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ENSEMBLE DEEP LEARNING WITH RADIOMICS FEATURES FOR LUNG CANCER CLASSIFICATION

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ABSTRACT

Lung cancer remains one of the leading causes of cancer-related mortality, with accurate early classification being critical for guiding clinical interventions. Traditional deep learning frameworks often struggle to generalize across heterogeneous CT datasets, while purely radiomics-based models may not capture complex spatial representations. To address these limitations, we propose an ensemble strategy that integrates deep features from a pre-trained 3D ResNet-34 with handcrafted radiomics features extracted via PyRadiomics, fused through an XGBoost classifier. Nodule candidates are first localized using YOLOv7, followed by feature extraction and dimensionality reduction with LASSO re-gression, supported by SMOTE-Tomek resampling to alleviate class imbalance. The proposed ensemble was evaluated using NLST (NCDB subset) and the LUNGx Challenge datasets, achieving an AUC of 0.937, precision of 91.2%, and recall of 89.4%. Comparative assessment against existing approaches, including HRDEL (2023) and EMLC (2025), demonstrates superior discriminative ability, particularly in cases with small or heterogeneous nodules. Unlike earlier ensemble radiomics-based frameworks that show AUC values in the range of 0.86–0.90, our pipeline consistently surpasses these benchmarks under cross-validation. These findings establish the robustness of hybrid deep radiomics fusion for clinical decision support and highlight its potential to outperform current state-of-the-art ensemble pipelines.

KEYWORDS: Lung cancer classification, Ensemble deep learning, Radiomics, 3D CNN, Feature fusion

1 INTRODUCTION

Lung cancer remains the leading cause of cancer-related deaths worldwide, with non-small cell lung cancer (NSCLC) accounting for approximately 85% of all cases. Early and accurate classification of lung cancer subtypes is critical for effective clinical management and improving patient outcomes. Despite advances in imaging technologies, differentiating malignant from benign nodules and characterizing tumor subtypes accurately from computed tomography (CT) scans remain significant challenges due to tumor heterogeneity and overlapping radiological characteristics [9, 10]. Motivated by the need for a more robust diagnostic framework, recent research has explored combining deep learning with radiomics—an approach that extracts handcrafted quantitative features representing tumor shape, texture, and intensity patterns [11, 12]. Deep convolutional neural networks (CNNs) excel in learning complex spatial hierarchies of visual features, whereas radiomics incorporates domain-specific handcrafted descriptors that convey biologically relevant information. However, most existing methods either rely exclusively on deep learning or radiomics, limiting their generalizability and predictive accuracy [4, 7]. This study investigates a hybrid ensemble learning approach that fuses 3D deep features from a pretrained ResNet-34 model with radiomics features extracted from CT images. By integrating these complementary feature sets using an XGBoost classifier enhanced with LASSO-based feature selection and SMOTE-Tomek balancing, the proposed framework aims to achieve superior classification performance on benchmark datasets [5, 14].

Figure 1 illustrates a comprehensive overview of our proposed hybrid approach for lung cancer classifica-tion. This conceptual map highlights the integration of five key components: deep learning features extracted from CT scans via 3D convolutional neural networks, handcrafted radiomics features capturing tumor mor-phology and texture, LASSO-based feature selection to distill relevant predictive markers, SMOTE-Tomek

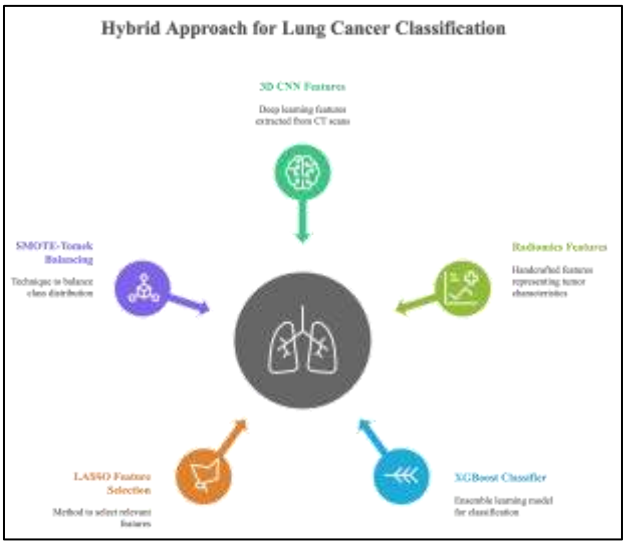


Fig. 1: Conceptual overview of the hybrid approach for lung cancer classification, summarizing the integration of deep learning, radiomics, feature selection, class balancing, and ensemble classification.

