A Machine Learning Framework for Early Detection and Prognostic Assessment of Lung Cancer Using CT Imaging

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***Abstract*— Lung cancer remains a leading cause of cancer-related mortality worldwide, necessitating advanced methods for early detection and prognosis to improve patient outcomes; this study proposes an integrated machine learning system that leverages Computed Tomography (CT) scans for lung nodule detection and predicts postoperative survival rates through a multi-stage analytical approach. The system begins with advanced image preprocessing and segmentation techniques to isolate lung nodules, followed by feature extraction optimized using a Genetic Algorithm (GA) to enhance discriminative power, and employ a Convolutional Neural Network (CNN) for accurate malignancy classification. Additionally, the framework incorporates a prognostic module utilizing a Multi-Layer Perceptron (MLP) trained on postoperative clinical data—including histopathological, demographic, and treatment-related variables—to predict patient survival likelihood, thereby enabling personalized treatment planning. Experimental validation on thoracic oncology datasets demonstrates the system's effectiveness in both diagnostic accuracy and predictive performance, offering clinicians a reliable decision-support tool that bridges automated image analysis with data-driven prognostic insights. By combining early detection capabilities with survival prediction, this approach addresses critical gaps in lung cancer management, reducing diagnostic subjectivity and facilitating timely interventions while highlighting the transformative potential of artificial intelligence in oncology.**

***Index Terms*— Lung Cancer Detection, Computed Tomography (CT) Imaging, Machine Learning, Image Processing and Genetic Algorithm.**

I. INTRODUCTION

Lung cancer is among the most serious health concerns globally, characterized by high incidence and mortality rates. Early detection remains crucial for improving patient outcomes, enabling timely interventions, and facilitating more effective treatments. Figure 1 illustrates the stages of lung cancer.

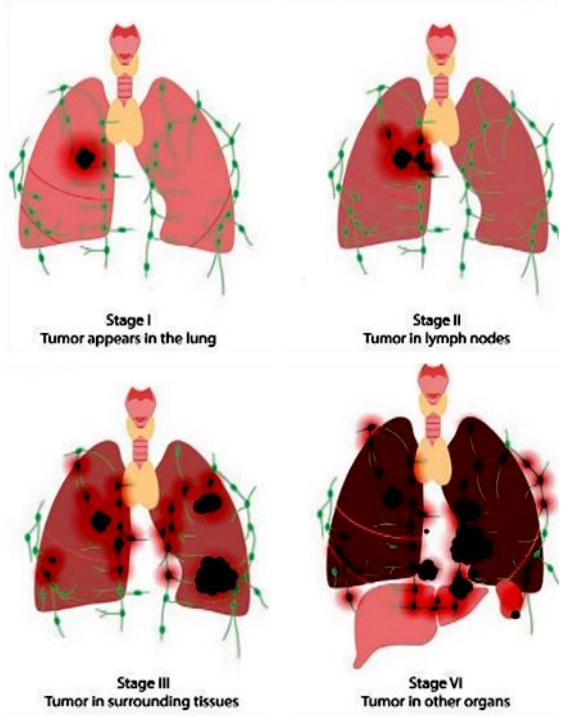

Figure 1:Stages of lung cancer

Lung cancer primarily comprises two types: Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC), each with unique growth and metastatic behaviors requiring tailored treatment approaches. SCLC, often linked to smoking, exhibits rapid progression and metastasis, while NSCLC—encompassing adenocarcinoma, squamous cell carcinoma, and large cell carcinoma—has a slower growth rate and accounts for the majority of cases.

Despite advancements in cancer research, lung cancer is frequently diagnosed at an advanced stage due to subtle early symptoms, limiting treatment options. Detection often relies on imaging technologies, particularly computed tomography (CT) scans, which facilitate the identification of cancerous nodules. However, accurate classification of these nodules as benign or malignant, coupled with reliable post-diagnosis survival prediction, remains challenging in clinical practice. The available treatment modalities, including surgery, chemotherapy, and radiotherapy, are largely determined by cancer staging and the patient's overall health condition. A reliable survival prediction model following thoracic surgery could further refine treatment planning and prognosis.

