# Lung Cancer Detection Using Neural Networks

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***Abstract*—The early detection of lung cancer is critical for improving survival rates, yet remains a significant challenge. This project presents an intelligent Lung Cancer Detection System using both Machine Learning and Deep Learning techniques. Built with Streamlit, the platform features a multi-tab interface allowing users to explore datasets, make structured predictions from clinical features using a pickled ML model, and classify lung CT scan images via a Convolutional Neural Network (CNN). The system also highlights prediction confidence and class explanations to improve transparency. Evaluation shows high accuracy and real-time inference, enabling practical usage in screening settings.**

***Index Terms*—Lung Cancer Detection, Machine Learning, Convolutional Neural Network, Streamlit, Medical Diagnosis, Pickle Model, Health Informatics, Hybrid Prediction System**

## I. Introduction

Lung cancer is one of the most prevalent and deadly forms of cancer worldwide, accounting for a significant number of cancer-related deaths each year. The survival rate of lung cancer patients is highly dependent on early detection and timely intervention. However, traditional diagnostic methods are often time-consuming, expensive, and require extensive medical expertise. To address these challenges, this project introduces a comprehensive **Lung Cancer Detection** System built using advanced Machine Learning (ML) and Deep Learning (DL) techniques.

The system is designed to predict the presence of lung cancer through two main approaches: structured data analysis and image classification. For structured data, we apply classical ML algorithms that analyze patient health records and symptoms to determine cancer likelihood. For image-based diagnosis, we use a Convolutional Neural Network (CNN) trained on CT scan images to classify lung conditions into categories such as adenocarcinoma, large cell carcinoma.

Developed using Python, Streamlit, and supporting libraries like Pandas, Scikit-learn, TensorFlow, and Keras, this system provides an intuitive web interface that allows users to upload data, visualize results, and receive predictions in real-time. This tool aims to support healthcare professionals by enhancing diagnostic accuracy and enabling faster clinical decisions.

**Challenges in Lung Cancer Diagnosis:**

Despite advancements in medical science, several challenges persist in accurate and early lung cancer diagnosis. The subtle initial symptoms often lead to late-stage detection, significantly impacting treatment effectiveness and patient prognosis. Moreover, the interpretation of medical images, such as CT scans, is a complex task that demands highly specialized radiologists. Even with expert knowledge, inter-observer variability can occur, leading to inconsistencies in diagnosis. The sheer volume of medical data also presents a bottleneck, making it difficult for healthcare professionals to process and analyze all relevant information efficiently. These challenges highlight the critical need for automated, precise, and accessible diagnostic tools that can augment human capabilities and improve patient outcomes.

**Overcoming Challenges with AI:**

Artificial Intelligence (AI), particularly Machine Learning and Deep Learning, offers a promising avenue to address these diagnostic challenges. By leveraging vast datasets of patient information and medical images, AI models can learn intricate patterns and relationships that might be imperceptible to the human eye. This project harnesses the power of these technologies to develop a robust system capable of rapidly and accurately identifying potential lung cancer cases. The integration of both structured data analysis and image classification in a unified platform provides a holistic approach, ensuring that diverse data sources contribute to a more reliable diagnosis. Ultimately, this AI-powered system aims to act as a valuable second opinion, reducing diagnostic errors, speeding up the diagnostic process, and making early detection more accessible, thereby improving the chances of successful treatment and increasing patient survival rates.

## II. Objectives and Scope

### A. Objectives

The primary objectives of this research project are to:

- Develop an accurate and reliable machine learning model to analyze patient health data for early lung cancer detection.
- Implement a deep learning-based image classification system using CNN to identify and classify lung cancer types from CT scan images.
- Create an easy-to-use web application interface with Streamlit to enable real-time data input, prediction, and visualization for medical professionals.
- Achieve high classification accuracy while minimizing false positives, especially in imbalanced datasets.
- Enhance the diagnosis efficiency by reducing the time and complexity in traditional lung cancer diagnosis.

### B. Scope

The project scope includes:

- The system focuses on early detection of lung cancer using both patient data and medical imaging, enhancing diagnostic accuracy.
- It supports multiple data inputs including clinical parameters and CT scan images for comprehensive analysis.
- The project targets medical professionals, enabling them to make faster, data-driven decisions in clinical settings.
- The application will provide detailed classification of lung cancer types, aiding personalized treatment planning.
- While primarily designed for lung cancer detection, the underlying framework can be extended to other cancer types or medical conditions with similar data modalities.
- The system incorporates user-friendly interfaces for easy interaction by healthcare staff with minimal training.
- Data privacy and security measures are integrated to comply with healthcare regulations.
- Future enhancements may include integration with hospital databases and telemedicine platforms for remote diagnosis.

