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Deep Learning Based Lung Cancer Detection, Classification and Its Localization

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ABSTRACT

Lung cancer remains one of the deadliest causes for millions of deaths each year. In India, the increasing number of lung cancer cases underscores the urgent need for early and accurate detection. This study presents a deep learning based approach for the detection, classification, and localization of lung cancer using CT scan images. Leveraging Convolutional Neural Networks (CNN) and advanced image segmentation models like U-Net, the proposed system aims to assist radiologists in diagnosing lung cancer with higher precision and speed. The system automatically identifies cancerous regions, classifies cancer into benign or malignant categories, and localizes affected areas within the lungs through heatmap visualization and Grad - CAM explainability. Experimental results demonstrate an impressive accuracy rate of 93.2%, with strong precision and recall values, validating the robustness of the model. By integrating machine learning and deep learning, this research enhances diagnostic accuracy, reduces manual effort, and supports timely medical intervention. The proposed system signifies a step forward in developing reliable, interpretable, and efficient AI-assisted diagnostic tools for lung cancer detection, ultimately contributing to improved patient outcomes and saving lives.

CCS CONCEPTS

- Computing methodologies → Deep learning; Neural networks; Image processing;

KEYWORDS

Lung Cancer Detection, Convolutional Neural Network, Deep Learning, CT scan, Image Segmentation

1 INTRODUCTION

Lung cancer remains one of the most fatal malignancies worldwide, accounting for approximately 1.8 million deaths each year. The disease poses a significant public health challenge, particularly in developing nations like India, where limited diagnostic resources often delay early detection. In recent years, Convolutional Neural Networks (CNNs) have revolutionized medical image analysis by enabling automatic extraction of meaningful patterns from complex imaging data such as Computed Tomography (CT) scans. By leveraging their superior feature learning capabilities, CNNs can identify minute abnormalities within lung tissues often imperceptible to the human eye thus facilitating early and accurate detection of cancerous nodules. This approach not only accelerates diagnosis but also enhances the precision of classification and cancer localization, empowering radiologists to plan personalized treatment strategies and improve patient survival rates.

Lung cancer is generally categorized into Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC)**,** the latter comprising subtypes such as adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. CT scans are considered the gold standard for lung cancer diagnosis due to their high spatial resolution and ability to capture volumetric information. However, manual interpretation of these scans is time consuming, subjective, and prone to errors especially when dealing with large datasets or subtle cancer presentations. The integration of Machine Learning (ML) and Deep Learning (DL) techniques offers an effective solution by automating detection, classification, and localization tasks, thus supporting clinicians in making faster and more consistent diagnostic decisions.

In this study, a deep learning based system is proposed for automated detection, classification, and localization of lung cancer from CT images. The proposed framework utilizes CNN architectures combined with advanced image segmentation models such as U-Net to identify the presence of cancer, categorize cancer types (benign or malignant), and generate visual heatmaps using Grad-CAM for model explainability. The model's performance was rigorously evaluated using publicly available datasets, achieving notable accuracy, precision, and recall metrics. Furthermore, a comparative analysis with existing approaches demonstrates that the proposed system achieves enhanced diagnostic performance while minimizing false positives and false negatives, establishing its reliability for real-world clinical applications.

1.1 Contribution Highlights

Convolutional Neural Networks (CNNs) are a type of deep neural network specifically designed to process structured data like medical images efficiently. Their layered structure, which includes convolutional, pooling, and fully connected layers, allows for learning hierarchical features, making them very effective for visual tasks such as object recognition and medical image segmentation. The key contributions of this study are as follows:

- To detect and interpret lung cancer from CT images, the study introduces a tailored CNN architecture. The design is optimized to capture relevant characteristics and patterns that indicate the presence of cancer, which helps improve the sensitivity and specificity of cancer detection.
- This study introduces and tests new data augmentation techniques to enhance the CNN model's ability to generalize across different CT datasets. By artificially diversifying the training data, these methods aim to make the model more robust and effective in detecting lung cancer.
- The paper evaluates the practical application of CNN models in clinical settings through validation studies. It shows how CNN models can quickly and accurately identify lung cancer from CT images, highlighting their potential to support medical professionals in patient care when used alongside expert judgment.