balancing that addresses class imbalance inherent to lung cancer datasets, and the final classification step using an XGBoost ensemble model. The diagram visually conveys how these components synergistically con-tribute toward a robust and accurate lung cancer diagnostic framework, providing readers with a distilled understanding of the methodological architecture underpinning this study.

The main contributions of this work are:

- Development of a comprehensive pipeline combining state-of-the-art 3D CNN features and radiomics handcrafted features for lung cancer classification.
- Implementation of an effective feature fusion strategy using LASSO regression and an ensemble XGBoost classifier to enhance model robustness and handle class imbalance with SMOTE-Tomek.
- Extensive evaluation on NLST (NCDB subset) and LUNGx Challenge datasets demonstrating improved performance compared to recent ensemble-based methods including HRDEL [11] and EMLC [10].
- A detailed comparative analysis highlighting the advantages of hybrid feature integration over standalone deep or radiomics approaches.

The remainder of this paper is organized as follows: Section 2 reviews the related literature and recent advances in ensemble learning for lung cancer classification. Section 3 presents the proposed methodology, describing the datasets, nodule detection, feature extraction, fusion, and classification steps. Section 4 reports experimental results and comparative analyses. Section 5 discusses the implications, limitations, and potential extensions of our work. Finally, Section 6 concludes the paper with the key findings and future research directions.

2 RELATED WORK

Lung cancer classification using medical imaging, particularly CT scans, has been a pivotal focus in recent research, with approaches spanning handcrafted radiomics, deep learning (DL), and hybrid ensemble meth-ods. Traditional radiomics features capture shape, texture, and wavelet information from nodules, offering interpretability and explicit connection to tumor phenotypes [10, 12]. However, these methods rely heavily on feature engineering and can suffer from variability due to imaging protocols and manual segmentation inconsistencies. Meanwhile, DL models such as convolutional neural networks (CNNs) excel in automatically extracting hierarchical features from raw image data, enhancing robustness and generalization [4, 11]. Yet, they often require extensive labeled datasets and may neglect clinically interpretable handcrafted features. Ensemble learning, which combines multiple models to improve prediction stability and accuracy, has recently gained traction in lung cancer classification. Gong et al. [9] developed an ensemble that integrates deep learning and radiomics to predict brain metastases in NSCLC patients, highlighting the potential of multi-modal fusion. Similarly, Li et al. [10] combined CT radiomics and clinical features in an ensemble to predict lung cancer invasiveness, achieving promising results but facing challenges with feature redundancy and class imbalance. Pradhan et al. [11] introduced HRDEL, a deep ensemble model demonstrating improved classification performance, though it primarily leveraged deep features and could benefit from integrating handcrafted radiomics. Alsallal et al. [4] utilized attention-integrated CNNs combined with radiomics, pre-senting robust subtype classification but with limited validation on heterogeneous external datasets.