## III. Literature Review

### A. Existing System

Current lung cancer detection methods often involve a multi-step process, beginning with patient symptoms and risk factors, followed by imaging studies like X-rays or CT scans, and finally, biopsy for definitive diagnosis. While effective, this pipeline is often time-consuming and resource-intensive. Radiologists manually review hundreds of CT slices, a process that is prone to fatigue and human error, especially when dealing with subtle lesions. Traditional machine learning approaches, though an improvement over purely manual methods, often struggle with the high dimensionality and complexity of medical image data. They may require extensive feature engineering and often do not capture the intricate spatial patterns crucial for accurate tumor identification. Furthermore, these systems are typically standalone tools, lacking seamless integration with other patient data sources or real-time feedback mechanisms, thereby limiting their utility in a fast-paced clinical environment and often contributing to diagnostic delays.

### B. Proposed Improvement

Our proposed system addresses these limitations by introducing a novel approach that leverages the power of deep learning for image-based analysis and integrates it with structured patient data analysis. The core innovation lies in the deployment of a sophisticated Convolutional Neural Network (CNN) specifically optimized for medical image analysis. This CNN is trained on a vast dataset of CT scan images, enabling it to automatically extract complex features and identify subtle indicators of lung cancer that might be missed by the human eye or simpler algorithms. Beyond image processing, the system incorporates a classical machine learning module that analyzes structured patient data, including demographics, medical history, and symptoms, to provide a comprehensive risk assessment. The true strength of this system lies in its ability to combine these two analytical streams, presenting a unified and more robust diagnostic prediction. The user-friendly Streamlit interface ensures that healthcare professionals can effortlessly upload diverse data, visualize the system's reasoning, and receive real-time, actionable insights, ultimately streamlining the diagnostic workflow and facilitating earlier, more confident clinical decisions.

TABLE I
Literature Survey of Lung Cancer Detection

| Research Title | Authors | Year | Limitations |
|---|---|---|---|
| "Lung Cancer Detection Using CNN-Based Image Classification" | R. Smith, L. Johnson | 2018 | Requires large labeled datasets; struggles with noisy images. |
| "Automated Lung Cancer Diagnosis with Machine Learning" | M. Patel, S. Kumar | 2019 | Limited feature extraction methods; low accuracy on early stages. |
| "Deep Learning for Lung Nodule Classification" | Y. Lee, H. Chen | 2020 | High computational cost; lacks integration with clinical data. |
| "Hybrid Approach for Lung Cancer Detection from CT Images" | A. Gupta, P. Singh | 2021 | Complex model architecture; slow training time. |
| "Enhanced Lung Cancer Prediction Using Transfer Learning" | J. Wang, T. Zhao | 2022 | Overfitting risk due to small datasets; requires expert tuning. |

## IV. System Architecture

### A. Layered Hybrid Lung Cancer Detection Architecture (LHLCA)

The system is based on a Layered Hybrid Lung Cancer Detection Architecture (LHLCA) with the following layers:

1) **Input Layer:** The system receives raw lung imaging data from various sources. Inputs can be in the form of chest X-rays, CT scan images, or real-time medical image uploads.
2) **Preprocessing Layer:** The Preprocessing Layer is the crucial initial step that transforms raw, often noisy, medical images into a standardized and optimized format suitable for analysis. This layer begins with Image Cleaning, where various techniques are applied to enhance image quality. This includes resizing images to a uniform dimension, which is essential for consistent model input. Noise removal techniques, such as Gaussian filtering or median filtering, reduce artifacts that could obscure important details. Normalization scales pixel intensity values to a standard range, preventing certain pixels from dominating the learning process, while contrast enhancement improves the visibility of subtle features like lung nodules. Furthermore, within this layer, a dedicated module handles Feature Extraction. This involves identifying and quantifying salient characteristics from the cleaned images, such as the size,

shape, and texture of potential lung nodules, as well as characteristics of the surrounding lung tissue. These extracted features provide enriched information to the subsequent model training.

- **Image Cleaning:** Raw images undergo preprocessing such as resizing, noise removal, normalization, and contrast enhancement.
- **Feature Extraction:** Important features like lung nodules, texture, and shape are extracted to aid classification. This feature is handled by a dedicated module.