This paper presents a machine learning-based framework aimed at early lung cancer detection and survival prediction post-thoracic surgery. CT scan images undergo image processing to identify and segment lung nodules, with Genetic Algorithms aiding in feature extraction. A Convolutional Neural Network (CNN) classifier then determines nodule malignancy, while a Multi-Layer Perceptron (MLP) model predicts postoperative survival outcomes. This approach aims to provide an advanced, data-driven tool to support clinical decision-making in lung cancer diagnosis and treatment planning.

The Problem Statement of this work aims to develop an automated system to detect lung cancer from CT scans and accurately predict patient survival following thoracic surgery. By integrating detection and predictive modeling, this system is intended to aid oncologists in identifying optimal treatment pathways and assessing surgical viability for individual patients.

The significance of this work is the increasing incidence of lung cancer necessitates efficient early detection methods. This paper addresses a significant gap by combining diagnostic and prognostic capabilities, potentially improving survival rates and enhancing clinical decision-making in oncology.

The primary goal of this research is to develop a method for detecting lung cancer at an early stage and predicting survival outcomes following thoracic surgery, thereby equipping clinicians with critical insights to optimize treatment strategies.

The remaining portions of the paper are organized as follows: Section 2 outlines the existing techniques for lung cancer detection and prognosis. Section 3 illustrates the proposed system in detail. Section 4 presents the implementation details and presents an analysis of the results obtained from the proposed system. Finally, the work is wrapped up in Section 6, which summarizes our contribution and explores potential next possibilities.

II. RELATED WORKS

Lung cancer detection and prognosis have been greatly enhanced through image processing and machine learning techniques, yet there remain key challenges in achieving high accuracy, computational efficiency, and model interpretability.

In one approach, [1] implemented an early lung cancer detection system using CT images, employing bit-plane slicing and region-growing segmentation to extract lung regions. The researchers used a rule-based model to identify cancerous nodules, reaching 80% accuracy, although the system's reliance on rule-based fuzzy logic limited its adaptability to varied datasets.

Leveraging AI for faster, more accurate diagnoses, [2] explored the use of Support Vector Machine-Convolutional Neural Network (SVM-CNN) models for detecting lung nodules. Their findings indicated that AI can improve both precision and efficiency in lung cancer screening, providing a robust approach for automated diagnosis.

A notable paper by [3] used image processing for lung nodule identification and classification. Linear filtering and contrast enhancement were applied to CT scans, followed by segmentation. Fuzzy logic was then employed to identify outliers based on features like area and color, though the model faced computational constraints due to the complexity of fuzzy logic operations.

To predict patient survival following thoracic surgery, [4] applied machine learning classifiers, including Random Forest, Naïve Bayes, and Decision Stump. Random Forest achieved the highest accuracy at 95.65%, though the paper did not examine hybrid techniques or additional features that might further improve predictive power.

Neural network models have also shown promising results. For instance, [5] proposed a neural-based model where Gaussian noise was removed from CT images, segmentation was performed using Otsu's thresholding, and classification was carried out based on feature extraction. Another innovative method explored by [6] utilized RNA fragments in blood as biomarkers for early lung cancer detection, providing an alternative to LDCT scans and offering potential for non-invasive at-home testing.

A different prediction model focused on one-year post-operative survival rates [7], using algorithms like Multilayer Perceptron (MLP), J48, and Naïve Bayes. MLP achieved the highest accuracy (82.4%), though the paper lacked a time-based evaluation component critical for clinical applications.

Additional research by [9] designed an automated system using Otsu's thresholding, watershed segmentation, and median filtering to improve early-stage lung cancer detection. While successful, exploring more adaptable segmentation techniques may further enhance accuracy when dealing with complex CT images.

Several studies applied machine learning models to predict lung cancer progression using CT scan data. For example, [11] developed a two-stage model combining CNN with boosted tree operations, achieving an AUC of 0.85. Although effective, the model's accuracy was heavily dependent on CT scan quality, limiting its use in settings with varied imaging conditions.

