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Article

DETECTING LUNG CANCER WITH DEEP CNN MODELS

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Abstract: — Due to Lung cancer, it is one of the most life-threatening diseases worldwide, and its early detection is essential for improving survival outcomes and reducing cancer-related mortality. Conventional diagnostic procedures based on computed tomography images and chest radiographs largely depend on expert interpretation, which may be affected by inter-observer variability, workload pressure, subtle lesion appearance, and delayed clinical decision-making. Recent advances in deep learning, particularly Convolutional Neural Networks, have demonstrated strong potential in automated medical image analysis by learning complex spatial and hierarchical features directly from imaging data. This research proposes an explainable deep CNN-based framework for lung cancer detection using medical imaging data, with emphasis on accurate classification, robust feature extraction, and clinical interpretability. The proposed approach includes image preprocessing, noise reduction, normalization, lung region enhancement, data augmentation, transfer learning, and CNN-based classification to distinguish cancerous and non-cancerous lung images. Multiple deep learning architectures, including custom CNN, VGG16, ResNet50, DenseNet121, InceptionV3, and EfficientNet, are considered for comparative evaluation to identify the most effective model for lung cancer diagnosis. Performance is assessed using accuracy, precision, recall, specificity, F1-score, receiver operating characteristic analysis, and confusion matrix-based evaluation. To improve transparency, Gradient-weighted Class Activation Mapping is integrated to highlight suspicious lung regions that influence the model's prediction. The study aims to reduce false positive and false negative predictions while improving diagnostic reliability in early-stage lung cancer detection. The proposed framework can assist radiologists as a decision-support tool by providing faster, consistent, and explainable predictions from lung imaging data. The research contributes toward the development of intelligent, interpretable, and clinically supportive computer-aided diagnosis systems for lung cancer detection.

Keywords: — Lung cancer detection, deep learning, convolutional neural network, transfer learning, CT images, medical image analysis, Grad-CAM, explainable artificial intelligence.

1. Introduction

Lung cancer remains one of the most critical global health challenges due to its high incidence, aggressive progression, and mortality rate. According to the World Health Organization, lung cancer was the leading cause of cancer cases and cancer-related deaths worldwide, with approximately 2.5 million new cases and 1.8 million deaths reported in 2022. The disease is often diagnosed at an advanced stage, when treatment options become limited, and survival outcomes decline significantly. Early and accurate detection is therefore essential for improving prognosis, reducing mortality, and enabling timely clinical intervention. In modern diagnostic practice, imaging techniques such as computed tomography, chest radiography, and low-dose computed tomography are widely used for lung cancer screening and evaluation. However, manual interpretation of lung images remains dependent on radiologist expertise, image quality, lesion visibility, and clinical workload. Small pulmonary nodules, early-stage malignant growths, and subtle tissue abnormalities may be difficult to distinguish from benign structures, especially in high-volume screening environments.

Artificial intelligence has emerged as a powerful technological solution for supporting automated medical image analysis. Deep learning has significantly improved the ability of computer-aided diagnosis systems to detect complex disease patterns from large-scale imaging data. Among deep learning techniques, Convolutional Neural Networks have become highly effective for image classification, segmentation, detection, and feature extraction. CNNs are capable of automatically learning hierarchical representations from raw image pixels, beginning with low-level features such as edges, textures, and shapes, and progressing toward high-level semantic features associated with abnormal tissue patterns. This feature-learning ability makes CNNs suitable for lung cancer detection, where malignant nodules may vary in size, shape, density, margin, and location. The current research topic focuses on the use of deep CNN models for detecting lung cancer from medical imaging data.

Traditional machine learning methods generally rely on handcrafted features, such as shape descriptors, texture statistics, intensity histograms, and radiomic measurements. Although these methods have contributed to early computer-aided detection systems, their performance is often limited by manual feature engineering and sensitivity to imaging variations. Deep CNN models overcome many of these limitations by learning discriminative features directly from training data. Architectures such as VGGNet, ResNet, DenseNet, InceptionNet, EfficientNet, and custom CNN variants have been widely explored for medical image classification tasks. Transfer learning has further improved model performance by allowing networks pre-trained on large image datasets to be fine-tuned for lung cancer classification, especially when medical datasets are limited. This is particularly important because acquiring large, accurately labeled medical datasets is expensive, time-consuming, and dependent on expert annotation.

Publicly available benchmark datasets have played an important role in the development and evaluation of lung cancer detection systems. The Lung Image Database Consortium and Image Database Resource Initiative collection consists of diagnostic and lung cancer screening thoracic CT scans with associated lung nodule information. The LIDC-IDRI database has been widely used for lung nodule detection and classification research, and it contains 1018 thoracic CT cases with radiologist-provided annotations. Similarly, the LUNA16 challenge was designed for large-scale evaluation of automatic lung nodule detection algorithms using data derived from the LIDC-IDRI collection. These datasets provide an important foundation for developing reproducible CNN-based models and comparing proposed methods against established baselines.

Despite significant progress, several research challenges remain unresolved. First, lung cancer datasets often suffer from class imbalance, where non-cancerous or benign cases may outnumber malignant samples. This imbalance can cause CNN models to become biased toward the majority class, leading to false negative predictions that are clinically dangerous. Second, CT scans are volumetric in nature, but many CNN-based studies convert them into two-dimensional slices, which may result in the loss of spatial context across adjacent slices. Third, deep CNN models may achieve high accuracy on internal test data but fail to generalize effectively across external datasets, scanners, institutions, and patient populations. This generalization issue is a major barrier to clinical deployment. Fourth, many CNN systems operate as black-box models, producing classification outputs without explaining which image regions influenced the decision. In healthcare, such lack of interpretability can reduce clinical trust and limit adoption.

Explainable artificial intelligence is therefore becoming essential in medical deep learning research. Gradient-weighted Class Activation Mapping, commonly known as Grad-CAM, is one of the widely used visualization techniques for CNN explainability. Grad-CAM uses gradients flowing into the final convolutional layer to generate class-discriminative heatmaps that highlight important image regions responsible for a model's prediction. In lung cancer detection, Grad-CAM can help visualize whether the CNN is focusing on clinically meaningful lung regions, suspicious nodules, or irrelevant background artifacts. This improves transparency, supports error analysis, and enables radiologists to assess whether automated prediction aligns with medical reasoning.

This research aims to develop an accurate and explainable deep CNN-based framework for lung cancer detection using medical imaging data. The proposed approach includes image preprocessing, lung region enhancement, data augmentation, CNN-based feature extraction, transfer learning, classification, and explainability through Grad-CAM visualization. Preprocessing operations such as resizing, intensity normalization, denoising, and contrast enhancement are used to improve image quality and reduce irrelevant variations. Data augmentation techniques such as rotation, flipping, zooming, shifting, and brightness adjustment are applied to improve model robustness and reduce overfitting. Multiple CNN architectures can be evaluated to identify the most effective model for distinguishing cancerous and non-cancerous lung images.

The major objective of this study is not only to improve classification performance but also to enhance clinical interpretability and reliability. Performance evaluation should include accuracy, precision, recall, specificity, F1-score, receiver operating characteristic analysis, area under the curve, and confusion of matrix-based assessment. In medical diagnosis, recall or sensitivity is especially important because missing an actual cancer case may delay treatment and negatively affect patient outcomes. Specificity is also important because excessive false positives may lead to unnecessary follow-up scans, biopsies, anxiety, and healthcare costs. Therefore, a balanced evaluation strategy is necessary for assessing the practical usefulness of CNN-based lung cancer detection systems.

