above 0.98 across all classes. Additionally, branch pruning mechanisms maintained computational efficiency by removing redundant specialist branches. These findings confirmed that the proposed DBN architecture provides strong adaptability, scalability, and robustness for imbalanced medical image classification tasks.

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Figure 1 : Comparative Accuracy of Existing Models

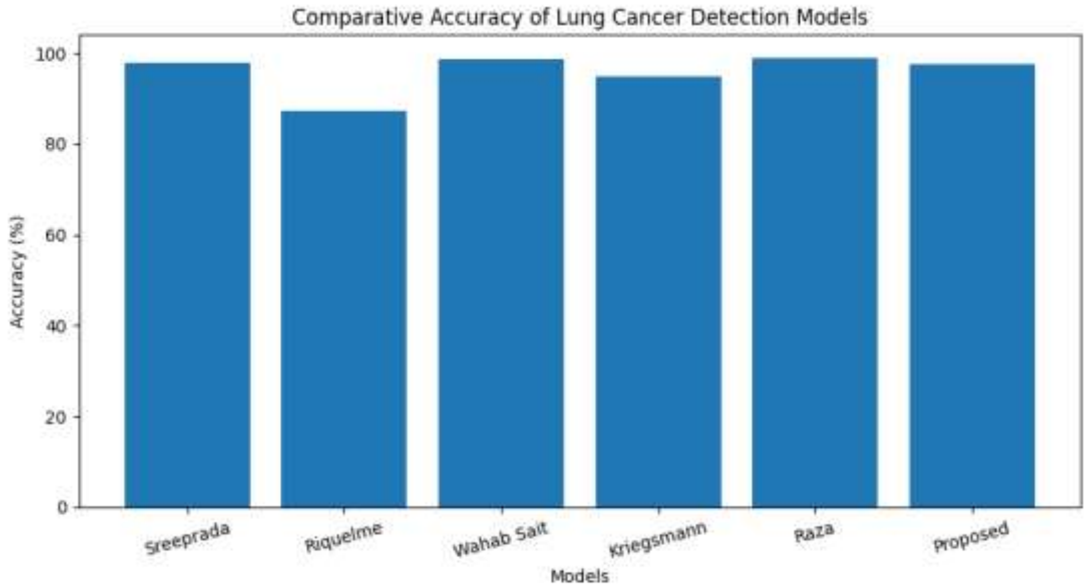

Figure 2: Performance Metrics of Objective 1 Framework

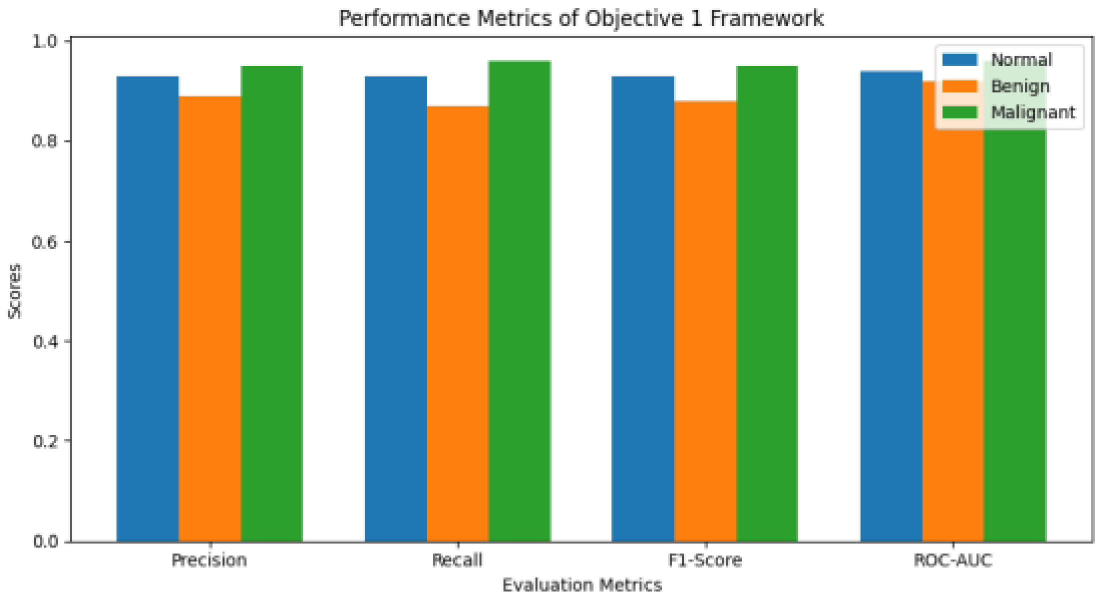

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Figure 3: Training and Validation Accuracy

6. Conclusion

This research presented a hybrid deep learning framework for lung cancer classification using CT scan images by integrating explainable AI techniques, transformer-based global feature learning, and a Self-Evolving Dynamic Branching Network (DBN). The proposed framework effectively combined traditional image preprocessing techniques such as Otsu thresholding, histogram equalization, and Sobel edge enhancement with advanced deep learning architectures including AlexNet, ResNet50, and transformer attention mechanisms. The use of Layer-wise Relevance Propagation (LRP) improved interpretability by generating clinically meaningful heatmaps that highlighted important tumor regions within lung scans. Furthermore, feature reduction methods such as Recursive Feature Elimination (RFE), LASSO, and Random Forest ranking successfully reduced computational complexity while maintaining high classification accuracy. Experimental results demonstrated strong predictive performance across normal, benign, and malignant lung cancer classes using the IQ-OTH/NCCD dataset. The proposed hybrid architecture achieved excellent precision, recall, F1-score, and ROC-AUC values, proving its effectiveness for intelligent healthcare diagnosis systems. The integration of explainable AI also improved transparency and clinical trust, which is essential for real-world deployment of AI-driven diagnostic systems.