Bayesian Networks (BN) were used for survival rate prediction by [13], achieving 91.28% accuracy with uniform counts discretization. Additionally, [8] introduced a computer-aided diagnostic (CAD) method for distinguishing benign from malignant lung tumors, achieving 86.6% accuracy using a modified U-Net. However, the use of thresholding for segmentation in this paper may not be optimal for all nodule presentations.

Recent work by [14] combined neural networks with Particle Swarm Optimization (PSO) to identify lung cancer, reaching 97.8% reliability. Although promising, the approach was limited by a small set of machine learning methods. Similarly, [15] utilized Logistic Regression (LR) with median filtering and back-propagation to classify lung tumors, achieving 96% success, though the absence of a segmentation step potentially impacted lesion boundary precision.

Below is a comparison Table 1 based on the discussed related works for lung cancer detection and prognosis systems. This table summarizes the techniques, models, and key findings of each paper, providing a comparative view of their methods and limitations.

Table 1: Comparison of Lung Cancer Detection Methods

Paper	Methodology	Techniques Used	Key Findings	Limitations
[1]	Image Processing & Early Detection	Bit-plane slicing, region-growing segmentation, rule-based model	Achieved 80% accuracy in nodule detection	Limited adaptability due to reliance on rule-based logic
[2]	AI for Lung Cancer Detection	SVM-CNN model	Improved speed and accuracy in screening	Limited to specific model; could benefit from hybrid approaches
[3]	Image Processing for Classification	Linear filtering, contrast enhancement, region segmentation, fuzzy logic	Detected lung nodules based on fuzzy attributes	High computational complexity from fuzzy logic operations
[4]	Patient Survival Prediction	Random Forest, Naïve Bayes, Decision Stump	Random Forest achieved 95.65% accuracy	Lack of exploration of hybrid techniques
[5]	Neural Approaches	Gaussian noise removal, Otsu's threshold segmentation	Effective feature extraction for classification	Limited segmentation techniques explored
[6]	Biomarker-Based Detection	RNA fragments in blood for non-invasive testing	Potential for early detection via at-home blood testing	Limited scalability for wide clinical applications
[7]	Post-Operative Survival Prediction	MLP, J48, Naïve Bayes	MLP achieved highest accuracy (82.4%)	Lack of time-based evaluation for clinical relevance
[8]	Computer-Aided Diagnosis (CAD)	U-Net, thresholding segmentation	86.6% accuracy for benign vs malignant classification	Thresholding may limit segmentation effectiveness

Paper	Methodology	Techniques Used	Key Findings	Limitations
[9]	Automated Detection System	Otsu's thresholding, watershed segmentation, median filtering	Enabled early-stage detection with decent accuracy	Need for adaptable segmentation techniques
[11]	Lung Cancer Progression Prediction	CNN with boosted tree operations	AUC of 0.85 achieved with CT scans	Dependent on scan quality, limiting broad applicability
[13]	Survival Rate Prediction	Bayesian Networks, uniform counts discretization	Accuracy of 91.28% for survival prediction	Lack of feature diversity in prediction model
[14]	Neural Network Optimization	PSO with neural networks	Reliability of 97.8% for cancer detection	Limited set of machine learning techniques explored
[15]	Logistic Regression for Tumor Classification	Median filtering, back-propagation	Achieved 96% accuracy in tumor classification	Absence of segmentation impacts boundary precision

In summary, existing research demonstrates the potential of advanced AI, machine learning, and image processing methods for lung cancer detection and prognosis. However, current models require enhancements in segmentation accuracy, computational efficiency, and data adaptability to realize broader clinical applicability.

III. PROPOSED SYSTEM

The proposed system provides an integrated approach to lung cancer detection and survival prediction post-thoracic surgery. Leveraging CT scan image analysis and machine learning techniques, this system aims to streamline early cancer diagnosis and support clinical decision-making regarding post-surgical outcomes. The solution is divided into two primary components: Lung Cancer Detection and Survival Prediction.