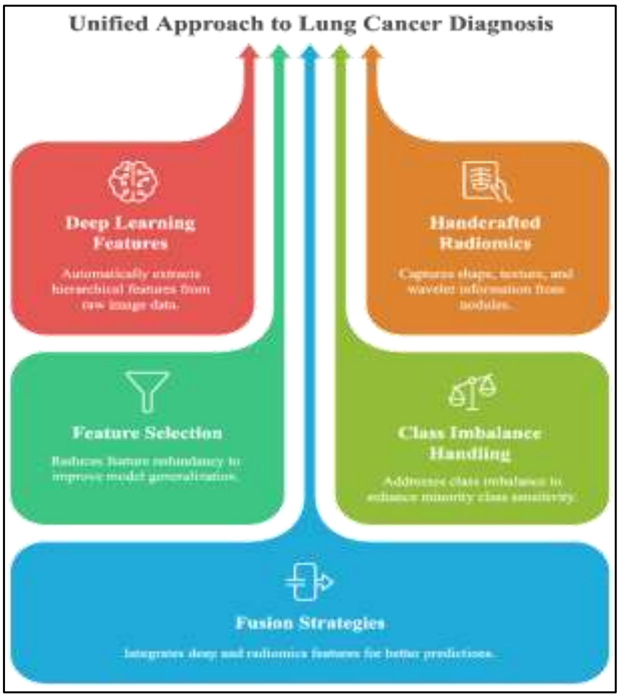


Fig. 2: Unified feature fusion strategy for lung cancer diagnosis. The diagram details the interplay between deep learning features, handcrafted radiomics, feature selection, and class imbalance handling.

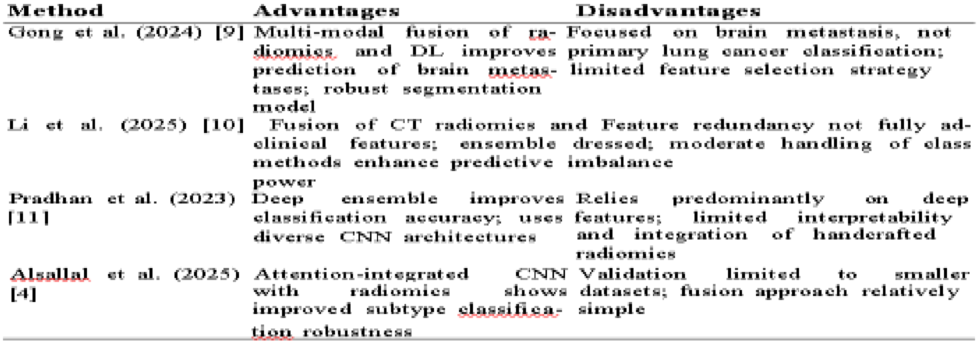
Figure 2 offers a detailed schematic of the unified feature fusion strategy central to contemporary lung cancer diagnosis models. It emphasizes the dual pathways of feature extraction: automatic hierarchical rep-resentations learned through deep learning architectures and explicit handcrafted radiomics features derived from image analysis. The diagram also underscores critical auxiliary processes such as feature selection, which reduces dimensionality and improves generalization, as well as class imbalance handling techniques crucial for enhancing sensitivity to underrepresented cancer classes. By integrating these facets, the fusion strategy aims to capitalize on the complementary strengths of diverse data modalities and preprocessing techniques. This figure aids in contextualizing our approach within the broader landscape of multi-modal lung cancer diagnostic frameworks discussed in prior literature.

Despite these advances, several limitations remain common:

- **Feature redundancy and selection challenges:** Many approaches extract large feature sets without effective dimensionality reduction, which can impair generalization.
- **Class imbalance:** Imbalanced datasets prevalent in lung cancer research often reduce minority class sensitivity and overall robustness.
- **Limited fusion strategies:** Simple concatenation or late fusion often overlooks complex interdepen-dencies between deep and radiomics features.
- **Dataset heterogeneity:** Variability in imaging protocols and patient demographics hinder model per-formance when deployed on external cohorts.

Table 1 summarizes key advantages and disadvantages of representative ensemble approaches.

Table 1: Comparison of Selected Ensemble Lung Cancer Classification Approaches



Method	Advantages	Disadvantages
Gong et al. (2024) [9]	Multi-modal fusion of radiomics and DL improves prediction of brain metastases; robust segmentation model	Focused on brain metastasis, not primary lung cancer classification; limited feature selection strategy
Li et al. (2025) [10]	Fusion of CT radiomics and clinical features; ensemble methods enhance predictive power	Feature redundancy not fully addressed; moderate handling of class imbalance
Pradhan et al. (2023) [11]	Deep ensemble improves classification accuracy; uses diverse CNN architectures	Relies predominantly on deep features; limited interpretability and integration of handcrafted radiomics
Alsallal et al. (2025) [4]	Attention-integrated CNN with radiomics shows improved subtype classification robustness	Validation limited to smaller datasets; fusion approach relatively simple