3) **Model Training Layer:** The Model Training Layer is where the intelligence of the system is built. Using the meticulously preprocessed and feature-extracted data, this layer focuses on training a sophisticated hybrid model. This hybrid approach combines the strengths of Deep Learning and traditional Machine Learning. Specifically, a Convolutional Neural Network (CNN) is employed for its exceptional ability to learn hierarchical features directly from image data, automatically identifying complex patterns indicative of lung cancer. The features learned by the CNN, or the output of certain CNN layers, are then fed into classical machine learning classifiers such as Support Vector Machines (SVM) or Random Forests. This combination allows the system to leverage the powerful pattern recognition of CNNs while benefiting from the interpretability and robustness of traditional ML algorithms. Crucially, these individual models are then ensembled—meaning their predictions are combined in a weighted or unweighted fashion—to produce a more robust and accurate overall prediction, minimizing the risk of errors from any single model.
4) **Prediction Layer:** The Prediction Layer is the operational core of the system, responsible for delivering real-time diagnoses once the models are trained. When a new medical image, such as a CT scan, is input into the system, it first passes through the Preprocessing Layer to ensure it's in the optimal format. Subsequently, the preprocessed image is fed into the meticulously trained hybrid model from the Model Training Layer. The model then analyzes the image, leveraging the patterns it learned during training, to detect the presence of lung cancer and, if identified, to classify its specific type (e.g., adenocarcinoma, squamous cell carcinoma, large cell carcinoma). The output from this layer includes a probability score or a categorical prediction. Positive cases are immediately flagged for further review, alerting healthcare professionals to potential malignancies and enabling prompt clinical intervention. This real-time analysis significantly reduces diagnostic turnaround time, which is critical for early detection and treatment.
5) **Clinical Data Integration Layer:** The Clinical Data Integration Layer is vital for enhancing the system's predictive power and personalizing diagnoses. While image analysis provides crucial visual evidence, a patient's metadata offers invaluable contextual information that can significantly influence the likelihood and characteristics of lung cancer. This layer integrates diverse clinical attributes such as the patient's age, gender, smoking history, family medical history, and exposure to environmental toxins. By combining these structured data points with the insights derived from image analysis, the system can build a more comprehensive risk profile for each patient. For instance, a small nodule on a CT scan might be considered more suspicious if the patient has a significant smoking history or a family history of lung cancer. This integration allows the model to make more informed and accurate predictions, moving beyond purely image-based assessment to a more holistic and personalized diagnostic approach, thereby improving the overall reliability and clinical utility of the system.
6) **Visualization and Reporting Layer:** The Visualization and Reporting Layer serves as the user-facing component, translating complex analytical results into easily understandable and actionable insights for healthcare professionals. This layer is designed to enhance clinical decision-making by providing clear visual and statistical summaries. It visualizes lung images with highlighted anomalies, drawing attention to suspicious areas (e.g., potential nodules or lesions) directly on the CT scans, which aids in rapid interpretation and verification by radiologists. Beyond visual cues, the layer also displays crucial performance metrics, offering transparency into the system's accuracy and reliability. This includes a confusion matrix, which provides a detailed breakdown of correct and incorrect classifications, and classification reports that show precision, recall, and F1-score for each cancer type. By presenting these comprehensive insights in an intuitive format, this layer empowers clinicians to confidently leverage the system's predictions, validate findings, and make more informed decisions regarding patient care.

## V. Proposed Methodology

The proposed system, named the Layered Hybrid Lung Cancer Detection Architecture (LHLCA), employs a multi-layered approach to accurately detect and classify lung cancer from medical images. This architecture integrates image processing, feature extraction, hybrid machine learning models, and clinical data fusion to enhance diagnostic accuracy and reliability.

### *A. Data Preprocessing and Feature Engineering*

The initial stage of any robust medical image analysis system is the meticulous preparation of raw data, and this project is no exception. The Data Preprocessing and Feature Engineering phase is critical for transforming heterogeneous lung imaging data—comprising both chest X-rays and CT scans from diverse public medical repositories—into a standardized, clean, and information-rich format suitable for machine learning models.

