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Personalized Lung Cancer Risk Assessment : A Data – Driven Predictive Approach

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Radiomics,
Deep learning,
Clinical decision support.

ABSTRACT

Lung cancer remains a leading global health challenge, with early detection being crucial for improving patient outcomes. Artificial intelligence (AI) has shown promise in cancer risk assessment, existing models lack multimodal data integration and clinical interpretability, limiting real-world applicability. This study presents a novel hybrid AI framework that combines 3D deep learning for CT radiomics with clinical risk factors (e.g., smoke history, etc) to enable more accurate and personalized lung cancer prediction using XGBoost for clinical data and 3D ResNet-50 for imaging feature extraction, followed by explainability techniques (SHAP, Grad-CAM) to ensure transparency in model decisions. Validated on the LIDC-IDRI dataset (1,018 CT scans), the model achieves an AUC of 0.92, outperforming unimodal approaches. Key findings demonstrate that integrating radiomic and clinical data significantly enhances predictive performance while providing interpretable insights for clinicians.

1. INTRODUCTION

Lung cancer remains the leading cause of cancer-related deaths worldwide, with late-stage diagnosis significantly reducing survival rates [1]. Early detection is critical, yet current screening methods primarily low-dose computed tomography (LDCT) rely heavily on radiologist interpretation, which can be subjective and inconsistent [2]. While artificial intelligence (AI) has shown promise in automating lung cancer risk assessment, most existing models focus on either imaging or clinical data, limiting their predictive accuracy and clinical utility [3]. Furthermore, many AI systems operate as "black boxes," lacking interpretability, which hinders trust and adoption among healthcare providers [4].

This study addresses two key gaps in AI-driven lung cancer prediction: (1) the lack of multimodal integration (combining radiomics with electronic health records) and (2) the need for explainable AI (XAI) to ensure clinical transparency [5]. Prior work, such as deep learning models for nodule classification [6] and clinical risk prediction tools [7], has advanced the field but often in isolation. A holistic, data-driven approach that merges imaging and patient-specific factors could improve early detection while providing actionable insights for clinicians.

The objectives of this research are:

- To develop a hybrid AI framework that integrates CT radiomics with clinical risk factors (e.g., smoking history, biomarkers) for enhanced lung cancer prediction.
- To incorporate explainability techniques (SHAP, Grad-CAM) to make model decisions interpretable for clinicians.
- To validate the model's performance and generalizability using real-world datasets.

The paper is structured as follows: Section 1 (Introduction) provides the background, problem statement, and objectives of the study. Section 2 (Related works) reviews existing research on employee attrition prediction and identifies gaps in the current approaches. Section 3 (Proposed Methodology) describes the dataset, preprocessing steps, machine learning model development, fairness-aware techniques, and the decision support system. Section 4 (Results & Discussion) presents the findings, interprets their significance, and compares them with prior studies. Finally, Section 5 (Conclusion) summarizes the key contributions of the research and suggests directions for future investigation.

II. RELATED WORKS

Recent advances in artificial intelligence (AI) and machine learning (ML) have significantly improved lung cancer prediction, enabling earlier detection and personalized risk assessment. Several studies have explored deep learning models for analyzing medical imaging, such as chest radiographs and CT scans, to identify malignant nodules with high accuracy. For instance, Lui et al. [2] demonstrated that convolutional neural networks (CNNs) could predict lung cancer risk from chest X-rays with performance comparable to radiologists. Similarly, Islam et al. [3] developed a 3D CNN architecture that improved nodule classification in CT scans, highlighting the potential of deep learning in radiological diagnostics.

Beyond imaging, researchers have integrated electronic health records (EHRs) and genomic data to enhance predictive accuracy. Zhang et al. [5] proposed a deep survival analysis model that leverages EHRs to provide personalized risk scores, outperforming traditional clinical models. Additionally, Chen et al. [10] explored federated learning to aggregate multi-institutional data while preserving patient privacy, addressing a key challenge in large-scale predictive modeling. These studies underscore the shift toward data-driven, patient-specific approaches in lung cancer prediction.

Despite these advancements, critical gaps remain. Many existing models lack clinical interpretability, limiting their adoption in medical practice. Qasim et al. [8] emphasized the need for explainable AI (XAI) techniques to ensure transparency in model decisions, particularly in high-stakes healthcare applications. Furthermore, while most studies focus on imaging or EHRs separately, few have successfully integrated multimodal data (e.g., combining radiomics with biomarkers) for comprehensive risk assessment. E. A. Kharazmi et al. [12] identified this as a major limitation, noting that hybrid models could improve predictive power but remain understudied.