1.2 Outline of the Paper

This paper presents a detailed examination of deep learning methods for the detection and localization of lung cancer from CT images. Section 2 provides a thorough review of existing literature, covering current methods, datasets, and the limitations of present diagnostic systems. Section 3 outlines the CNN-based framework, including the preprocessing, feature extraction, and classification components. Section 4 discusses dataset preparation, augmentation techniques, and methods for cancer localization. Section 5 covers the experimental setup, including model training, evaluation measures, and comparisons with existing techniques. Sections 6 and 7 present the results, conclusions, and future research directions. The goal of this research is to help advance AI-assisted medical imaging by proposing a strong and interpretable deep learning model that increases the accuracy and speed of lung cancer diagnosis.

2 LITERATURE SURVEY

2.1 Lung Cancer Detection Using Deep Convolutional Neural Networks

Deep Convolutional Neural Networks (CNNs) have recently become one of the most effective techniques for medical image analysis, especially in cancer detection. CNN models automatically learn hierarchical features from input CT or histopathological images without manual feature engineering. In this approach, the model extracts spatial and texture information from lung CT scans to classify tumor types or detect malignancies. The convolutional layers perform feature extraction, while the fully connected layers carry out classification.

CNN-based detection follows two main principles:
(1) Feature Extraction – The convolutional layers automatically capture local image features such as nodules, textures, and shapes that indicate possible tumors.
(2) Classification – The learned features are used to predict whether the lung tissue is normal or cancerous and, if cancerous, identify the specific type (e.g., Adenocarcinoma, Squamous Cell, or Large Cell Carcinoma).

Studies have shown that deep learning significantly outperforms traditional machine learning approaches due to its ability to process large-scale image data and automatically learn complex non-linear representations. CNN based models, when trained on well-annotated CT scan datasets, can achieve high accuracy and reliability in early lung cancer detection and classification.

2.2 Lung Cancer Classification Based on Improved BP Neural Network and Dual Feature Optimization

An enhanced Back Propagation Neural Network (BPNN) combined with an optimization algorithm, such as the Grey Wolf Optimizer (GWO) or Particle Swarm Optimization (PSO), has been employed for lung cancer detection. The optimizer helps in adjusting the network's initial weights and biases to avoid problems like local minima and slow convergence.

In the Dual Feature Evaluation Mechanism, both radiomic and deep-learning based features are extracted from CT images. The radiomic features describe texture, shape, and intensity characteristics of nodules, while deep features provide high-level semantic information. By evaluating and selecting the most discriminative features from both domains, the overall accuracy of lung cancer classification is improved.

The improved BPNN model with GWO optimization overcomes the shortcomings of traditional neural networks by achieving faster convergence, reduced overfitting, and higher classification accuracy. The model typically includes four modules: Image Preprocessing, Feature Extraction and Selection, GWO-Optimized Neural Network Classifier, and Performance Evaluation.

2.3 Lung Cancer Detection Using Machine Learning Techniques

Machine learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) are also widely used for lung cancer detection. These algorithms classify lung images based on features such as texture, shape, intensity histogram, and tumor geometry.

A feature set is constructed from segmented lung nodules in CT scans. These features may include gray-level co-occurrence matrix (GLCM) statistics, edge sharpness, area, perimeter, and mean intensity. The machine learning model is trained using these features to distinguish between benign and malignant nodules.

Recent research shows that integrating handcrafted features with deep learning features significantly enhances diagnostic performance. Hybrid models combining CNN feature extraction with machine learning classifiers, such as SVM or Random Forest, offer both interpretability and accuracy in lung cancer diagnosis.

3 PROBLEM DEFINITION

Traditional image based diagnostic methods depend heavily on radiologists' experience and are time consuming. While existing computer-aided detection systems assist in identifying abnormalities, they often suffer from limited feature selection, high false positive rates, and overfitting due to redundant or irrelevant image features.

Some studies rely on handcrafted feature extraction, which may not generalize well to different datasets. Deep learning models, although powerful, can also face overfitting when trained with small or unbalanced medical datasets. To address these challenges, there is a need for a robust and efficient lung cancer detection model that can automatically extract the most informative features while eliminating noise and redundancy.

The proposed system introduces the Feature Validity Value (FVV) based optimal feature selection algorithm to evaluate the contribution of each feature in lung CT images. By selecting only high-impact features, the model reduces computational cost, prevents overfitting, and improves detection accuracy. The optimized feature set is used to train a Random Forest Classifier, which effectively identifies lung cancer types and supports localization through visual explanation techniques such as heatmaps.