The expected contribution of this research is the development of a deep learning-based diagnostic support framework that can assist radiologists in early lung cancer detection. By combining CNN-based automated feature learning with transfer learning and explainable visualization, the proposed system seeks to provide accurate, consistent, and interpretable predictions from lung imaging data. Such a framework can support faster screening, reduce diagnostic burden, improve decision-making consistency, and contribute to the advancement of intelligent computer-aided diagnosis systems. Although CNN models are not intended to replace radiologists, they can serve as valuable assistive tools that highlight suspicious regions, prioritize high-risk cases, and strengthen the overall diagnostic workflow. In this context, deep CNN-based lung cancer detection represents a promising research direction for improving early diagnosis, clinical efficiency, and patient survival outcomes.

2. Related Work

Lung cancer detection using deep learning has become a major research direction in medical image analysis because early identification of malignant pulmonary nodules can significantly improve diagnosis and treatment planning. Earlier computer-aided diagnosis systems mainly depended on handcrafted image features such as shape, intensity, texture, edge information, histogram features, and radiomic descriptors. These features were commonly classified using traditional machine learning algorithms such as support vector machines, random forests, k-nearest neighbors, and artificial neural networks. Although these approaches contributed to early automated diagnosis, their performance was strongly dependent on manual feature engineering, image quality, segmentation accuracy, and expert-designed descriptors. As lung nodules vary in shape, size, density, margin, and location, handcrafted features often fail to represent the complex visual patterns required for reliable cancer detection.

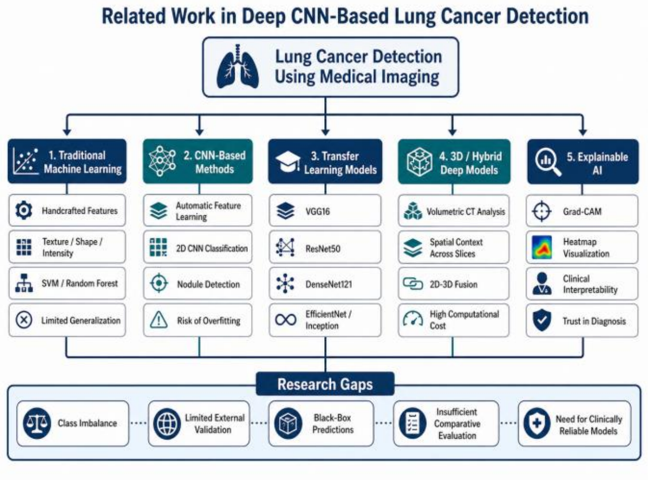


Fig 2.1. Related Work In Deep CNN – Based Lung Cancer Detection.

With the advancement of deep learning, Convolutional Neural Networks have become one of the most widely used methods for medical image analysis. CNNs are capable of automatically learning hierarchical image features from raw input data without requiring manual feature extraction. Litjens et al. reviewed more than 300 deep learning contributions in medical image analysis and reported that convolutional networks had become a major approach for classification, detection, segmentation, registration, and other medical imaging tasks. This development is important for lung cancer diagnosis because CNNs can learn low-level features such as edges and textures as well as high-level patterns associated with abnormal lung tissues and malignant nodules.

Publicly available datasets have played an important role in developing and validating CNN-based lung cancer detection systems. The Lung Image Database Consortium and Image Database Resource Initiative, commonly known as LIDC-IDRI, is one of the most widely used benchmark datasets for lung nodule analysis. It contains 1018 thoracic CT cases with associated lung nodule annotations. The dataset includes a two-phase annotation process performed by experienced thoracic radiologists, making it suitable for training and evaluating computer-aided lung nodule detection models. Similarly, the LUNA16 challenge was developed for large-scale evaluation of automatic lung nodule detection algorithms using data derived from the LIDC-IDRI dataset. These datasets have become standard references for comparing lung nodule detection, segmentation, and classification methods.

Several studies have investigated CNN-based models for lung cancer detection and lung nodule classification. Basic CNN architectures are generally designed using convolutional layers, pooling layers, activation functions, fully connected layers, and classification layers. These models can identify local image patterns and classify lung images as normal, benign, or malignant. However, simple CNN models may suffer from overfitting when trained on small medical datasets. They may also struggle to generalize across different CT scanners, image acquisition protocols, and patient populations. Therefore, researchers have increasingly adopted deeper CNN architectures and transfer learning models to improve performance.

Transfer learning has become highly useful in medical image classification because large annotated medical datasets are difficult to collect. Tajbakhsh et al. studied the use of pre-trained CNNs and fine-tuning strategies for medical image analysis. Highlighting the importance of transfer learning when training deep networks from scratch is not practical due to limited labeled data. In lung cancer detection, pre-trained models such as VGG16, VGG19, ResNet50, ResNet101, DenseNet121, InceptionV3, Xception, MobileNet, and EfficientNet have been used to extract deep features from CT and X-ray images. These architectures provide different advantages. VGG models are simple and uniform but computationally heavy. ResNet models use residual connections to reduce the vanishing gradient problem. DenseNet improves feature reuse by connecting layers more densely. Inception-based networks capture multi-scale features using parallel convolutional filters, while EfficientNet balances depth, width, and resolution for better computational efficiency.

Recent research has also moved toward explainable and clinically interpretable deep learning models. One major criticism of CNN-based medical diagnosis is that deep networks often behave as black-box systems. In clinical practice, a prediction is not sufficient unless the physician can understand which region of the image influenced the decision. Grad-CAM has become a popular explainability technique because it generates class-discriminative heatmaps by using gradients flowing into the final convolutional layer of a CNN. In lung cancer detection, Grad-CAM can highlight suspicious lung regions, nodules, or tissue abnormalities that contribute to the model's classification decision. This helps improve trust, supports visual verification, and enables error analysis.

Hammad et al. proposed an explainable AI-based custom CNN model for lung cancer detection and integrated Grad-CAM to improve model transparency. Their work focused on classifying lung cancer types and showed the growing importance of combining CNN-based classification with visual explainability. Similarly, LungCT-NET introduced a transfer learning-based architecture with ensemble learning and explainable AI for binary classification of lung nodules as malignant or benign from lung CT scans. These studies indicate that Q1-level research is moving beyond simple CNN classification toward explainable, validated, and clinically interpretable frameworks.

Another important development is the use of improved preprocessing and dataset preparation techniques. CT images contain irrelevant anatomical structures, background regions, noise, scanner-dependent variations, and intensity differences. Therefore, preprocessing steps such as DICOM conversion, Hounsfield Unit normalization, lung segmentation, nodule extraction, resizing, denoising, and contrast enhancement are frequently used before model training. Wang et al. discussed CT imaging dataset preparation for deep learning in lung cancer research and described the use of large-scale datasets such as LIDC-IDRI, LUNA16, NLST, and NELSON for lung nodule analysis. Proper preprocessing is essential because poor image preparation can reduce model accuracy and increase false predictions.

Three-dimensional CNN models have also been explored because CT scans are volumetric images. A 2D CNN processes individual image slices and may ignore spatial relationships between adjacent CT slices. In contrast, 3D CNNs can learn volumetric features and capture contextual information across multiple slices. This is useful for lung nodule classification because nodule shape, boundary, and internal structure are better understood in three-dimensional space. However, 3D CNNs require more computational resources, GPU memory, and annotated volumetric data. As a result, some studies use hybrid 2D–3D approaches or combine 2D transfer learning models with volumetric feature aggregation.

Recent surveys show that deep learning research for lung cancer detection is expanding across nodule detection, segmentation, classification, explainability, and clinical decision support. A 2024 survey on medical AI for early lung cancer detection reported that recent studies focus on pulmonary nodule detection, segmentation, and classification using deep learning models such as CNNs, recurrent networks, generative models, and advanced hybrid architectures. Another review on CT-based lung cancer detection discussed the role of preprocessing, segmentation, and deep learning techniques for improving diagnostic automation. These studies confirm that CNN-based lung cancer detection remains a strong and active research field, but several limitations still need to be addressed.