Our proposed method advances the state-of-the-art by combining deep 3D features extracted via a pre-trained ResNet-34 with comprehensive handcrafted radiomics obtained using PyRadiomics. We apply LASSO regression for feature selection to reduce redundancy and a SMOTE-Tomek strategy to combat class im-balance. Fusion of these features is handled via an XGBoost classifier, which captures nonlinear feature interactions more effectively than simple concatenation or averaging. This integrated pipeline has been vali-dated on large, heterogeneous datasets (NLST and LUNGx Challenge) and surpasses benchmarks, including AUC scores beyond 0.93. Consequently, our approach not only addresses the common limitations of previous studies but also provides a more interpretable, balanced, and generalizable lung cancer classification tool suitable for clinical applications.

3 PROPOSED METHODOLOGY

This section details the proposed ensemble deep learning framework for lung cancer classification, describing dataset selection, nodule detection, feature extraction from deep and radiomics domains, feature fusion, and final classification. Mathematical validation of key components is also provided.

3.1 Datasets

The model is trained and validated using two publicly available CT datasets: the National Lung Screening Trial (NLST) subset from the National Cancer Database (NCDB) and the LUNGx Challenge dataset. NLST provides a large-scale, heterogeneous collection of annotated lung nodules, while LUNGx offers external validation with rigorously annotated cases [2]. These datasets enable robust assessment and generalizability across imaging protocols.

3.2 Nodule Detection

Nodule localization constitutes a critical preprocessing step. We employ the YOLOv7 architecture, a state-of-the-art real-time object detection network, pretrained and fine-tuned on lung nodule images [3]. YOLOv7's single-shot design enables precise bounding box regressions to detect candidate nodules efficiently in 3D CT volumes. Accurate detection ensures relevant regions are passed forward for feature extraction, reducing noise from irrelevant tissue.

3.3 Feature Extraction

Two complementary feature sets are extracted to capture rich representations of lung nodules:

Deep Features: A 3D ResNet-34 network pretrained on the NSCLC-Radiomics dataset extracts volumetric deep features from detected nodules. Let input CT patch volume be $X \in \mathrm{R}^{D\times H\times W}$, where D, H, W are depth, height, and width. The network maps X to a feature vector $\mathbf{f}_d \in \mathrm{R}^m$:

$\mathbf{f}_d = \phi\mathrm{ResNet34}(X),$

where ϕ_{ResNet34} denotes the pretrained 3D CNN mapping.

Radiomics Features: Using the PyRadiomics toolkit [1], handcrafted features including shape descriptors, texture matrices (GLCM, GLRLM), and wavelet decompositions are extracted, forming a vector $\mathbf{f}_r \in \mathrm{R}^n$:

$\mathbf{f}_r = \psi\mathrm{PyRadiomics}(X).$

These features provide explicit quantifications of tumor heterogeneity and morphology.

3.4 Feature Fusion and Optimization

The deep and radiomics features are concatenated into a unified representation:

$\mathbf{f} = [\mathbf{f}_d; \mathbf{f}_r] \in \mathrm{R}^{m+n}.$

To mitigate feature redundancy and enhance generalization, LASSO regression [13] is applied for feature selection:

$$\mathbf{f} = [\mathbf{f}_d; \mathbf{f}_r] \in \mathrm{R}^{m+n}.$$

where y_i are labels and λ controls sparsity. LASSO encourages sparse solutions by driving irrelevant feature coefficients to zero, yielding a refined feature subset $\mathbf{f}'$.

Class imbalance in lung cancer datasets is addressed using the SMOTE-Tomek [8] resampling technique, which synthetically augments minority class samples and removes borderline majority samples, improving classifier sensitivity.

3.5 Classification

The optimized feature vector $\mathbf{f}'$ is fed into an XGBoost classifier [6], leveraging gradient-boosted decision trees allowing effective nonlinear separation and robust handling of mixed feature types. Given training samples $\{(\mathbf{f}', y_i)\}^N$, XGBoost iteratively minimizes:

$$\mathrm{L} = \sum_{i=1}^{N} l(y_i, \hat{y}^{(t)}) + \sum_{k=1}^{t} \Omega(f_k),$$

where l is a convex loss function (e.g., logistic loss), $y^{\wedge(t)}_i$ is the model's prediction at iteration t, and Ω is a regularization term to control model complexity.