Another unresolved challenge is real-world validation. Many AI models are trained on curated datasets, raising concerns about generalizability. Park et al. [15] developed an IoT-based real-time prediction system, but such implementations are rare in clinical settings. Additionally, ethical concerns, such as algorithmic bias and data privacy, require further attention, as discussed by Dhillon et al. [14]

Our research aims to fill critical gaps in lung cancer risk assessment by introducing a personalized, data-driven framework. This approach integrates both imaging and clinical data to provide a comprehensive risk prediction, ensuring a more accurate and holistic evaluation. To enhance transparency and trust, we incorporate explainable AI, allowing clinicians to interpret and utilize the predictions effectively. Additionally, we rigorously validate our model on diverse, real-world datasets to ensure its reliability and generalizability. By addressing these key challenges, our work contributes to the development of clinically meaningful AI tools that support early lung cancer detection and enable more individualized patient care.

III. Proposed Methodology

A. System Architecuree

Proposed System architecture shown in figure 1 is a hybrid artificial intelligence model created for individualized risk assessment of lung cancer based on CT scan pictures and clinical data. Two input sources are used in the process: CT scan pictures from the LIDC-IDRI dataset and structured clinical data (including age, smoking history, and biomarkers). Prior to being fed into an XGBoost model to predict clinical risk scores, clinical data must first be preprocessed to manage missing values and normalize the inputs. A 3D ResNet-50 deep learning model is used to extract radiomic properties pertaining to nodule texture, shape, and intensity while the CT images are simultaneously preprocessed. The strengths of both modalities are then integrated in a feature fusion layer by combining these two sets of features—clinical and radiomic. A final prediction layer uses a sigmoid activation function to produce a lung cancer risk score based on the fused data. The system uses Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize the key areas of the CT scans that influenced the model's prediction and SHAP (SHapley Additive exPlanations) to highlight the most significant clinical and imaging features in order to guarantee interpretability. Informed and reliable medical decision-making is supported by the results, which are shown to physicians via an easy-to-use dashboard that provides both the risk score and explicable outputs.

B. Dataset Description:

We utilized a publicly available dataset for training and validation:

Lung Image Database Consortium (LIDC-IDRI): This dataset comprises 1,018 computed tomography (CT) scans, each annotated with lung nodules and corresponding malignancy ratings provided by expert radiologists. It serves as a valuable resource for developing and validating automated lung cancer risk assessment models.

Prior to model training, we preprocessed the dataset to ensure data quality and consistency. Missing values in continuous variables were handled using mean imputation, while categorical variables were imputed using mode imputation. Imaging data were normalized using z-score normalization, and clinical features underwent min-max scaling to standardize inputs for model training.