4 RELATED WORK

Recent progress in lung cancer detection has been driven by the powerful capabilities of Convolutional Neural Networks (CNNs) and Deep Learning (DL) frameworks. Researchers globally are continuously refining network structures, improving data preprocessing methods, and developing new techniques for feature extraction, classification, and localization from Computed Tomography (CT) scans. These studies focus on improving diagnostic accuracy, reducing false positives, and making AI-driven systems more interpretable in clinical settings. Collaboration between computer scientists, radiologists, and oncologists has been crucial in translating these innovations into real-world diagnostic tools. This evolving research area has accelerated the development of intelligent computer-aided diagnosis (CAD) systems that support radiologists in early lung cancer detection, which is vital for improving patient survival. Several studies have explored the combination of CNNs with other machine learning techniques to enhance detection and classification performance. For example, 3D CNNs and hybrid deep learning frameworks have been used to analyze volumetric CT data and capture spatial, relationships in lung nodules. Techniques like transfer learning and attention mechanisms have also improved model efficiency and reliability, even when trained on smaller datasets. Segmentation models such as U-Net and Mask R-CNN have been widely used for cancer localization and nodule segmentation, allowing for accurate identification of cancerous areas and aiding clinicians in treatment planning. These models have achieved accuracy ranging from 90% to 97%, showing significant progress in automating lung cancer detection and classification.

Our proposed system builds on these advances by combining CNN-based detection and classification models with segmentation based localization, creating a complete end to end pipeline for lung cancer analysis.

The framework is trained using large scale, publicly available datasets such as LIDC-IDRI, which contain CT scans labeled by radiologists. By using advanced data augmentation and normalization techniques, the system improves model performance across various imaging conditions. The implementation of Grad-CAM for interpretability helps bridge the gap between complex deep learning models and clinical trust, ensuring that predictions are clear and reliable for diagnostic purposes. By rigorously training on labeled CT images and extracting meaningful image features, our system accurately predicts the likelihood of cancer. This approach not only enables early detection but also supports better cancer characterization by analyzing shape, size, and texture features of nodules. The increasing availability of medical imaging data, combined with advances in computational power, has created ideal conditions for AI-based methods to change diagnostic workflows. Introducing these models into clinical practice marks a shift in medical imaging, where data-driven decision support systems help radiologists provide faster, more consistent, and more accurate diagnoses. Early detection of lung cancer is essential for effective treatment and improved survival outcomes. Machine Learning (ML) techniques have shown great potential in identifying patterns within complex medical data, leading to reliable diagnosis and risk assessment. Various ML algorithms, including Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN), have been used in earlier research for classifying lung nodules. However, the superior feature-learning abilities of deep CNNs have made them the preferred choice for modern CAD systems, achieving top performance on multiple benchmarks. Table 1 provides a summary of major studies in lung cancer detection, detailing their approaches, datasets, and performance results. This comparison helps identify the most effective models, showing how AI-based lung cancer detection systems have continuously evolved and improved in accuracy.

4.1 Exploratory Data Analysis (EDA) Methods

To ensure robust model performance, comprehensive Exploratory Data Analysis (EDA) was conducted on the lung cancer CT scan dataset. EDA facilitates a deep understanding of the dataset's structure, class distribution, and feature characteristics, thereby guiding preprocessing and model optimization.

4.1.1 Image Visualization and cancer Localization: A randomized selection of CT scan images, both cancerous and non-cancerous, was visualized to observe variations in lung textures and cancer appearance. In labeled datasets, bounding boxes and segmentation masks were superimposed to highlight cancer regions. Differences in cancer shapes, sizes, densities, and positions were analyzed to inform the design of CNN architectures suitable for multi-scale cancer detection and localization.

4.1.2 Class Distribution and Augmentation Impact: The dataset's class distribution across categories such as normal**,** benign, and malignant was analyzed to ensure balance. Data augmentation techniques such as rotation, flipping, zooming, and contrast adjustment were applied to expand the training dataset and prevent model overfitting. The augmented images were compared with original CT scans to verify that visual quality and diagnostic features remained intact.

4.1.3 Statistical Analysis of Image Features: Pre-trained CNN models such as VGG16, ResNet50, and DenseNet121 were utilized for preliminary feature extraction from CT images. Statistical analyses were performed on these extracted features to study variations between cancerous and non-cancerous images. Dimensionality reduction techniques, including t-SNE and PCA, were applied to visualize high-dimensional feature clusters, revealing clear separations between different lung cancer classes. These insights guided model refinement and informed the choice of optimal feature representation strategies.