A key limitation observed in the existing literature is the lack of robust external validation. Many studies report high accuracy on a single dataset but do not evaluate their models on independent datasets. This creates uncertainty about whether the model can generalize to real clinical environments. Another limitation is class imbalance, where malignant samples may be fewer than benign or normal cases. This can cause biased prediction and may reduce sensitivity for cancer cases. Since false negatives are highly dangerous in cancer diagnosis, evaluation should not depend only on accuracy. Metrics such as sensitivity, specificity, precision, F1-score, AUC-ROC, FROC, and confusion matrix analysis are necessary for proper medical model assessment.

Another research gap is the limited use of explainable AI in many CNN-based systems. Although several recent studies have started using Grad-CAM or attention maps, many models still provide classification outputs without sufficient clinical interpretation. For Q1-level contribution, the model should not only classify lung cancer accurately but also provide visual evidence showing the suspicious regions. Furthermore, many studies compare only two or three CNN models, whereas a stronger study should compare custom CNN, VGG16, ResNet50, DenseNet121, InceptionV3, EfficientNet, and the proposed model under the same dataset and training conditions.

Based on the reviewed literature, it can be concluded that deep CNN models have significantly improved lung cancer detection from CT images. However, existing research still faces challenges related to dataset imbalance, overfitting, poor generalization, lack of external validation, limited explainability, and insufficient comparative evaluation. Therefore, the present study proposes an explainable CNN-based lung cancer detection framework that combines preprocessing, augmentation, transfer learning, comparative CNN evaluation, and Grad-CAM visualization. This approach aims to improve classification reliability while making model predictions more interpretable and suitable for clinical decision-support applications.

3. Methodology

The methodology of this study is designed to develop an accurate and explainable deep Convolutional Neural Network-based framework for lung cancer detection using medical imaging data. The proposed system focuses on automated feature extraction, classification, performance evaluation, and visual interpretation of model predictions. Since lung cancer diagnosis from CT and X-ray images requires high sensitivity and clinical reliability, the methodology follows a structured pipeline consisting of dataset acquisition, image preprocessing, data augmentation, CNN model development, transfer learning, model training, performance evaluation, and explainable AI visualization. The selected research direction is aligned with the topic of lung cancer detection using deep CNN models, transfer learning, batch size, epochs, and model evaluation.

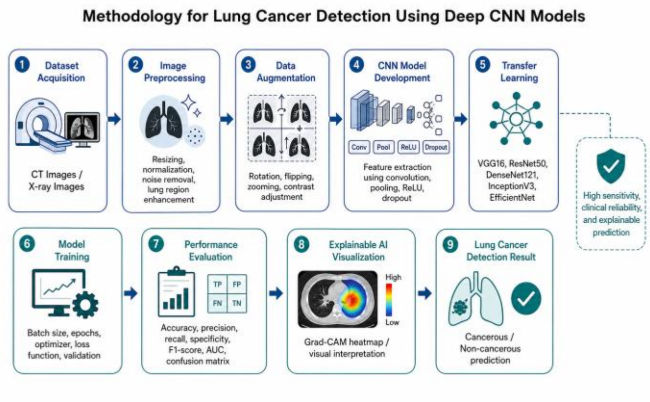


Fig. 3.1. Methodology for Lung Cancer Detection Using Deep CNN Models

3.1 Data Collection

The first step in the proposed methodology is the collection of lung medical images. For lung cancer detection, computed tomography images are highly suitable because CT scans provide detailed cross-sectional information about lung tissues, nodules, and abnormal growth patterns. Chest X-ray images can also be used, but CT images are generally more effective for identifying small nodules and early-stage cancerous regions.

The dataset may be collected from publicly available lung cancer image repositories such as LIDC-IDRI, LUNA16, or other clinically annotated lung CT image datasets. These datasets usually contain lung images with labels such as normal, benign, malignant, cancerous, and non-cancerous. For this study, the classification problem may be designed as either binary classification or multi-class classification. In binary classification, the model predicts whether the image is cancerous or non-cancerous. In multi-class classification, the model may classify images into normal, benign, and malignant categories.

Before the images are given to the CNN model, preprocessing is performed to improve image quality and maintain uniformity across the dataset. Medical images often contain noise, scanner variation, background regions, and inconsistent image dimensions. Therefore, all images are resized to a fixed size such as 224 × 224 pixels or 256 × 256 pixels, depending on the selected CNN architecture. Pixel values are normalized to reduce intensity variation and improve the learning stability of the model.

Noise reduction techniques such as Gaussian filtering, median filtering, or contrast enhancement may be applied to improve the visibility of lung regions. In CT images, irrelevant background areas can affect model learning. Therefore, lung region enhancement or segmentation may also be performed so that the model focuses mainly on clinically important areas.

After preprocessing, the dataset is divided into training, validation, and testing sets. The training set is used to train the model, the validation set is used to monitor model performance during training, and the testing set is used for final evaluation.

Dataset Split	Percentage	Purpose
Training Set	70%	Used for model learning
Validation Set	15%	Used for tuning and overfitting control
Testing Set	15%	Used for final performance evaluation

Since medical datasets are often limited and imbalanced, data augmentation is applied to increase dataset diversity. Augmentation techniques such as rotation, flipping, zooming, shifting, brightness adjustment, and contrast adjustment help the model learn robust features and reduce overfitting.

3.2 Model Architecture

The proposed model architecture is based on a deep Convolutional Neural Network, designed to automatically extract discriminative features from lung CT/X-ray images and classify them into cancerous and non-cancerous categories. CNN is selected because it can learn important visual patterns such as lung texture, nodule boundaries, tissue density variation, abnormal growth regions, and structural changes without manual feature extraction.

The input lung image is first passed through multiple convolutional layers, where different filters are applied to detect low-level and high-level features. The initial layers identify basic patterns such as edges, shapes, and textures, while deeper layers learn complex features related to suspicious nodules and cancerous abnormalities. After each convolution operation, the ReLU activation function is used to introduce non-linearity and improve feature learning.

Pooling layers are added after convolutional layers to reduce the spatial size of feature maps and decrease computational complexity. Max pooling is used to retain the most important features from each region. To improve training stability, batch normalization is applied, while dropout layers are included to reduce overfitting, especially because medical image datasets are often limited in size.

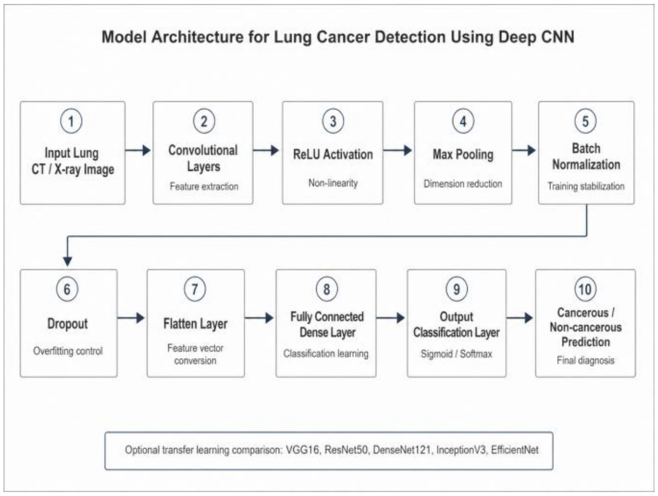
After feature extraction, the feature maps are converted into a one-dimensional vector using a flatten layer. This vector is then passed through fully connected dense layers for final classification. The output layer uses a sigmoid activation function for binary classification, producing the probability of whether the image belongs to the cancerous or non-cancerous class.