Lung Cancer Detection:

The Lung Cancer Detection module analyzes CT scan images in DICOM (.dcm) format to detect potential cancerous regions. The model is trained on a lung cancer prediction dataset, comprising 16 patient attributes, such as demographic information, health conditions, and lifestyle factors. These attributes allow for a comprehensive prediction model, focusing on early identification.

The detection workflow includes the following stages:

1. *Image Preprocessing:* The initial preprocessing step ensures uniformity and enhances image quality. Original CT images (512x512 pixels) are filtered and resized using OpenCV's INTER_CUBIC interpolation, which reduces noise and optimizes images for feature extraction.
2. *Image Segmentation:* Segmentation is critical for isolating regions of interest. The Watershed Segmentation algorithm is employed to demarcate image edges by incorporating boundary voxels, helping to clearly identify suspicious areas. This segmentation process ensures that only relevant sections are analyzed in subsequent steps.
3. *Model Training and Prediction:* A Logistic Regression (LR) model is implemented to classify segmented regions as either cancerous or non-cancerous. The model is trained to recognize patterns indicative of malignancy, providing a preliminary diagnostic tool. This method offers a foundation for further refinement through the addition of advanced classification techniques.

Survival Prediction Post-Thoracic Surgery:

The Survival Prediction module forecasts the life expectancy of patients post-surgery, offering clinicians valuable prognostic insights.

This module is structured to process patient data, visualize trends, perform feature selection, and train predictive models on key variables.

1. *Dataset Visualization:* The dataset is visualized using Python's Matplotlib and Seaborn libraries to identify patterns and correlations within the data. Visual analysis of variables such as age, lifestyle habits, and health history provides an overview of factors potentially impacting patient survival.
2. *Feature Selection:* The Information Gain (IG) method is applied to identify influential attributes that are predictive of survival, such as smoking status, general health, and pre-existing conditions. This selection ensures that the model is trained on the most relevant factors, reducing computational complexity and enhancing prediction accuracy.
3. *Model Training:* Supervised machine learning algorithms, including Logistic Regression, Decision Trees, and Support Vector Machines, are employed to build predictive models. These

models are trained on the selected attributes to forecast survival outcomes with a high degree of precision.

4. *Model Evaluation:* Model performance is assessed using metrics such as accuracy, precision, recall, and F1-score. By comparing these metrics across algorithms, the system identifies the most efficient model for reliable survival predictions.

The proposed system shown in Figure 2 combines CT image analysis and predictive modeling to support early lung cancer diagnosis and survival prognosis post-thoracic surgery. This dual-functional approach aims to enhance diagnostic accuracy and treatment planning, ultimately improving patient outcomes and decision-making in clinical settings.