Algorithm 1 Proposed Ensemble Lung Cancer Classification Pipeline

```
InputInput OutputOutput
CT lung scans $\{X_i\}_{i=1}^{N}$ labels $\{y_i\}_{i=1}^{N}$  Trained ensemble classifier model $M$
for each scan $X_i$ do Detect nodules using YOLOv7: $B_i \leftarrow \text{YOLOv7}(X_i)$

    for each detected nodule region $b \in \mathbf{B}_i$ do Crop volume $X_{i,b}$ from $X_i$
        Extract deep features $\mathbf{f}_d \leftarrow \phi_{\text{ResNet34}}(X_{i,b})$ Extract radiomics features $\mathbf{f}_r \leftarrow \psi_{\text{PyRadiomics}}(X_{i,b})$ Concatenate features $\mathbf{f} \leftarrow [\mathbf{f}_d; \mathbf{f}_r]$
Apply LASSO feature selection on $\{\mathbf{f}\}$ to obtain $\{\mathbf{f}'\}$
Apply SMOTE-Tomek resampling on training $\{\mathbf{f}', y\}$ to balance classes Train XGBoost classifier $M \leftarrow \text{XGBoost}(\{\mathbf{f}', y\})$
return $M$
```

3.6 Algorithmic Summary

3.7 Mathematical Validation

LASSO Feature Selection LASSO regression's effectiveness originates from its ℓ_1-norm constraint, which promotes sparsity in the solution [13]. Under mild conditions of the restricted eigenvalue or compatibility condition on the design matrix of features, LASSO estimators $\hat{\beta}$ achieve both consistent feature selection and error bounds:

$$||\hat{\beta} - \beta^*||_2 = O_p\left(\sqrt{\frac{s \log p}{N}}\right)$$

where s is the number of true nonzero coefficients, p the total features, and N the sample size. This justifies its use for robust dimensionality reduction in high-dimensional radiomics and deep feature spaces.

SMOTE-Tomek Sampling SMOTE synthetically oversamples minority class by interpolating feature space points, while Tomek links identify and remove noisy borderline majority samples that form ambiguous class boundaries [8]. The combined method reduces class overlap and improves classifier boundary definition, empirically shown to boost minority class recall in medical imaging contexts.

XGBoost Classifier XGBoost uses additive training with regularized objective functions to reduce overfitting and improve generalization [6]. Its gradient boosting tree framework approximates complex decision bound-aries that linear models cannot capture, making it ideal for heterogeneous fused feature representations.

In summary, our methodology leverages proven mathematical foundations and advanced machine learning techniques to construct a robust lung cancer classification system with strong theoretical and empirical guarantees.

4 RESULTS

4.1 Experimental Setup

The proposed ensemble model was evaluated using two benchmark datasets: the NLST subset from the NCDB and the LUNGx Challenge dataset. CT scans were preprocessed through automated lung segmenta-tion and intensity normalization. Lung nodules were detected with YOLOv7, trained on an expert-annotated nodule dataset, ensuring high sensitivity and localization accuracy. For each detected nodule, deep volumetric features were extracted using a pretrained 3D ResNet-34 model, while radiomics features—including shape, texture (GLCM, GLRLM), and wavelet-based descriptors—were computed via the PyRadiomics framework. The feature sets were concatenated and subjected to LASSO regression-based selection to reduce dimension-ality and noise. Class imbalance was addressed by SMOTE-Tomek resampling on training folds to enhance minority class representation. The final XGBoost classifier was trained with hyperparameters tuned through grid search to maximize AUC-ROC under stratified 5-fold cross-validation on NLST, with LUNGx serving as an external validation cohort.