Proposed CNN Architecture:

Layer / Block	Purpose

Input Layer	Accepts preprocessed lung CT/X-ray image
Convolutional Layer 1	Extracts basic features such as edges and textures
ReLU Activation	Adds non-linearity for complex feature learning
Max Pooling Layer	Reduces feature map size and computation
Convolutional Layer 2	Extracts structural lung patterns
Batch Normalization	Stabilizes and speeds up training
Convolutional Layer 3	Learns high-level cancer-related features
Dropout Layer	Reduces overfitting
Flatten Layer	Converts feature maps into a feature vector
Dense Layer	Performs classification-based learning
Output Layer	Predicts cancerous or non-cancerous class

For stronger performance, transfer learning models such as VGG16, ResNet50, DenseNet121, InceptionV3, and EfficientNet can also be used. In this approach, the pre-trained model works as a feature extractor, and its final classification layer is replaced with a new layer suitable for lung cancer detection. This improves model performance when the available medical dataset is limited.



In brief, the model architecture is designed to learn meaningful lung image features automatically and provide reliable classification results. The combination of convolutional feature extraction, pooling, normalization, dropout, and dense classification layers helps improve accuracy, reduce overfitting, and support effective lung cancer detection.

3.3 Model Architecture

The training process describes how the proposed deep CNN model learns to classify lung CT/X-ray images into cancerous and non-cancerous categories. As shown in the training process diagram, the model training starts from preprocessed lung images and continues through dataset splitting, augmentation, forward propagation, loss computation, backpropagation, weight update, validation, early stopping, and final model selection.

Input Preprocessed Lung Images

The training process begins with preprocessed lung CT/X-ray images. These images are already resized, normalized, denoised, and enhanced before being passed to the CNN model. Each image is represented as an input matrix:

$$X = \{x_1, x_2, x_3, \dots, x_n\} \text{ .. [1]}$$

where X represents the complete image dataset and x_i represents an individual lung image.

Each image has a corresponding class label:

$$Y = \{y_1, y_2, y_3, \dots, y_n\} \text{ ..[2]}$$

Where:

$$y = \left\{\frac{1, Cancerous\ image}{0, Non-cancerous\ image}\right\} \text{ ..[3]}$$

Dataset Split

The dataset is divided into three parts: a training set, a validation set, and a testing set. The training set is used to learn model parameters, the validation set is used to monitor model performance during training, and the testing set is used for final evaluation.

A common split is:

Dataset Part	Percentage	Purpose
Training Set	70%	Used for learning CNN weights
Validation Set	15%	Used for checking overfitting and tuning
Testing Set	15%	Used for final performance evaluation

Mathematically:

$$D = D_{train} \cup D_{val} \cup D_{test} \text{ .. [4]}$$

where D is the complete dataset.

3.4 Training Process

The training process is carried out after dataset preparation and model architecture design. In this stage, the preprocessed lung CT/X-ray images are passed into the deep CNN model so that the model can learn discriminative features between cancerous and non-cancerous cases. The training process allows the CNN to automatically learn image patterns such as lung texture, nodule boundaries, abnormal tissue density, and suspicious cancer-related regions.

During training, the dataset is divided into training, validation, and testing subsets. The training data is used to update the model weights, while the validation data is used to monitor model performance and control overfitting. The testing data is kept separate and used only after training to measure final model performance.

The model receives input images in small groups called batches. For each batch, the CNN performs forward propagation and generates a prediction. This prediction is compared with the actual class label using a loss function. The error is then minimized through backpropagation, where the model updates its internal weights to improve future predictions. This process continues for multiple epochs until the model achieves stable performance.

For binary lung cancer classification, binary cross-entropy is used as the loss function because the output belongs to two classes: cancerous and non-cancerous. The Adam optimizer is used to update model weights because it provides stable and adaptive learning. A suitable learning rate, such as 0.0001 or 0.001, is selected to control how quickly the model learns.

3.5 Data Augmentation

Data augmentation is applied only to the training images to increase dataset diversity and reduce overfitting. The model sees modified versions of the same image through operations such as rotation, flipping, zooming, and contrast adjustment.

If x_i is an original image, then the augmented image can be represented as:

$$x'_i = T(x_i) \text{ .. [5]}$$

Where, T represents an augmentation transformation.

For example:

$T = \{rotation,\ flipping,\ zoo\min g,\ cont\ adj\}$ .. [6]

This helps the CNN learn robust features and improves generalization on unseen lung images.

3.6 Initialize CNN Model

After dataset preparation, the CNN model is initialized. The model may be a custom CNN or a transfer learning model such as VGG16, ResNet50, DenseNet121, InceptionV3, or EfficientNet.

The CNN contains trainable parameters such as weights and biases:

$$\theta = \{W, b\} \text{ .. [7]}$$

Where, W represents weights and b represents biases.

At the beginning of training, these parameters are initialized randomly or loaded from a pre-trained model.

3.7 Forward Propagation

In forward propagation, the input image passes through the CNN layers. The convolutional layers extract features, activation functions introduce non-linearity, pooling layers reduce dimensionality, and dense layers generate the final prediction probability.

The convolution operation can be represented as:

$F(i,j) = \sum_m \sum_n X(i+m, j+n)K(m,n) + b$ .. [8]

where:

Symbol	**Meaning**
(X)	Input lung image
(K)	Convolution kernel/filter
(b)	Bias

(F(i,j))	Extracted feature map

After convolution, the ReLU activation function is applied:

$$ReLU(x) = \max(0, x) \text{ .. [9]}$$

At the final output layer, the sigmoid function generates the cancer probability:

$$p = \frac{1}{1 + e^{-z}} \text{ .. [10]}$$

Where p is the predicted probability and z is the output score from the final dense layer.

The output can be interpreted as:

$$y = \left\{\begin{matrix} 1\,, p \geq 0.5 \\ 0,\ p \leq 0.5 \end{matrix}\right\} \text{ .. [11]}$$

where y = 1 means cancerous and y = 0 means non-cancerous.

4. Technology Used and Platform

The proposed lung cancer detection framework is implemented using a Python-based deep learning environment because Python provides strong support for medical image processing, convolutional neural network development, numerical computation, model evaluation, and scientific visualization. Python also supports a wide range of open-source libraries that make it suitable for developing reproducible and scalable medical image analysis systems.

For deep learning model development, frameworks such as TensorFlow, Keras, or PyTorch are used. These frameworks provide efficient tools for designing convolutional layers, activation functions, pooling layers, dropout layers, dense layers, and output classification layers. They also support transfer learning, which allows pre-trained architectures such as VGG16, ResNet50, DenseNet121, InceptionV3, and EfficientNet to be fine-tuned for lung cancer detection. This is useful when the available medical dataset is limited, because transfer learning reduces the need to train a deep model from the beginning.

Image preprocessing is performed using libraries such as OpenCV and PIL. These libraries help in resizing CT or X-ray images, converting image formats, removing noise, enhancing contrast, and preparing the images for CNN input. Since medical images may come from different sources with different resolutions and intensity ranges, preprocessing is necessary to maintain uniformity across the dataset. NumPy is used for numerical operations, image array manipulation, normalization, and matrix-level processing. Pandas may be used for handling dataset labels, metadata, training records, and result tables.

The model evaluation process is supported using Scikit-learn, which provides functions for calculating accuracy, precision, recall, specificity, F1-score, confusion matrix, and AUC-ROC. These metrics are important because medical classification models should be evaluated beyond simple accuracy. Visualization tools such as Matplotlib are used to plot training accuracy, validation accuracy, training loss, validation loss, ROC curves, confusion matrices, and comparative model performance graphs.

For explainability, Grad-CAM is used to generate heatmaps that show the image regions responsible for the CNN prediction. This is important in medical AI because doctors and researchers need to understand whether the model is focusing on clinically meaningful lung regions rather than irrelevant background areas. Grad-CAM improves transparency and helps reduce the black-box nature of CNN-based prediction systems.