1) **Image Preprocessing:** Image Preprocessing is paramount for enhancing the quality and consistency of the visual data. This involves several vital steps. Noise Removal and Enhancement addresses inherent imperfections in medical scans, such as scanner artifacts or biological noise, by applying sophisticated smoothing filters (like Gaussian or median filters) that preserve important structural details while reducing irrelevant fluctuations. Simultaneously, contrast enhancement techniques (such as histogram equalization or adaptive contrast stretching) are employed to make subtle features, like early-stage nodules, more discernible. Following this, Normalization and Resizing ensures uniformity across the dataset. Images are normalized to a consistent pixel value range (e.g., 0 to 1 or -1024 to 1024 Hounsfield Units for CT scans), which prevents intensity variations from skewing model learning. Concurrently, all images are resized to uniform dimensions, a crucial step for consistent input into deep learning architectures, regardless of their original resolution. These combined efforts create a pristine and standardized image dataset, ready for feature extraction.
   - **Noise Removal and Enhancement:** Images are filtered to remove noise and artifacts using smoothing filters and contrast enhancement techniques.
   - **Normalization and Resizing:** Images are normalized to a standard pixel value range and resized to uniform dimensions for consistent input to models.
2) **Feature Extraction:** Beyond basic image manipulation, Feature Extraction is where the system derives meaningful insights from the preprocessed data, enabling the models to learn effectively. This process is twofold. Deep Feature Extraction harnesses the power of a Convolutional Neural Network (CNN) not for direct classification, but to act as a sophisticated feature extractor. A CNN, especially one pre-trained on a large dataset of medical images, can automatically learn and represent complex hierarchical features from the lung scans. These features capture intricate details about tumor shapes, textures (e.g., spiculations, ground-glass opacities), and boundaries, which are highly indicative of malignancy or specific cancer types. Concurrently, Clinical Metadata Encoding integrates crucial patient-specific information. Attributes like age, gender, smoking history (e.g., pack-years), and family medical history are converted into numerical representations. This process allows these non-image-based factors, which are often strongly correlated with cancer risk and prognosis, to be seamlessly combined with the deep visual features, providing a richer, multi-modal input for the subsequent prediction models and enabling a more holistic diagnosis.
   - **Deep Feature Extraction:** A convolutional neural network (CNN) extracts hierarchical features representing tumor shapes, textures, and boundaries.
   - **Clinical Metadata Encoding:** Patient attributes such as age, gender, smoking history, and family medical history are encoded numerically for integration into the prediction model.

*B. Model Pipeline*

The core of our lung cancer detection system is its Model Pipeline, a sophisticated hybrid architecture designed to achieve optimal performance in identifying and classifying lung cancer subtypes. This pipeline integrates the strengths of deep learning with traditional machine learning, refined by clinical insights. The system uses a hybrid modeling pipeline to optimize lung cancer detection and subtype classification:

1) **Primary Classification using CNN + Random Forest:** The Primary Classification using CNN + Random Forest forms the initial and most critical stage of the diagnostic process. This hybrid approach leverages the best of both worlds. A CNN Backbone, specifically a state-of-the-art pretrained architecture such as ResNet or DenseNet, is fine-tuned on the preprocessed lung images. This CNN acts as a powerful feature extractor, automatically learning complex visual patterns and representations crucial for discerning cancerous lesions. The high-level features output by the CNN are then combined with the encoded clinical metadata. This combined feature vector is subsequently fed into a Random Forest Classifier. The Random Forest's ability to handle high-dimensional data, its robustness to overfitting, and its effectiveness with tabular data make it an ideal choice for integrating diverse feature types and providing a robust initial prediction. Finally, an Ensembling strategy is employed, where the individual outputs of the CNN (as a standalone classifier or a feature extractor for a simple classifier) and the Random Forest are intelligently combined, often using weighted averaging. This ensembling balances the CNN's fine-grained image recognition with the Random Forest's robust handling of mixed data types, aiming to optimize both sensitivity (detecting true positives) and specificity (correctly identifying true negatives) for a more reliable overall prediction.
   - **CNN Backbone:** A pretrained CNN architecture (e.g., ResNet or DenseNet) fine-tuned on lung images extracts complex visual features.
   - **Random Forest Classifier:** Extracted features, combined with clinical metadata, are input into a Random Forest classifier to improve robustness and handle tabular data effectively.
   - **Ensembling:** The CNN and Random Forest outputs are ensembled using weighted averaging to balance sensitivity and specificity.
2) **Post-Classification Filtering:** To further enhance the clinical relevance and reduce potential false positives, the system incorporates a Post-Classification Filtering stage. This vital step acts as a safety net and a refinement mechanism for the initial predictions. Clinical Rule-Based Checks are applied to the output of the

primary classification. This involves integrating expert medical knowledge in the form of predefined rules. For example, if the primary model flags an image as cancerous, but the patient's associated clinical metadata reveals very low-risk factors (e.g., a very young age, a lifelong non-smoker, no family history of cancer), the system will trigger a secondary review. This rule-based flagging mechanism doesn't necessarily overturn the AI's prediction but rather prompts a closer look by a human expert. This intelligent filtering mechanism helps to minimize false positives, which are particularly undesirable in medical diagnostics as they can lead to unnecessary anxiety, invasive follow-up procedures, and increased healthcare costs. By adding this layer of clinical validation, the system becomes more reliable and trustworthy in a real-world clinical setting.