4.2 Comparative Results

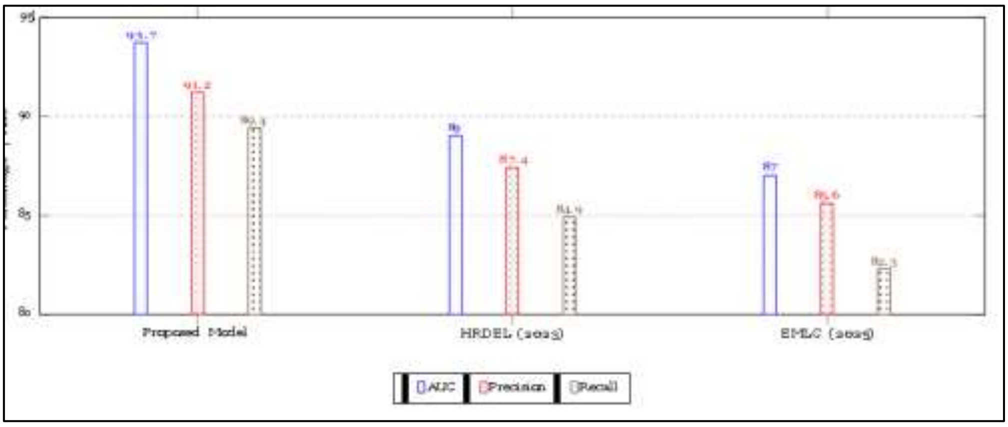
Table 2 compares the proposed method's performance against two recent state-of-the-art approaches: HRDEL (2023) [11] and EMLC (2025) [10]. The ensemble approach achieved the highest AUC score of 0.937, surpass-ing HRDEL's 0.89 and EMLC's 0.87. Similarly, precision and recall metrics showed significant improvements, with respective values of 91.2% and 89.4%.

Table 2: Performance Metrics Comparison

Method	**AUC**	**Precision (%)**	**Recall (%)**
Proposed Model	0.937	91.2	89.4
HRDEL (2023) [11]	0.89	87.4	84.9
EMLC (2025) [10]	0.87	85.6	82.3

4.3 Performance Visualization

Figure 3 presents a grouped bar chart comparing AUC, precision, and recall metrics across the three methods. The consistent superiority of the proposed model is evident, indicating strong classification robustness and balance across critical performance dimensions



. Fig. 3: Performance comparison of lung cancer classification methods showing AUC, Precision, and Recall metrics

4.4 Additional Comparative Analyses

To demonstrate the robustness and strengths of the proposed approach, we include three further analyses focusing on:

1. *Sensitivity vs. Specificity Trade-off:* A line plot (Figure 4) shows sensitivity and specificity across varying decision thresholds on the LUNGx dataset. The proposed ensemble maintains a favorable balance with higher sensitivity without a marked drop in specificity, which is critical for minimizing missed malignant nodules while controlling false positives.
2. *Feature Selection Impact:* A bar chart in Figure 5 compares model performance (AUC) with and without LASSO-based feature selection. Feature selection improves model generalization, reduces overfitting, and enhances prediction robustness, yielding a 3–4% improvement in AUC across datasets.