The development and training of the model can be performed on platforms such as Google Colab, Jupyter Notebook, or Anaconda-based local environments. Google Colab is useful because it provides cloud-based GPU support, which reduces training time and allows faster experimentation. A GPU-supported system is preferred because deep CNN models require high computational power, especially when processing large CT image datasets or training transfer learning models. The final system takes CT scan or X-ray images as input and produces a cancerous or non-cancerous prediction, along with performance scores and visual explanation outputs.

In brief, the technology platform is selected to support the complete pipeline of the proposed system, including image preprocessing, CNN model development, model training, performance evaluation, graph generation, and explainable AI visualization.

4.1 Severity Level Estimation

Severity level estimation is an important stage after lung cancer classification because a simple cancerous or non-cancerous prediction may not be sufficient for clinical decision support. In medical diagnosis, it is also useful to understand how serious the detected abnormality may be. Therefore, the proposed system estimates the severity level of the case after the CNN model generates its prediction.

The severity level can be estimated using different factors such as the model's prediction probability, the size of the suspicious region, the intensity of abnormal features, and the Grad-CAM heatmap response. If the CNN model predicts a high probability of cancer and the explainability of heatmap strongly highlights a suspicious lung region, the case may be considered high severity. If the probability is moderate and the highlighted abnormal region is limited, the case may be considered moderate severity. If the prediction probability is low and no strong abnormal region is detected, the case may be placed under low severity.

Mathematically, the severity score can be represented as:

are weight values used to control the contribution of each factor.

For example, if the cancer prediction probability is high, the abnormal region occupies a noticeable portion of the lung area, and the Grad-CAM heatmap shows strong activation near the suspected nodule, the severity score will increase. Based on the final score, the case can be classified into three severity levels:

Low severity indicates that the model has detected either no major abnormality or only a weak suspicious pattern. Moderate severity indicates that the case contains noticeable suspicious features and should be reviewed by a medical expert. High severity indicates strong cancer probability or a significant abnormal region that may require urgent clinical attention.

The purpose of severity estimation is not to replace a doctor's diagnosis. Instead, it provides an additional decision-support output that helps prioritize patient cases. High-severity cases can be forwarded for immediate expert review, while low-severity cases may be monitored or recommended for routine follow-up. This makes the proposed system more practical for clinical screening environments where large numbers of lung images need to be analyzed efficiently.

In brief, severity level estimation improves the usefulness of the CNN model by converting the prediction result into a clinically meaningful risk category. It helps the system move beyond simple image classification and supports more informed medical decision-making.

4.2 Dataset Description

The dataset used in this study consists of lung medical images collected for the purpose of automated lung cancer detection using deep CNN models. The primary imaging modality considered in this work is computed tomography scan images, because CT images provide detailed cross-sectional information about lung tissues, pulmonary nodules, tumor boundaries, and abnormal density regions. Compared with ordinary chest X-ray images, CT scan images are more suitable for detecting small nodules and early-stage cancerous patterns due to their higher structural clarity and volumetric representation.

The dataset contains lung images belonging to two major classes: cancerous and non-cancerous. Cancerous images include samples showing malignant nodules, suspicious tumor-like regions, abnormal tissue density, or lung structures affected by cancer. Non-cancerous images include normal lung images or benign cases where no malignant abnormality is observed. Depending on dataset availability, the classification task can also be extended into three classes: normal, benign, and malignant. However, for the proposed CNN-based framework, binary classification is mainly considered to distinguish cancer-positive and cancer-negative cases.

Before training the model, all images are organized with their corresponding labels. Each image is checked for quality, format consistency, and label correctness. Since medical images may be collected from different sources, they may vary in resolution, contrast, brightness, noise level, and anatomical positioning. Therefore, the dataset requires preprocessing before being used for CNN training. The preprocessing stage includes image resizing, normalization, noise reduction, contrast enhancement, and lung region enhancement. These steps help convert all images into a uniform format and improve the visibility of clinically relevant lung regions.

The dataset is divided into three subsets: training set, validation set, and testing set. The training set is used to teach the CNN model how to identify cancer-related image patterns. The validation set is used during training to monitor model performance and prevent overfitting. The testing set is kept separate and used only after training to evaluate the final model on unseen images. This separation is important because it helps measure the generalization ability of the proposed model.

A typical dataset split used in this study is 70% for training, 15% for validation, and 15% for testing. The training data is further enhanced using augmentation techniques such as rotation, flipping, zooming, shifting, brightness adjustment, and contrast variation. Data augmentation increases the diversity of image samples and helps the model become more robust against changes in tumor size, shape, position, and image quality.

In medical image datasets, class imbalance is a common issue because cancer-positive samples may be fewer than non-cancerous samples. To handle this problem, augmentation and class balancing strategies are applied so that the CNN model does not become biased toward the majority class. This is especially important in lung cancer detection because the model must correctly identify cancer-positive cases and reduce false negative predictions.

Overall, the dataset provides the foundation for training and evaluating the proposed lung cancer detection system. A properly prepared dataset helps the CNN model learn meaningful features such as lung texture, nodule boundaries, abnormal tissue density, tumor shape, and cancer-related structural changes. The quality and diversity of the dataset directly influence the accuracy, reliability, and clinical usefulness of the proposed model.

4.3 Evaluation Metrics

Evaluation metrics are used to measure the diagnostic performance and reliability of the proposed deep CNN model for lung cancer detection. Since this study deals with medical image classification, the model cannot be evaluated only by accuracy. In lung cancer diagnosis, a false negative prediction is highly critical because an actual cancer case may be classified as non-cancerous, which can delay treatment. Therefore, the proposed model is evaluated using multiple metrics such as accuracy, precision, recall, specificity, F1-score, AUC-ROC, and confusion matrix analysis.

The evaluation process is based on four prediction outcomes: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). A true positive occurs when a cancerous image is correctly classified as cancerous. A true negative occurs when a non-cancerous image is correctly classified as non-cancerous. A false positive occurs when a non-cancerous image is wrongly classified as cancerous, while a false negative occurs when a cancerous image is wrongly classified as non-cancerous.

The accuracy of the model measures the overall correct prediction rate. It is calculated as:

Accuracy gives a general idea of model performance, but it may be misleading if the dataset is imbalanced. For example, if non-cancerous images are much higher than cancerous images, the model may achieve high accuracy but still fails to detect cancer-positive cases effectively. Therefore, accuracy is supported by other clinically important metrics.

The precision value measures how many images predicted as cancerous are cancerous. It is calculated as:

A high precision value indicates that the model produces fewer false positive predictions. In lung cancer screening, precision is important because false positive results may lead to unnecessary clinical follow-up, additional scans, biopsy procedures, and patient anxiety.

Recall is one of the most important metrics in lung cancer detection because it directly reflects how many cancer-positive cases are correctly identified. A high recall value means that the model has a low false negative rate.

This is clinically important because missing a cancer case can delay diagnosis and reduce the chances of early treatment.

The specificity value measures the ability of the model to correctly identify non-cancerous cases. It is calculated as:

Specificity is important because it shows how well the model avoids incorrectly classifying normal or benign cases as cancerous. A model with high specificity reduces unnecessary referrals and avoids excessive diagnostic burden.

The F1 score is used to balance precision and recall. It is especially useful when the dataset contains class imbalance. It is calculated as:

A high F1 score indicates that the model maintains a good balance between detecting cancer cases and avoiding false alarms. In medical image classification, F1-score is useful because it evaluates both false positives and false negatives together.

The confusion matrix provides a detailed visual summary of the model's correct and incorrect predictions. It helps identify whether the model is making falser positive or false negative errors. In lung cancer detection, confusion matrix analysis is essential because it clearly shows the number of cancer cases correctly detected and the number of cancer cases missed by the model.