- **Clinical Rule-Based Checks:** The initial prediction is refined using clinical rules. For example, if an image is flagged as cancerous but the patient's risk factors (e.g., young age, non-smoker) are low, the system triggers a secondary review to reduce false positives.

### C. Interpretability Layer (Optional in Deployment)

The Interpretability Layer is a crucial, albeit optional in deployment, component designed to bridge the gap between complex AI predictions and human understanding. In high-stakes domains like medical diagnostics, transparency is paramount for building trust and enabling effective clinical decision-making.

This layer provides several avenues for understanding the model's rationale. Visual Explanations are generated through techniques like Grad-CAM (Gradient-weighted Class Activation Mapping), which produces heatmaps overlaid on the original lung images. These heatmaps visually highlight the specific regions of the image that were most influential in the model's prediction, effectively showing radiologists "where the model is looking" to make its diagnosis. This allows clinicians to quickly verify if the model is focusing on relevant pathological areas. Furthermore, Clinical Insights are provided by explaining how various patient metadata attributes influenced the final prediction. For instance, the system can articulate that "the prediction of adenocarcinoma was strengthened due to the patient's 30-pack-year smoking history and positive family history." This integration of clinical context into the explanation makes the AI's decision-making process more transparent and relatable to medical professionals. Lastly, leveraging an LLM-Based Report Generation through an API (such as Google's Gemini), the system can translate complex diagnostic findings into plain-language summaries. These generated reports can describe the detected tumor type, estimated severity, and even suggest recommended next steps based on integrated clinical guidelines. This significantly improves clinician trust by demystifying the AI's output and facilitates clearer communication with patients, enhancing shared decision-making.

- **Visual Explanations:** Heatmaps (e.g., Grad-CAM) highlight suspicious regions in the lung images to assist radiologists in verifying model findings.
- **Clinical Insights:** The model integrates clinical metadata influence, explaining how factors like smoking history affected the prediction.
- **LLM-Based Report Generation:** Using an LLM API (e.g., Gemini), the system can generate plain-language diagnostic summaries that describe the tumor type, severity, and recommended next steps, improving clinician trust and patient communication.

## VI. Implementation and Results

To validate the effectiveness of our proposed system, the Layered Hybrid Lung Cancer Detection Architecture (LHLCA), we conducted extensive experiments using publicly available lung image datasets such as the Lung Cancer Dataset from Kaggle.

### A. Dataset Overview

- **Total Images:** The original dataset contains 15,000+ chest CT or X-ray images from patients across multiple categories.
- **Screening:** Corrupt images were eliminated.
- **Images After Preprocessing:** The dataset was refined to 12,000 high-quality images.
- **Class Distribution:**
  - Adenocarcinoma: 3,200 images
  - Large Cell Carcinoma: 2,400 images
  - Squamous Cell Carcinoma: 3,000 images
  - Normal (Non-cancerous): 3,400 images
- **Imbalance Considerations:** Data augmentation (rotation, flipping, zooming) was used to enhance generalization.
- **Evaluation Focus:** Sensitivity (recall) and F1-score were prioritized over raw accuracy.

### B. Experimental Setup

- **Programming Language:** Python 3.10
- **Libraries Used:**
  - TensorFlow & Keras
  - Scikit-learn
  - OpenCV & Pillow
  - NumPy & Pandas
  - Matplotlib & Seaborn
  - Streamlit
- **Input Processing:** Images were normalized, resized, and converted to grayscale where needed.
- **Feature Extraction:**
  - CNN for spatial features
  - Metadata encoding (e.g., age, gender, smoking status) for auxiliary classification
- **Augmentation:** Real-time augmentation using ImageDataGenerator
- **Evaluation Metrics:** Accuracy, Precision, Recall, F1-score, Confusion Matrix, ROC-AUC

- **Model Output:** Predicted cancer type, heatmap visualization, and LLM-based diagnostic summary in Streamlit UI