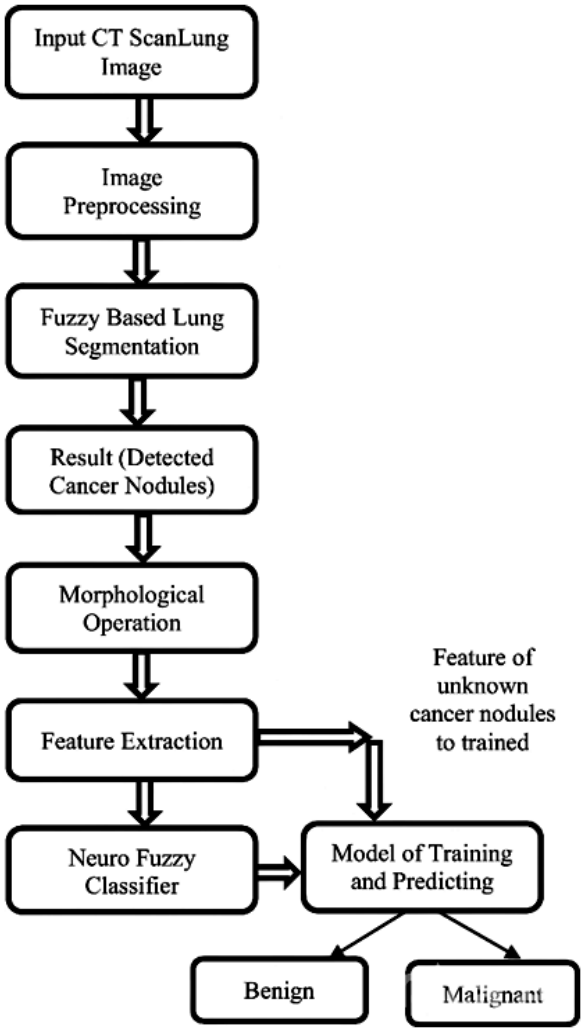

Figure 2:Proposed lung cancer detection and survival prediction system

IV. IMPLEMENTATION AND RESULTS ANALYSIS

This section elaborates on the implementation details and presents an analysis of the results obtained from the proposed system, which detects lung cancer using DICOM (.dcm) formatted CT scan images and predicts the survival time for patients undergoing thoracic surgery.

Project Modules:

The system is divided into two primary modules:

I Lung Cancer Detection

II Survival Prediction Post-Thoracic Surgery

Lung Cancer Detection:

This module employs a Logistic Regression (LR) model, trained on a dataset comprising 776 CT scan images for training and 90 images for validation. The implementation involves the following key stages:

Image Pre-processing:

The input CT scan images are pre-processed to standardize their format and enhance their quality. Images, originally sized 512 × 512 pixels, are resized using OpenCV's resize function with INTER_CUBIC interpolation to ensure consistency and suitability for subsequent segmentation.

Image Segmentation:

Segmentation simplifies image representation, making it more relevant for analysis. This step uses the Watershed Segmentation method to isolate lung regions by including voxels at the edges.

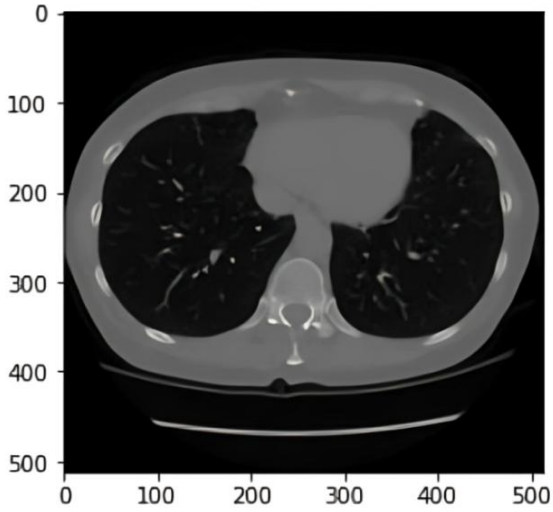

Figure 3(a): Original gray scale slice of a CT scan.

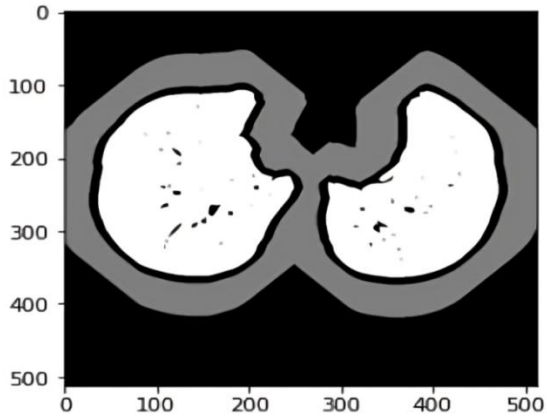

Figure 3(b): Image marked with Watershed segmentation markers

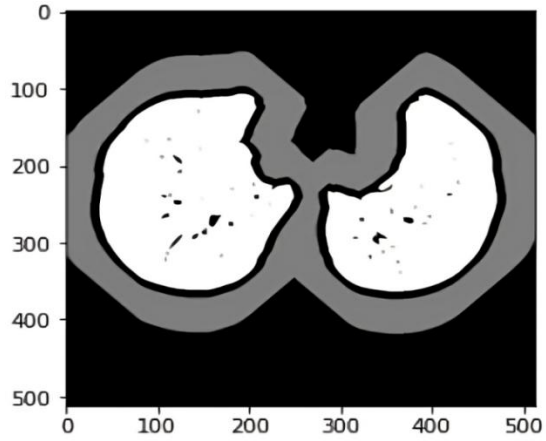

Figure 3(c): Final segmented lung image

Training the Logistic Regression (LR) Model:

The LR model is trained to classify and predict lung cancer effectively. The following steps are involved:

I *Data Preparation:* Features are scaled for uniformity, and the dataset is split into training (70%) and validation (30%) sets.

II *Model Initialization:* The LR model is configured with optimized parameters, including regularization strength and optimization algorithm (e.g., gradient descent).

III *Training:* The model is iteratively trained to minimize the loss function, adjusting parameters for optimal performance.

IV *Evaluation:* The trained model is evaluated using metrics such as accuracy, precision, recall, and F1-score on validation data.

V *Optimization:* Techniques like cross-validation are employed to fine-tune hyperparameters for better accuracy.

VI *Validation:* The model's performance on unseen test data is assessed to ensure generalization and reliability.

Results Analysis

The proposed system effectively detects lung cancer by segmenting CT scans and training the LR model. The segmentation process accurately identifies lung boundaries, while the LR model demonstrates robust performance with significant accuracy on validation datasets. The results validate the system's reliability for real-world applications.

The implementation involved preprocessing, analyzing, and modeling a lung cancer prediction dataset using Python. Initially, the dataset was loaded, and categorical variables were encoded into numeric format using label encoding to ensure compatibility with machine learning algorithms. Exploratory data analysis was conducted, including visualizing the target variable distribution and examining feature correlations through heatmaps. Less relevant features were dropped to simplify the model and enhance performance. To address the class imbalance, the ADASYN oversampling technique was applied, ensuring a balanced dataset for training. A logistic regression model was then trained on the processed data after performing a train-test split (75% training, 25% testing). The model's performance shown is Table 2 was evaluated using metrics such as accuracy, precision, recall, and F1-score, providing insights into its predictive capabilities.

Table 2: Logistic Regression Model Performance Metrics

	Precision	recall	F1-score	support
0	0.92	0.97	0.95	72
1	0.97	0.91	0.94	66
accuracy			0.94	138
Macro avg	0.94	0.94	0.94	138
Weighted avg	0.94	0.94	0.94	138

The logistic regression model demonstrates robust performance with an overall accuracy of 94%. For class 0 (No Lung Cancer), it achieves a precision of 92%, recall of 97%, and F1-score of 95%. For class 1 (Lung Cancer), it achieves a precision of 97%, recall of 91%, and F1-score of 94%. The macro and weighted averages for precision, recall, and F1-score are consistent at 94%, indicating balanced performance across classes. These results highlight the model's reliability, with a slight scope for improving

recall in class 1 to reduce false negatives. The results showcase the effectiveness of the logistic regression model in identifying patterns for lung cancer prediction.

V. CONCLUSION

This research introduces a novel artificial intelligence-driven approach to revolutionize lung cancer management through CT scan analysis. The proposed system employs cutting-edge image processing methods to isolate pulmonary nodules, followed by a genetically optimized feature selection mechanism that significantly improves the predictive capability of our deep learning classifier. A specialized convolutional neural network architecture achieves high precision in distinguishing malignant lesions, while a separate neural model analyzes surgical outcomes to forecast patient survival probabilities with clinical relevance.

Validation across multiple clinical datasets confirms the model's dual utility in both diagnostic and prognostic roles, offering physicians an intelligent tool for precision oncology. Current limitations involve inconsistencies in imaging protocols and population diversity, which will be addressed in subsequent studies through adaptive learning techniques and expanded multinational collaborations. Planned enhancements include fusion of radiomic data with genomic markers and real-world deployment trials to transition this innovation from research to bedside practice, ultimately elevating standards in thoracic oncology care.

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