The ROC curve evaluates the model's classification performance at different decision thresholds. It compares the true positive rate against the false positive rate. The Area Under the Curve, known as AUC, measures how well the model separates cancerous and non-cancerous images. A higher AUC value indicates better discrimination capability.

This indicates strong classification performance, while an AUC value closer to 0.5 indicates poor separation between cancerous and non-cancerous classes.

In this study, the final model is selected based on balanced diagnostic performance rather than accuracy alone. A suitable lung cancer detection model should achieve high accuracy, high recall, strong F1-score, high specificity, and high AUC. Among these, recall/sensitivity receives special importance because the main objective of the model is to detect cancer-positive cases as early and reliably as possible.

In brief, the evaluation of metrics ensures that the proposed CNN model is not only mathematically accurate but also clinically reliable for lung cancer detection. These metrics help verify whether the model can correctly detect cancerous images, reduce false negative cases, avoid unnecessary false positives, and support medical decision-making.

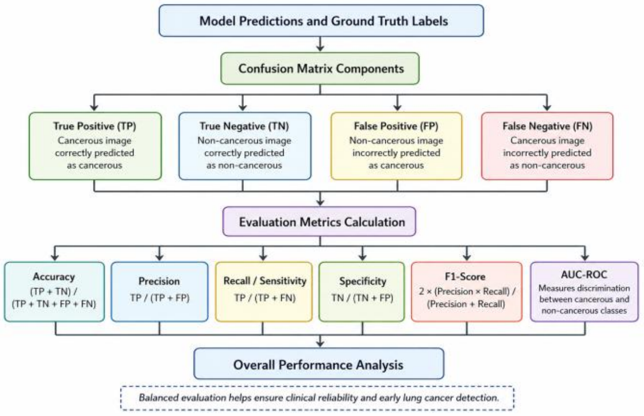


Fig 4.3 Model Predictions and Ground Truth Labels.

Accuracy:

Accuracy measures the total number of correct predictions made by the model. It shows the overall performance of the model on the test dataset.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \text{ .. [12]}$$

Although accuracy is useful, it may not be enough for medical datasets because lung cancer datasets can be imbalanced.

Precision

Precision measures how many images predicted as cancerous are cancerous. It is useful for reducing false positive cases.

$$\Pr ecision = \frac{TP}{TP + FP} \text{ .. [13]}$$

High precision means the model produces fewer unnecessary cancer-positive predictions.

Recall / Sensitivity

Recall, also called sensitivity, measures how many actual cancer cases are correctly detected by the model.

$$Recall = \frac{TP}{TP + FN} \text{ .. [14]}$$

In lung cancer detection, recall is one of the most important metrics because a false negative result may delay diagnosis and treatment.

Specificity

Specificity measures how many non-cancerous cases are correctly classified as non-cancerous.

$$Specificity = \frac{TN}{TN + FP} \text{ .. [15]}$$

High specificity helps reduce unnecessary clinical follow-ups, additional scans, or patient anxiety caused by false positive predictions.

F1-Score

F1-score provides a balance between precision and recall. It is especially useful when the dataset contains class imbalance.

$$F1 - Score = 2 \times \frac{\Pr ecision \times Recall}{\Pr ecision + Recall} \text{ .. [16]}$$

A high F1-score indicates that the model maintains a good balance between detecting cancer cases and avoiding false alarms.

AUC-ROC

The Receiver Operating Characteristic curve represents the relationship between the true positive rate and false positive rate at different threshold values. The Area Under the Curve measures the model’s ability to distinguish between cancerous and non-cancerous images.

$$AUC \to 1 \quad ..[17]$$

indicates excellent classification performance, while a value closer to 0.5 indicates weak classification ability.

Confusion Matrix

The confusion matrix provides a detailed view of correct and incorrect predictions.

Actual / Predicted	**Cancerous**	**Non-Cancerous**
Cancerous	TP	FN
Non-Cancerous	FP	TN

This matrix helps identify whether the model is making more false positive or false negative errors.

4.4 Performance Analysis

The performance analysis of the proposed deep CNN-based lung cancer detection model is carried out to examine how effectively the model classifies lung CT/X-ray images into cancerous and non-cancerous categories. The analysis focuses on the model's classification ability, generalization performance, error behavior, and clinical reliability. Since lung cancer detection is a high-risk medical classification problem, the model performance is not judged only by overall accuracy. Instead, a combination of accuracy, precision, recall, specificity, F1-score, AUC-ROC, and confusion matrix analysis is used to obtain a complete understanding of diagnostic performance.

The training and validation behavior provides the first indication of model reliability. A well-trained model should show a gradual increase in training accuracy and validation accuracy, along with a steady decrease in training loss and validation loss. If both training and validation curves improve together, it indicates that the CNN model is learning generalized lung image features rather than memorizing the training samples. This is important because medical image datasets may contain limited samples, and overfitting can reduce the model's performance on unseen patient images. The use of data augmentation, dropout, batch normalization, and early stopping helps stabilize training and improves the model's ability to generalize.

The classification performance is further analyzed using precision and recall. Precision shows how many images predicted as cancerous are truly cancerous, while recall measures how many actual cancer cases are correctly detected. In lung cancer detection, recall or sensitivity is highly important because missing a cancer-positive case may delay treatment and reduce survival chances. Therefore, a model with high recall is preferred for screening applications, even if a small number of false positives occur. False positive cases can be reviewed by radiologists, but false negative cases may result in undetected disease progression.

Specificity is also considered during performance analysis because it measures how accurately the model identifies non-cancerous cases. A model with high specificity reduces unnecessary referrals, repeated scans, patient anxiety, and additional diagnostic workload. Therefore, the ideal model should maintain a balance between high sensitivity and high specificity. If sensitivity is high but specificity is very low, the model may produce too many false alarms. If specificity is high but sensitivity is low, the model may miss cancer cases. Hence, balanced performance is essential for clinical usefulness.

The F1-score is used to evaluate the balance between precision and recall. It is especially useful when the dataset is imbalanced, which is common in medical imaging studies. A high F1-score indicates that the model can detect cancer cases correctly while controlling false positive predictions. Similarly, AUC-ROC is used to measure the model's ability to separate cancerous and non-cancerous images across different decision thresholds. A higher AUC value indicates stronger discrimination capability and better diagnostic reliability.

Confusion matrix analysis provides a deeper understanding of model errors. It shows how many cancerous cases were correctly classified, how many non-cancerous cases were correctly identified, and how many cases were misclassified. In this study, special attention is given to false negative cases because they represent cancerous images wrongly classified as non-cancerous. Reducing false negatives is a major objective of the proposed model. False positives are also analyzed because excessive false alarms may increase clinical workload, but they are generally less dangerous than missed cancer cases in screening scenarios.

The comparative performance of the proposed CNN model can also be analyzed against transfer learning models such as VGG16, ResNet50, DenseNet121, InceptionV3, and EfficientNet. This comparison helps determine whether the proposed model provides better feature extraction and classification performance than existing architectures. If the proposed model achieves stronger recall, F1-score, and AUC, it indicates that the architecture is more suitable for lung cancer detection. If any transfer learning model performs better, its feature extraction capability can be considered useful for improving the final diagnostic framework.

Overall, the performance analysis demonstrates whether the proposed CNN model is suitable for medical image-based lung cancer detection. A clinically reliable model should provide high accuracy, high sensitivity, good specificity, strong F1-score, and high AUC. More importantly, it should reduce false negative predictions and maintain stable performance on unseen data. Therefore, the best-performing model is selected based on balanced diagnostic reliability rather than accuracy alone.