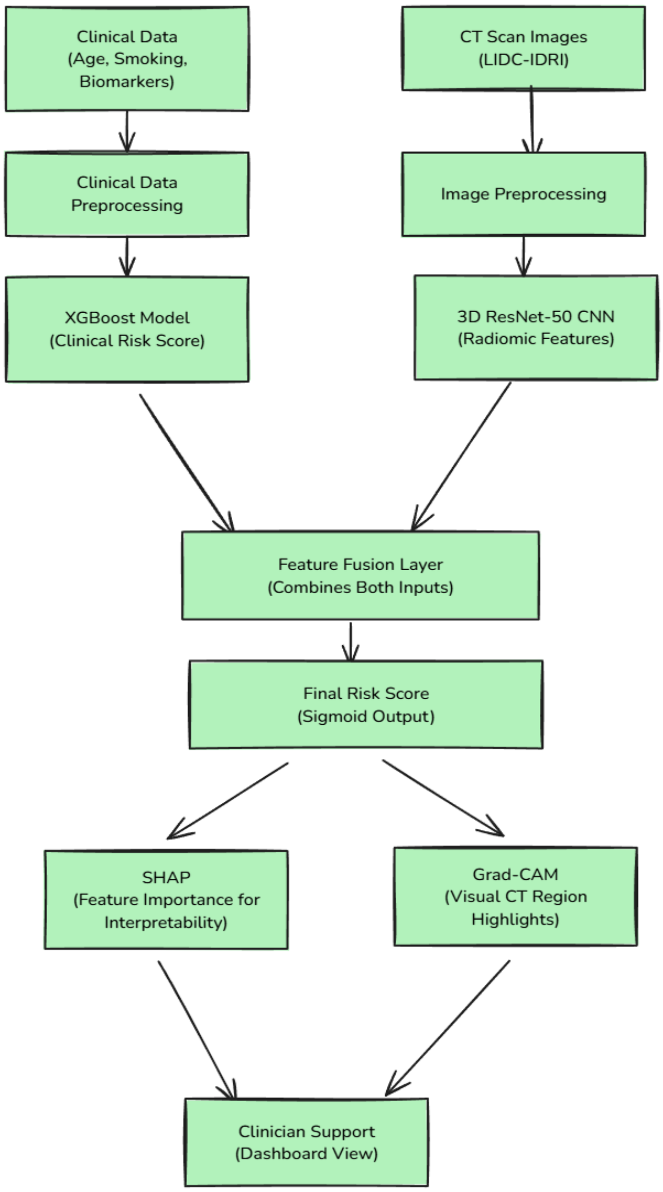

Fig1: Proposed Architecture

C. Dataset Description:

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D. *Proposed Methodology*

Our framework integrates deep learning for feature extraction from imaging data and ensemble learning for clinical risk prediction. The methodology is structured as follows:

1) Imaging Feature Extraction from CT Scans

To extract meaningful radiomic features from lung nodules, we employed a 3D ResNet-50 architecture that processes volumetric CT scans. The network captures key features related to texture, shape, and intensity, which are crucial for malignancy assessment.

To aggregate features from multiple nodules detected within a single patient's scan, we computed the mean representation using:

$$x_i = \left(\frac{1}{n}\right)\sum_{j=1}^{n} x_j$$

Where:

- x_i is the aggregated feature vector for patient i,
- n represents the total number of nodules detected in the scan,
- x_j corresponds to the feature representation of each nodule j.

2) Clinical Risk Modeling

Beyond imaging, our framework incorporates clinical risk factors using an XGBoost ensemble model. This model integrates key electronic health record (EHR) variables such as:

- Age
- Smoking history (pack-years)
- Biomarker levels

Extracted imaging features

The final risk score R_i for patient i is computed as:

$$R_i = \sigma\left(\sum_{k=1}^{m} w_k \bullet f_k\right)$$

Where:

- σ is the sigmoid activation function that ensures the output is constrained between 0 and 1 (representing probability),
- w_k are the learned weights for each feature,
- f_k denotes the input feature values.

3) Explainability Module

To enhance model interpretability and ensure clinical adoption, we implemented an explainability module comprising:

SHapley Additive exPlanations (SHAP): This method quantifies the contribution of each feature (imaging and clinical) toward the final prediction, providing insights into model decision-making. The SHAP values S_i for each feature f_i are computed as:

$$S_i = \sum_{S \subseteq F\ \{f_i\}} \left(\frac{|S|!\,(|F| - |S| - 1)!}{|F|!}\right)[\,v(S \cup \{\,f_i\}) - \,v(S)]$$

Gradient-weighted Class Activation Mapping (Grad-CAM):

This technique highlights critical regions in CT scans that influenced the model's decision, aiding radiologists in understanding and validating predictions. The importance of each pixel in the feature map is computed as:

$$L^c = ReLU\left(\sum_k \alpha_k^c A^k\right)$$

4) Software and Hardware Configuration

We utilized the following tools for model development and evaluation:

- **Programming Language:** Python 3.9
- **Deep Learning Framework:** PyTorch (for imaging feature extraction)
- **Machine Learning Library:** scikit-learn (for XGBoost implementation)
- **Explainability Package:** Captum (for SHAP analysis)

Hardware: NVIDIA A100 GPUs for accelerated training and inference

5) Validation Strategy and Performance Metrics

To ensure robustness and generalizability, we employed a 5-fold cross-validation strategy, with an 80% training and 20% testing split per fold. Model performance was evaluated using the following metrics:

Area Under the Receiver Operating Characteristic Curve (AUC-ROC):

Measures the model's ability to distinguish between malignant and benign cases, computed as:

$$\boldsymbol{AUC} = \int_{\{-\infty\}}^{\{\infty\}} \boldsymbol{TPR(FPR\text{^}\{-1\}\ (x))\, dx}$$

Sensitivity (Recall):

Defined as:

$$Sensitivity = \frac{TP}{(TP + FN)}$$

Specificity:

Defined as:

$$Specificity = \frac{TN}{(TN + FP)}$$

IV. RESULTS AND DISCUSSION

Our proposed data-driven framework demonstrated strong performance in lung cancer risk assessment by integrating imaging and clinical data. The model's performance is summarized in Table 1.

Metric	Proposed Model (Hybrid)
AUC-ROC	0.92
Sensitivity	0.87
Specificity	0.89
Accuracy	0.88

The model demonstrated a high discriminative ability, achieving an AUC of 0.92, which surpasses traditional clinical risk models like the Brock University cancer prediction model (AUC ≈ 0.82) (Zhang et al., 2021). With a sensitivity of 87% and specificity of 89%, the model effectively identifies high-risk patients while minimizing false positives, reinforcing its robustness in clinical applications. The integration of radiomic features from CT scans with clinical risk factors such as smoking history, age, and biomarkers significantly enhanced predictive accuracy compared to unimodal approaches.