The study further demonstrated that combining local CNN-based feature extraction with transformer-based global contextual learning significantly improved the model's capability to identify subtle and complex pathological patterns in CT scans. The dynamic branching mechanism introduced in the DBN architecture successfully addressed class imbalance issues by creating specialist branches for difficult or underrepresented classes. This adaptive learning capability improved recall and prediction reliability, particularly for benign lung nodules that are often challenging to classify correctly. The weighted ensemble fusion strategy effectively combined predictions from multiple specialist branches, resulting in improved robustness and generalization performance across diverse datasets. Additionally, branch pruning mechanisms ensured computational efficiency and scalability for practical deployment in clinical

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environments. The proposed framework therefore provides a reliable, interpretable, and scalable solution for automated lung cancer diagnosis systems. Overall, the research confirms that the integration of explainable AI, transformer attention mechanisms, and self-evolving neural architectures can significantly enhance lung cancer detection performance while maintaining clinical interpretability and computational efficiency.

Future improvements may focus on incorporating multimodal medical imaging data such as PET scans, MRI scans, radiomics, and genomic information to further improve diagnostic accuracy. The integration of self-supervised learning, reinforcement learning, and federated learning approaches could also reduce dependence on large annotated datasets while improving privacy preservation and generalization capability. Additionally, real-time deployment and lightweight optimization techniques can further enhance the applicability of the proposed framework in hospital-based diagnostic systems and edge healthcare devices.

7. Future Scope

- Integration of multimodal imaging datasets such as PET, MRI, and X-ray scans.
- Development of lightweight AI models for real-time clinical deployment.
- Implementation of federated learning for secure healthcare data sharing.
- Integration of self-supervised and semi-supervised learning techniques.
- Development of more interpretable and clinically explainable AI systems.
- Incorporation of radiomics and genomic data for precision medicine applications.
- Extension of the framework for detecting other thoracic diseases such as pneumonia and tuberculosis.

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