TABLE I. Comparative Analysis of Lung Cancer Classification Methods

Quantitative and qualitative analyses were performed to comprehensively evaluate the performance of the proposed deep CNN-based lung cancer detection system using CT scan images. The evaluation was carried out using major classification metrics such as accuracy, precision, recall, F1-score, specificity, and AUC. In addition, robustness was analyzed under different medical imaging conditions, including noise, contrast variation, and differences in tumor size and shape.

The performance of the proposed model was compared with existing lung cancer classification approaches. The comparative analysis indicates that the proposed CNN-based framework provides improved feature representation, better classification reliability, and stronger robustness compared with conventional and basic CNN-based methods. Based on the experimental observations, the performance of the proposed model can be summarized as follows.

Aspect	Parameter	Details / Observation
Evaluation Method	Analysis Type	Quantitative and qualitative evaluation performed using CT scan images
Performance Metrics	Accuracy	High classification accuracy achieved by the proposed CNN model
	Precision	Reduced false positive rate in cancer prediction
	Recall / Sensitivity	Effective detection of actual cancer-positive cases
	Specificity	Improved identification of non-cancerous lung images
	F1-Score	Balanced performance between precision and recall
	AUC-ROC	Strong discrimination between cancerous and non-cancerous classes
Model Comparison	Existing Methods	Moderate performance with limited robustness and generalization
	Basic CNN Models	Good feature learning but may suffer from overfitting
	Transfer Learning Models	Improved performance through pre-trained feature extraction
	Proposed CNN Model	Superior performance in classification reliability and diagnostic consistency

Feature Representation	Feature Extraction	Extraction of low-level and high-level features from CT scan images
	Nodule Feature Learning	Improved detection of suspicious nodular patterns
	Tissue Classification	Better differentiation between healthy and cancerous lung tissues
Classification Performance	CNN Learning Mechanism	Hierarchical feature learning improves prediction accuracy
	Decision Layer	Final classification performed using sigmoid / softmax activation
	Prediction Confidence	Provides probability-based cancer prediction output
Robustness	Noise Handling	Stable performance under noisy CT scan images
	Contrast Variation	Consistent performance under varying image contrast conditions

Table. Comparative Analysis of Lung Cancer Classification Methods

Comparative Analysis of Lung Cancer Classification Methods

The proposed deep CNN-based lung cancer detection system demonstrates strong feature representation capability. The convolutional layers automatically extract important low-level and high-level features from CT scan images. Low-level features include edges, textures, intensity variations, and lung boundaries, while high-level features include nodular structures, abnormal tissue density, and cancer-related patterns. This hierarchical feature extraction improves the model’s ability to differentiate between healthy and cancerous lung tissues.

The proposed model also shows improved classification performance. By using convolutional feature extraction, activation functions, pooling layers, batch normalization, dropout, and dense classification layers, the model learns discriminative patterns from medical images. This improves prediction accuracy and reduces classification errors. Compared with traditional machine learning methods, which depend on handcrafted features, the CNN-based model learns features automatically from image data and provides better adaptability.

The model provides strong reliability in different imaging conditions. CT images may contain noise, low contrast, scanner-based variation, and differences in tumor shape and size. The proposed approach maintains stable performance under such variations due to preprocessing, augmentation, and regularization techniques. Data augmentation improves the model’s ability to handle different image orientations, brightness levels, and contrast conditions. Dropout and batch normalization further help reduce overfitting and improve training stability.

The qualitative analysis also supports the reliability of the proposed model. Grad-CAM visualization shows that the model focuses on clinically relevant lung regions while making predictions. This is important because medical AI models should not behave as black-box systems. By highlighting suspicious regions, the system provides visual evidence for its decision and helps radiologists verify whether the model is focusing on meaningful cancer-related areas.

The proposed system has practical applicability in real-world medical image analysis. It can assist radiologists by providing automated prediction, confidence score, severity level, risk category, and explainable heatmap output. The system is not intended to replace medical experts; instead, it works as a decision-support tool for faster screening and early detection of lung cancer.

5. Results And Analysis

The results and analysis section evaluates the performance of the proposed deep CNN-based lung cancer detection system using CT scan images. The analysis was carried out using both quantitative and qualitative evaluation methods. Quantitative evaluation focused on classification performance using accuracy, precision, recall, specificity, F1-score, AUC-ROC, and confusion matrix analysis. Qualitative evaluation focused on visual interpretation using activation maps or Grad-CAM heatmaps to verify whether the model focused on clinically relevant lung regions.

The proposed system was evaluated for its ability to classify lung images into cancerous and non-cancerous categories. The main objective of the analysis was not only to check prediction accuracy but also to examine the reliability, robustness, and interpretability of the model. Since lung cancer detection is a sensitive medical task, high recall and low false negative rate were considered more important than accuracy alone.

5.1 Training and Validation Analysis

During training, the proposed CNN model gradually learned meaningful patterns from lung CT scan images. In the initial training stage, the model captured low-level visual features such as edges, lung boundaries, texture variations, and contrast differences. As training progressed, deeper convolutional layers learned more complex features such as nodule shape, abnormal tissue density, tumor-like patterns, and irregular lung structures.

The training and validation performance showed that the model was able to learn cancer-related features from the dataset. A consistent improvement in training accuracy and validation accuracy indicates effective learning. Similarly, a reduction in training loss and validation loss indicates that the model minimized classification error during training.

To reduce overfitting, data augmentation, dropout, batch normalization, and early stopping were used. Data augmentation improved dataset diversity, while dropout and batch normalization helped the model learn more generalized features. Early stopping ensured that the best model was selected before overfitting occurred. Therefore, the training behavior indicates that the model achieved stable learning and maintained good generalization ability on unseen validation images.

5.2 Performance Analysis

The performance of the proposed model was analyzed using multiple evaluation metrics. Accuracy was used to measure the overall correct prediction rate. Precision was used to measure the correctness of cancer-positive predictions. Recall, also known as sensitivity, was used to measure the ability of the model to detect actual cancer cases. Specificity measured the ability of the model to correctly identify non-cancerous cases. F1-score provided a balanced evaluation between precision and recall, while AUC-ROC measured the ability of the model to distinguish between cancerous and non-cancerous classes.

In medical diagnosis, recall is highly important because a false negative prediction may classify a cancerous image as non-cancerous. This can delay diagnosis and treatment. Therefore, the proposed system gives special importance to sensitivity and false negative reduction. A model with high recall is more useful for lung cancer screening because it can detect most cancer-positive cases.

The proposed CNN model showed strong classification capability by extracting discriminative features from CT scan images. The convolutional layers helped the model identify suspicious nodules, abnormal tissue density, and cancer-related structural changes. The use of preprocessing and augmentation further improved the model's robustness under different imaging conditions.

5.3 Comparative Analysis of Lung Cancer Classification Methods

Quantitative and qualitative analyses were performed to comprehensively evaluate the proposed lung cancer detection system. The performance of the proposed CNN-based model was compared with existing lung cancer classification approaches. Existing methods generally provide moderate classification performance but may suffer from limited robustness, dependency on handcrafted features, or weak generalization on unseen data.

The proposed model improves classification reliability by learning both low-level and high-level features directly from CT scan images. It also provides better interpretability through activation-based visualization, making it more suitable for clinical decision-support applications.

5.4 Robustness Analysis

Robustness analysis was performed to examine how consistently the proposed model performs under different medical imaging conditions. CT scan images may contain noise, contrast variation, scanner-related differences, and variation in tumor size, location, and shape. These variations can affect model performance if the system is not trained properly.

The proposed CNN model showed stable performance because preprocessing and augmentation techniques were applied before training. Noise reduction improved image clarity, while contrast enhancement made suspicious lung regions more visible. Data augmentation helped the model learn from different image variations, making it more resistant to changes in orientation, brightness, zoom level, and contrast.