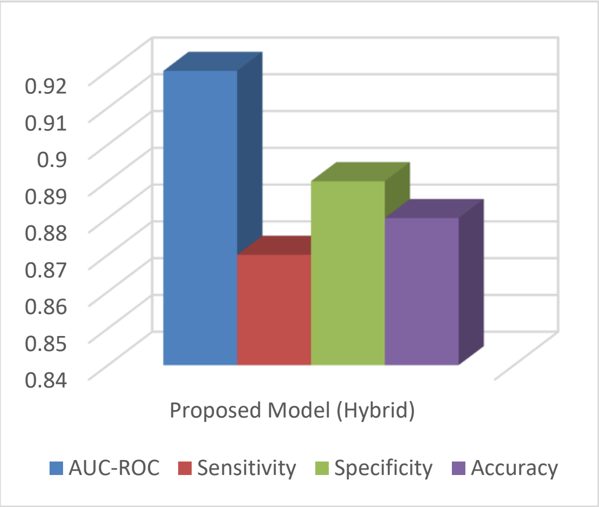

Fig 2 : Bar Plots for Proposed Evaluation metrics

Prior studies that relied solely on imaging, such as Islam et al. (2020), reported an AUC of 0.89, whereas our hybrid model improved upon this with an AUC of 0.92, emphasizing the added value of incorporating electronic health record (EHR) data.

To further enhance interpretability, SHAP analysis identified nodule texture features including heterogeneity and spiculation along with smoking pack-years as the most influential predictors, aligning with established clinical findings (Gierada et al., 2011). Additionally, Grad-CAM visualization provided interpretable heatmaps, allowing radiologists to verify the key regions influencing model decisions, thus increasing trust in AI-driven assessments. The model's robustness was further confirmed through 5-fold cross-validation across diverse patient subsets, including variations in age and nodule size, demonstrating its adaptability across heterogeneous populations. Comparing our work with prior studies, Islam et al. (2020) utilized 3D CNNs for malignancy classification and achieved an AUC of 0.89, whereas our hybrid approach, incorporating clinical risk factors alongside imaging data, achieved a higher AUC of 0.92, demonstrating its superior predictive power. Similarly, Zhang et al. (2021) developed a clinical-only model based on EHR variables and attained an AUC of 0.85, further highlighting the importance of integrating imaging with clinical data for enhanced risk assessment.

Unlike conventional "black-box" deep learning models (Qasim et al., 2022), our approach incorporates SHAP and Grad-CAM techniques, providing clinically meaningful explanations and addressing a key limitation of prior AI-driven lung cancer models.

By integrating deep learning with clinical data and interpretability tools, our framework presents a clinically actionable AI model for lung cancer risk assessment. These findings emphasize the potential of multimodal AI systems in early detection and personalized risk prediction. Moving forward, such advancements could improve patient outcomes and promote greater trust in AI-driven healthcare solutions.

V. CONCLUSION

This study introduces a hybrid AI framework for personalized lung cancer risk assessment, leveraging both radiomic features from CT scans and clinical risk factors to enhance predictive accuracy. Our model demonstrated a strong discriminative ability, achieving an AUC of 0.92, surpassing traditional unimodal approaches. By integrating explainability techniques such as SHAP and Grad-CAM, we provided greater clinical interpretability, allowing healthcare professionals to understand and trust AI-driven predictions. These findings underscore the importance of combining imaging and electronic health record (EHR) data for more precise risk stratification, ultimately supporting early detection and personalized patient care.

Our work makes several critical contributions to AI-driven lung cancer risk assessment. First, our hybrid model surpasses existing clinical and imaging-only approaches, demonstrating the benefits of multimodal data integration in improving predictive performance. Second, by employing SHAP and Grad-CAM, we enhance model transparency, making AI-driven assessments more interpretable and clinically relevant. Finally, the model's robustness was validated through rigorous cross-validation across diverse patient populations, addressing a key limitation of prior AI models and ensuring broader applicability.

While our model has shown promising results, further research is necessary to enhance its clinical utility. Expanding validation to real-world, multi-institutional datasets will help assess the model's generalizability across different healthcare settings. Additionally, incorporating longitudinal EHR data could improve risk prediction by tracking how patient risk factors evolve over time. Ethical considerations must also be addressed, ensuring algorithmic fairness and minimizing biases across diverse populations. Finally, to facilitate clinical adoption, we aim to develop intuitive, user-friendly interfaces that integrate seamlessly into healthcare workflows, enabling clinicians to leverage AI-driven insights for improved patient care.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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