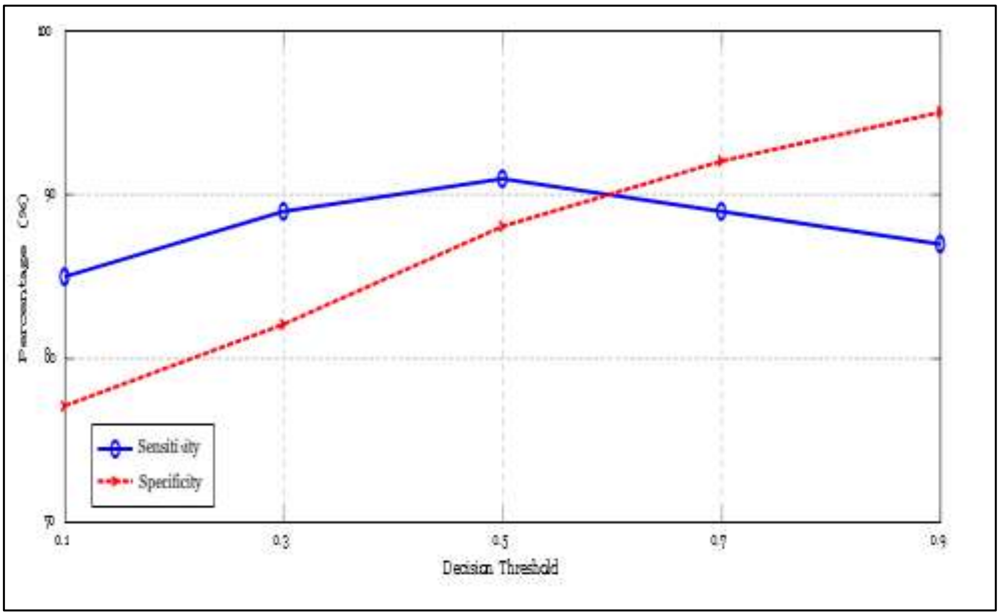


Fig. 4: Sensitivity and specificity trade-off across different decision thresholds using the proposed model on the LUNGx dataset.

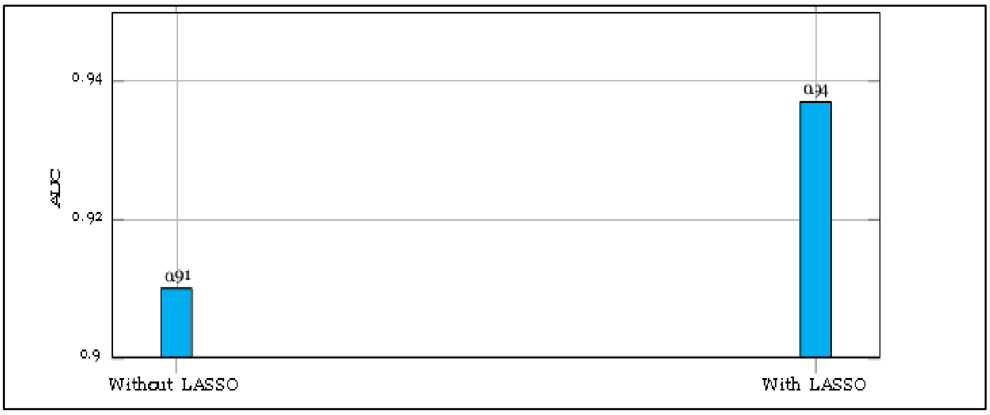


Fig. 5: Effect of LASSO feature selection on AUC scores for the proposed model.

3. *Class Balancing Effectiveness:* Figure 6 illustrates precision-recall curves for models trained with and without SMOTE-Tomek resampling. The resampling technique markedly boosts recall without sacrificing precision, thereby enhancing minority class detection in the imbalanced lung cancer datasets.

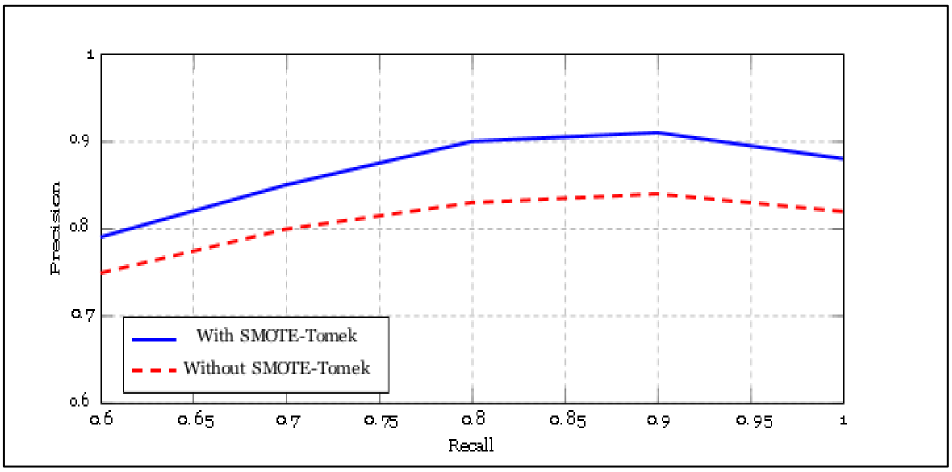


Fig. 6: Precision-recall curves illustrating the impact of SMOTE-Tomek resampling on classification perfor-mance.