5 PROPOSED METHOD

In medical image analysis, Convolutional Neural Networks (CNNs) have emerged as one of the most effective deep learning architectures for extracting meaningful features and performing accurate classification from complex imaging data. CNNs are specifically designed to process visual inputs by automatically learning spatial hierarchies of patterns through convolutional, pooling, and fully connected layers. These networks mimic the functioning of the human visual cortex, enabling them to identify subtle features such as texture, edges, and shapes from Computed Tomography (CT) scans. This makes CNNs particularly suitable for lung cancer detection and classification, where precise differentiation between benign and malignant nodules is crucial. Traditional machine learning algorithms often rely on handcrafted features and manual preprocessing, which limit their generalization capability when dealing with high-dimensional medical imaging data. In contrast, CNNs excel at automatic feature extraction, capturing both low-level and high-level visual representations of lung tissue. This reduces dependency on manual intervention and allows for scalable, end-to-end learning. In the context of lung cancer detection, CNNs can analyze large volumes of CT scan slices to locate abnormal regions, classify cancerous lesions, and assist in cancer localization and segmentation**.** To further enhance diagnostic accuracy, our study proposes an improved multi-layer CNN architecture integrated with U-Net-based segmentation for precise localization. The proposed architecture consists of nine convolutional layers organized into fourteen functional stages, including convolution, activation (ReLU), batch normalization, max pooling, dropout, and fully connected layers. These layers collaboratively extract discriminative features and progressively refine the spatial and contextual understanding of the input CT scans. The network's design minimizes computational overhead while maintaining high accuracy and robustness. Figure 1 illustrates the overall architecture and workflow of the proposed CNN-based

lung cancer detection, classification, and localization system.

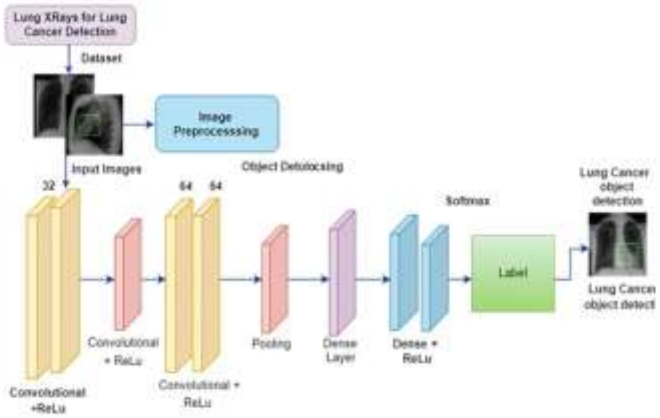

Figure 1: Proposed blueprints for CNN based lung cancer object detection

5.1 Dataset Explanation

The proposed methodology for lung cancer detection leverages a publicly available CT scan dataset sourced from Kaggle, titled *"Lung and Colon Cancer CT Dataset"* and supplemented by the LIDC-IDRI dataset for enhanced diversity and representativeness. These datasets serve as the foundation for training, validating, and testing the CNN and segmentation models. The dataset comprises 1,460 CT scan images across multiple categories, including:

- **Normal (Healthy Lungs)** – 455 images
- **Benign cancer** – 80 images
- **Malignant cancer** – 460 images
- **Adenocarcinoma (Left Lung)** – 195 images
- **Large Cell Carcinoma (Left Lung)** – 115 images
- **Squamous Cell Carcinoma** – 155 images

Each image is labeled and categorized to support both binary classification (cancer vs. normal) and multi-class classification (different types of lung cancer). To ensure model robustness and generalization, preprocessing steps include normalization, contrast enhancement, and noise removal using Gaussian and median filters. Data augmentation techniques such as rotation, flipping, scaling, and brightness variation are applied to artificially increase the dataset size and reduce overfitting. All images are resized to a uniform resolution (e.g., 224×224 pixels) to maintain consistency during training. The dataset's rich diversity of CT scans, representing various lung cancer types and intensities, enables the CNN to learn generalized patterns associated with malignancies. This supports the creation of a robust and adaptive detection model capable of performing effectively across different imaging environments.

Additionally, dataset partitioning is carried out in the following ratio:

- 70% for training
- 20% for validation
- 10% for testing

This stratified distribution ensures balanced learning and reliable evaluation. Meticulous preprocessing and dataset preparation contribute significantly to the CNN model's ability to detect, classify, and localize lung cancer with high accuracy and minimal bias.