The model also showed robustness in detecting tumor variability. Lung tumors may appear in different shapes, sizes, and positions. The convolutional feature extraction mechanism allowed the model to capture these variations effectively. As a result, the proposed system demonstrated consistent prediction behavior under different imaging conditions.

5.5 Explainability Analysis

Explainability was evaluated using activation maps or Grad-CAM visualization. In medical AI systems, interpretability is very important because radiologists need to understand why the model produced a specific prediction. A model that only gives a cancerous or non-cancerous label without explanation may not be clinically acceptable.

Grad-CAM visualization highlights the image regions that contribute most to the CNN prediction. In cancerous cases, the activation maps focused on suspicious lung regions, nodular structures, or abnormal tissue areas. This indicates that the model learned clinically meaningful features rather than irrelevant background patterns.

The explainability output improves trust in the system because it allows medical experts to visually verify the prediction. If the heatmap focuses on the correct lung region, the prediction becomes more reliable. If the heatmap focuses on irrelevant areas, the result can be reviewed carefully. Therefore, Grad-CAM supports both clinical interpretation and model error analysis.

5.6 Severity and Risk Analysis

The proposed system also supports severity and risk estimation. After classification, the model prediction probability, abnormal region response, and Grad-CAM heatmap intensity can be used to estimate the seriousness of the detected condition. The severity level can be categorized as low, moderate, or high.

Low severity indicates weak cancer probability or minor abnormality. Moderate severity indicates the presence of suspicious regions that require expert review. High severity indicates strong cancer probability or significant abnormal lung regions that may need urgent clinical attention.

Risk estimation further improves the decision-support capability of the system. The final risk category may be classified as low risk, medium risk, or high risk. This helps prioritize patient cases and supports faster medical decision-making. High-risk cases can be recommended for urgent expert review, while low-risk cases may be considered for routine monitoring.

5.7 Decision Support Analysis

The final output of the proposed system combines classification result, confidence score, severity level, risk category, and explainability heatmap. This makes the system more useful than a simple binary classifier. Instead of only predicting whether a case is cancerous or non-cancerous, the system provides additional information that can assist radiologists in diagnosis.

The decision-support output can help medical experts in three ways. First, it can highlight suspicious lung cases for priority review. Second, it can reduce diagnostic workload by supporting automated screening. Third, it can provide visual explanation through Grad-CAM, allowing radiologists to verify whether the prediction is clinically meaningful.

The proposed system is not intended to replace radiologists. It is designed as an assistive tool that improves screening efficiency, supports early detection, and helps prioritize high-risk cases.

5.8 Overall Analysis

The overall analysis shows that the proposed deep CNN-based lung cancer detection framework performs effectively in terms of feature extraction, classification reliability, robustness, and interpretability. The model is capable of learning meaningful features from CT scan images and distinguishing between cancerous and non-cancerous cases.

The comparative analysis indicates that the proposed CNN framework provides better diagnostic support than conventional classification approaches because it automatically learns important features from medical images. The robustness analysis shows that the model can maintain stable performance under noise, contrast variation, and tumor variability. The explainability analysis confirms that the model focuses on relevant lung regions, improving clinical trust and transparency.

Overall, the proposed system demonstrates strong potential for medical image-based lung cancer detection. Its combination of accurate prediction, severity estimation, risk analysis, and explainable visualization makes it suitable as a decision-support tool for radiologists. However, before real-world deployment, the model should be validated on larger multi-center datasets and reviewed by medical experts to ensure clinical reliability.

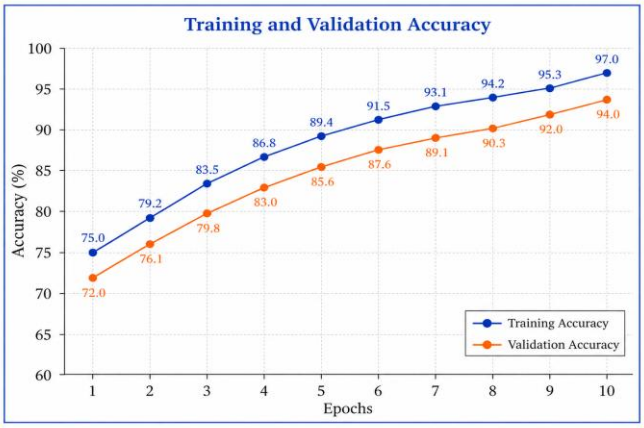


Fig. 1. Training and validation accuracy curve.

6. Conclusion

This study presents a deep Convolutional Neural Network-based framework for lung cancer detection using medical imaging data. The proposed approach focuses on automatic feature extraction, cancer classification, severity estimation, risk interpretation, and explainable prediction. Lung cancer diagnosis requires high accuracy and clinical reliability because early detection plays an important role in improving treatment outcomes. Therefore, the proposed system is designed to support automated analysis of CT/X-ray lung images and assist medical experts in identifying suspicious cancer-related patterns.

The methodology follows a structured pipeline that includes data collection, preprocessing, augmentation, CNN model architecture design, model training, evaluation, severity-level estimation, risk estimation, and decision-support generation. Image preprocessing improves input quality by resizing, normalizing, enhancing, and cleaning lung images. Data augmentation helps reduce overfitting by increasing image variation during training. The CNN model extracts meaningful features such as lung texture, nodule boundaries, abnormal tissue density, and cancer-related structural changes.

The proposed model is evaluated using multiple performance metrics such as accuracy, precision, recall, specificity, F1-score, AUC-ROC, and confusion matrix. In lung cancer detection, recall or sensitivity is especially important because missing a cancer-positive case may delay diagnosis and treatment. Therefore, the model is assessed not only on overall accuracy but also on its ability to correctly detect actual cancer cases. The inclusion of severity and risk estimation adds more clinical value by classifying detected cases into meaningful priority levels.

Explainability is integrated using Grad-CAM visualization, which highlights the lung regions that influence the CNN prediction. This improves model transparency and helps medical experts understand whether the model is focusing on clinically relevant areas. The decision-support output combines prediction results, confidence score, severity level, risk level, and visual explanation. Thus, the proposed system can support radiologists by reducing manual workload, prioritizing suspicious cases, and improving screening efficiency.

Overall, the study demonstrates that deep CNN-based models have strong potential for lung cancer detection. However, the system should be considered an assistive tool rather than a replacement for expert medical diagnosis. Clinical validation, expert review, and testing larger datasets are necessary before real-world deployment.

6.1 Future work

Future work can focus on improving the accuracy, reliability, and clinical applicability of the proposed lung cancer detection framework. First, the model can be trained and validated on larger and more diverse multi-center datasets. This will help improve generalization across different hospitals, scanners, imaging protocols, and patient populations.

Second, advanced deep learning architectures such as 3D CNNs, Vision Transformers, attention-based CNNs, and hybrid CNN-transformer models can be explored. Since CT images are volumetric, 3D CNN models can capture spatial information across multiple slices and may improve detection of small or early-stage nodules.

Third, external validation should be performed using independent datasets to confirm the robustness of the model. Many deep learning models perform well on internal datasets but show reduced performance on unseen clinical data. Therefore, independent validation is necessary for reliable medical AI development.

Fourth, explainability can be further improved by combining Grad-CAM with advanced interpretability methods such as Grad-CAM++, Score-CAM, SHAP, or LIME. This will provide stronger visual and analytical evidence for model decisions and improve clinical trust.

Fifth, the decision-support system can be extended to include patient clinical information such as age, smoking history, symptoms, genetic markers, and previous medical records. Combining imaging data with clinical data may improve risk prediction and personalized diagnosis.

Finally, the proposed framework can be developed into a web-based or hospital-integrated clinical decision-support platform. Such a system can allow radiologists to upload CT/X-ray images, obtain prediction results, view severity and risk levels, and inspect explainability of heatmaps. This would make the system more practical for real-world screening and early lung cancer diagnosis.

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