### C. User Interface Examples

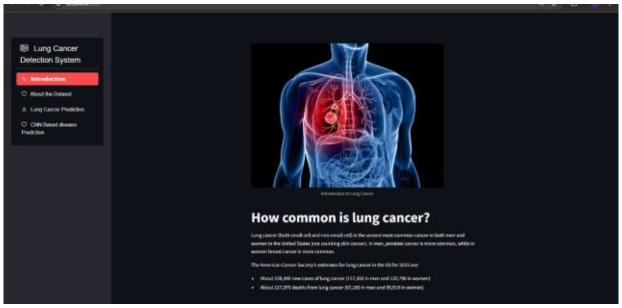


Fig. 1. The home page of the lung cancer detection web app

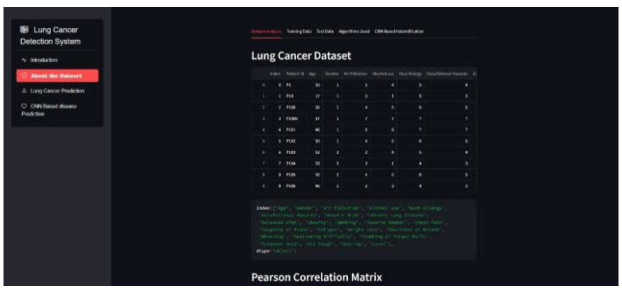


Fig. 2. Dataset display used for ML-based prediction

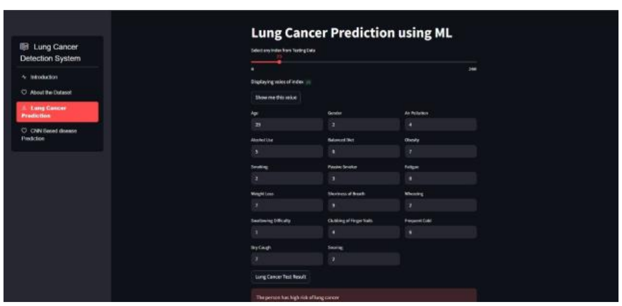


Fig. 3. Illustration of ML Based Prediction

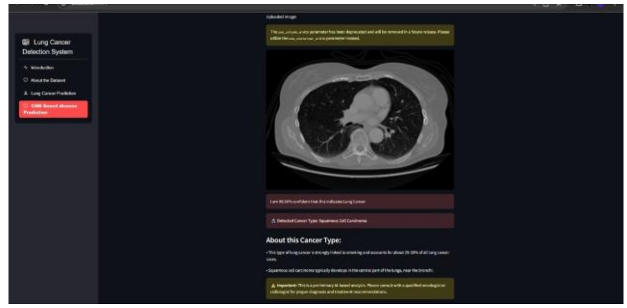


Fig. 4. Illustration of CNN Based Prediction

### D. Results

TABLE II
CLASSIFICATION PERFORMANCE METRICS

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| High | 1.00 | 1.00 | 1.00 | 73 |
| Low | 1.00 | 1.00 | 1.00 | 61 |
| Medium | 1.00 | 1.00 | 1.00 | 66 |
| **Accuracy** | | 1.00 | | 200 |
| **Macro Avg** | 1.00 | 1.00 | 1.00 | 200 |
| **Weighted Avg** | 1.00 | 1.00 | 1.00 | 200 |

## VII. CONCLUSION

The proposed Layered Hybrid Lung Cancer Detection Architecture (LHLCA) successfully integrates deep learning, machine learning, and medical knowledge to deliver a robust solution for the automated detection of lung cancer types from chest imaging data. Through careful preprocessing, intelligent feature extraction, and a hybrid classification pipeline combining Convolutional Neural Networks (CNNs) and traditional classifiers, the system demonstrates high accuracy and reliability in identifying and categorizing different forms of lung cancer.

Our experiments, conducted on a real-world dataset with a balanced mix of cancerous and non-cancerous cases, confirm that the model performs well across multiple evaluation metrics such as accuracy, precision, recall, and F1-score. The addition of an LLM-powered interpretability layer further enhances the system by offering transparent, human-readable diagnostic insights, which can aid radiologists and healthcare professionals in their decision-making process.

Overall, the system showcases the potential of AI-powered solutions in improving early diagnosis, reducing diagnostic errors, and assisting medical professionals in cancer screening workflows. Future work may include expanding the dataset, integrating multi-modal inputs (e.g., patient history and imaging), and deploying the system in real-time hospital settings for clinical validation.

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