Hybrid Deep Learning Framework Using AlexNet, VGG16, and PSO–GA Optimization for Lung Cancer Detection from CT Scans

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Abstract
Lung cancer remains one of the leading causes of cancer-related deaths worldwide, primarily due to delayed diagnosis and limitations in manual interpretation of CT scans. This study proposes a hybrid deep learning framework that integrates AlexNet and VGG16 for feature extraction with a hybrid Particle Swarm Optimization–Genetic Algorithm (PSO–GA) for feature selection and hyperparameter optimization. The framework was evaluated using publicly available LIDC-IDRI and NSCLC-Radiomics datasets containing benign and malignant CT images. Preprocessing techniques including normalization, denoising, resizing, and augmentation were applied to improve data quality and reduce overfitting. Deep features extracted from AlexNet and VGG16 were optimized through the PSO–GA mechanism to retain the most discriminative features while reducing redundancy. A dual-stage classifier was then employed for lung nodule classification. Experimental results demonstrated classification accuracies of 95.2% and 94.7% on LIDC-IDRI and NSCLC-Radiomics datasets respectively, outperforming baseline CNN approaches. Grad-CAM visualization further improved interpretability by highlighting clinically relevant regions in CT scans. The proposed framework provides an accurate, scalable, and clinically interpretable solution for automated lung cancer detection.

Keywords
Lung Cancer Detection, AlexNet, VGG16, PSO–GA, CT Scan Analysis, Deep Learning, Medical Imaging.

1. Introduction

Lung cancer is among the most critical health challenges worldwide and is responsible for millions of deaths every year. Early diagnosis significantly improves patient survival rates, yet conventional diagnostic approaches often fail to detect cancer at an early stage. Computed Tomography (CT) imaging plays a major role in identifying lung nodules; however, manual interpretation is time-consuming and prone to observer variability. Recent developments in Artificial Intelligence (AI) and deep learning have improved automated medical image analysis. Convolutional Neural Networks (CNNs) such as AlexNet and VGG16 can automatically learn complex image features from CT scans and provide high diagnostic accuracy. Despite these advantages, CNN-based systems often generate high-dimensional feature vectors containing redundant information, which may increase computational complexity and overfitting. To address these limitations, optimization techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been widely explored. PSO provides rapid convergence while GA enhances global search capability through evolutionary operations. Integrating these methods enables efficient feature selection and hyperparameter optimization. In this work, a hybrid framework combining AlexNet, VGG16, and PSO–GA optimization is proposed for accurate and interpretable lung cancer detection from CT scans.

2. Methodology

The proposed methodology consists of five major stages: data acquisition, preprocessing, feature extraction, hybrid optimization, and classification.

2.1 Data Acquisition and Preprocessing

The framework uses the LIDC-IDRI and NSCLC-Radiomics datasets containing annotated CT images of benign and malignant lung nodules. CT images were preprocessed using Gaussian and median filtering to reduce noise while preserving edge details. Intensity normalization was applied to standardize pixel values. Images were resized according to CNN input dimensions, and data augmentation methods such as flipping, rotation, and deformation were employed to improve generalization and handle class imbalance.

2.2 Feature Extraction

AlexNet and VGG16 were employed as feature extractors using transfer learning. AlexNet captures low-level features such as texture and edges, while VGG16 extracts deeper structural and spatial representations. Fine-tuning on lung CT datasets improved feature relevance for medical image analysis. Feature vectors obtained from both networks were combined to provide comprehensive image representation.

2.3 PSO–GA Hybrid Optimization

The extracted features were optimized using a hybrid PSO–GA algorithm. PSO was used for rapid convergence and optimal feature weighting, whereas GA enhanced feature subset selection using crossover and mutation operations. This hybrid strategy reduced redundant features, minimized overfitting, and optimized classifier hyperparameters.

2.4 Dual-Stage Classification and Interpretability

A dual-stage classification framework was implemented. The first stage performed coarse CNN-based screening to identify suspicious nodules, while the second stage used optimized features for refined classification. Grad-CAM visualization techniques were incorporated to highlight important regions influencing model decisions, thereby improving interpretability and clinical reliability.

3. Results and Discussion

The proposed framework was evaluated using accuracy, sensitivity, specificity, F1-score, and Area Under Curve (AUC). Table 1 summarizes the classification results.

Table 1: Performance Evaluation of Proposed Framework

Dataset/Validation	Accuracy	Sensitivity	Specificity	F1-Score	AUC
LIDC-IDRI	95.2%	93.8%	96.1%	94.5%	0.981
NSCLC-Radiomics	94.7%	93.2%	95.5%	94%	0.978

The results demonstrate that the proposed hybrid framework outperformed standalone CNN models due to effective feature optimization and dual-stage classification. AlexNet efficiently captured texture-level information, while VGG16 extracted higher-level structural features. The PSO–GA mechanism significantly reduced feature redundancy and improved classifier generalization. The computational performance was also suitable for practical implementation, with inference time remaining below one second per CT slice. Grad-CAM visualizations successfully highlighted suspicious nodule regions, improving transparency and assisting clinicians in validating automated predictions. These findings confirm that combining deep learning with nature-inspired optimization improves both diagnostic accuracy and interpretability.

4. Conclusion

This study presented a hybrid deep learning framework integrating AlexNet, VGG16, and PSO–GA optimization for lung cancer detection from CT scans. The framework effectively combined complementary CNN features with optimized feature selection to improve classification accuracy and reduce redundancy. Experimental evaluation on LIDC-IDRI and NSCLC-Radiomics datasets demonstrated superior performance compared to conventional CNN-based approaches.

The proposed method achieved high sensitivity and specificity while maintaining computational efficiency suitable for clinical applications. Grad-CAM-based interpretability further enhanced transparency and clinician trust. Future work may focus on multimodal imaging integration, lightweight architectures, and validation using larger multicenter datasets to improve real-world deployment.

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