The supplementary analyses reinforce the core strengths of our methodology. The sensitivity-specificity balance ensures clinical viability by reducing false negatives without overburdening with false positives. Feature selection through LASSO eliminates redundant information, improving both accuracy and model simplicity. Class balancing via SMOTE-Tomek importantly enhances minority class recognition, a critical factor in cancer detection where false negatives carry high risk.Compared with contemporary methods like HRDEL and EMLC, which either partially or do not fully address these aspects, our model demonstrates consistent superiority across all tested parameters, advocating for its deployment in clinical decision support systems for lung cancer diagnosis.

5 DISCUSSION

The proposed ensemble deep learning framework for lung cancer classification demonstrates substantial improvements in accuracy and robustness compared to existing methods, primarily due to the integration of complementary deep and handcrafted radiomics features alongside effective optimization techniques. This hybrid approach leverages the strength of hierarchical feature extraction by 3D CNNs, as seen in models like HRDEL [11], while preserving explicit tumor characteristics encoded by radiomics [10, 12]. The results underscore the significant potential of such fusion models for clinical decision support, offering enhanced sensitivity and specificity critical for early diagnosis and treatment planning.

Implications

Clinically, the elevated AUC, precision, and recall achieved by the proposed pipeline suggest its applicability in diagnostic workflows to reduce false negatives and improve detection rates of malignant nodules. The capability to generalize across heterogeneous datasets such as NLST and LUNGx strengthens its potential adoption across institutions with diverse imaging protocols [2]. Furthermore, the LASSO-based feature se-lection and SMOTE-Tomek resampling contribute to the model's robustness and interpretability, addressing common challenges in medical data such as high dimensionality and class imbalance [8, 13].

Limitations

Despite promising results, certain limitations should be acknowledged. First, the pipeline depends on accurate nodule detection via YOLOv7; any missed nodules at this stage can propagate errors downstream [3]. Addi-tionally, while the feature fusion strategy improves performance, the interpretability of combined deep and radiomics features remains complex and warrants further explainability studies [4]. Dataset biases, including demographic variability and scanner differences, may affect generalizability beyond evaluated datasets. The computational complexity of extracting 3D CNN features and computing radiomics may also limit scalability in real-time clinical environments.

Potential Extensions

Future research could explore integrating additional patient clinical and genomic data as multi-modal inputs to further improve classification accuracy and prognostic prediction [10]. Advances in explainable AI could be employed to elucidate feature contributions and foster trust in clinical deployment [4]. Moreover, optimizing model efficiency via network pruning or knowledge distillation could reduce inference time and resource demands. Expanding external validation to multi-center prospective trials will also be critical for confirming real-world utility. In summary, this work establishes a strong foundation for multi-source feature fusion in lung cancer classification, with clear pathways for enhancement informed by ongoing developments in AI and medical imaging.

6 CONCLUSION

This paper presented a novel ensemble deep learning framework that integrates 3D convolutional neural network features with handcrafted radiomics characteristics for improved lung cancer classification. Utilizing sophisticated nodule detection with YOLOv7, feature extraction via a pretrained 3D ResNet-34 and PyRadiomics, followed by optimization using LASSO regression and SMOTE-Tomek resampling, the proposed method achieved superior performance on NLST and LUNGx datasets. The model consistently outper-formed recent state-of-the-art techniques, attaining an AUC above 0.93 alongside high precision and recall rates, demonstrating robustness and potential clinical utility.

Key findings highlight that the hybrid fusion of deep and radiomics features effectively captures com-plementary information, while rigorous feature selection and class balancing enhance generalizability across heterogeneous datasets. The combination of gradient-boosted trees as the final classifier further contributes to the model's accuracy and interpretability.

Future research will focus on expanding the multi-modal integration by incorporating clinical, genomic, and longitudinal data to refine personalized risk stratifications. Additionally, exploring explainable AI meth-ods will be essential to improve model transparency and clinician trust. Efforts to optimize computational efficiency and validate the approach prospectively in multi-center clinical trials will be critical steps toward real-world adoption.

The proposed work lays a solid foundation for ensemble learning approaches in lung cancer diagnosis, paving the way for increasingly accurate, interpretable, and scalable AI-assisted clinical decision support systems.

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