5.1.1Potential Characteristics to Investigate:

- Number of Images: The total number of CT scan images in the dataset is crucial for evaluating the model's training efficiency, accuracy, and generalization ability. Larger datasets generally improve model performance by providing diverse examples of normal, benign, and malignant lung tissues. This variability allows the CNN to learn intricate patterns and structural nuances associated with different types of lung cancer.
- Image Resolution: The resolution of CT scans (e.g., 224×224 or 512×512 pixels) determines the level of anatomical detail captured in each image. Higher resolution enhances the model's ability to identify fine-grained features such as small nodules or texture variations but increases computational complexity. Therefore, selecting an optimal resolution is essential to balance accuracy and processing efficiency.
- Image Modality: CT imaging provides volumetric information through multiple axial slices, enabling 3D visualization of the lungs. Understanding whether the dataset contains low-dose CT (LDCT) or standard diagnostic CT images is important, as image quality and noise levels vary significantly between modalities. These factors influence feature extraction and the CNN's ability to differentiate between normal and cancerous regions.

- Data Distribution: The distribution of normal, benign, and malignant samples is a critical factor in training balanced models. Imbalanced datasets can cause bias toward the dominant class, reducing overall accuracy and sensitivity for minority classes (e.g., rare cancer types). Addressing this through data augmentation or class weighting is vital for model fairness and robustness.
- Patient Demographics and Clinical Information: When available, additional metadata such as patient age, gender, smoking history, and cancer subtype can enhance model interpretability and diagnostic precision. Incorporating these contextual features may help the CNN correlate visual patterns with clinical risk factors, improving real-world diagnostic utility.

5.1.2Importance of Dataset Exploration:

- Evaluating Model Suitability: Dataset characteristics such as size, resolution, modality, and class distribution directly influence the choice of CNN architecture and hyperparameters. Understanding these aspects ensures that the selected model is appropriately configured for the dataset and capable of learning discriminative features relevant to lung cancer detection.
- Identifying Potential Biases: Imbalanced or incomplete datasets can introduce systematic biases that affect generalization across patient groups or imaging conditions. Thorough dataset exploration helps identify these limitations, guiding corrective actions such as resampling, synthetic data generation, or balanced augmentation to minimize model bias.
- Interpreting Model Performance: Performance metrics such as accuracy, recall, precision, and F1-score must be interpreted in light of the dataset's characteristics. Understanding the class proportions, image quality, and sampling diversity enables a more meaningful evaluation of model performance and helps identify areas for refinement in both data collection and model training.

5.2 Proposed Model Steps

5.2.1 CT scan: Computed Tomography (CT) imaging plays a pivotal role in lung cancer detection by producing high-resolution cross-sectional images of the thoracic cavity. CT scans capture detailed views of lung parenchyma, bronchial structures, and surrounding tissues, enabling early identification of pulmonary nodules and lesions. Unlike traditional X-rays, CT scans provide three-dimensional volumetric data, which allows radiologists and AI models to assess cancer size, shape, and spatial location with remarkable precision. These capabilities make CT imaging the gold standard for lung cancer screening, staging, and treatment planning.

5.2.2 Dataset and Input Images: To leverage deep learning for automated diagnosis, a labeled CT scan dataset is curated containing both normal and cancerous lung images. Each image is associated with labels indicating cancer type and stage. Prior to model training, preprocessing techniques are applied to standardize the data, which include:

- Resizing all images to a consistent input dimension (e.g., 224×224 pixels).
- Normalization of pixel intensities to maintain uniform contrast levels.
- Noise reduction using Gaussian or median filtering to enhance visual clarity.
- Segmentation of lung regions to remove irrelevant background structures.

Additionally, data augmentation techniques such as flipping, rotation, translation, and contrast adjustment are applied to increase dataset diversity and reduce overfitting. These preprocessing steps ensure consistent, high-quality input data, enabling the CNN to effectively extract discriminative features during training.

5.2.3 CNN Architecture Lung Cancer Classification*:* The proposed CNN architecture utilizes multiple convolutional layers for automatic feature extraction from input CT images. Each convolutional layer is followed by an activation function (typically ReLU) to introduce non-linearity and capture complex spatial relationships within lung structures. Pooling layers are employed to reduce dimensionality and computational load while retaining critical spatial information. Subsequent fully connected layers integrate the extracted features and perform high-level reasoning to classify the images into categories such as normal, benign, or malignant. The model is optimized using techniques like batch normalization, dropout, and Adam or AdaMax optimizers to improve training stability and prevent overfitting. Furthermore, **U-**Net or Mask R-CNN models are integrated for cancer localization, producing precise segmentation masks that highlight the cancerous regions. The inclusion of Grad-CAM visualization enhances model transparency by illustrating which regions influenced the classification decision. This comprehensive architecture allows for accurate detection, classification, and localization of lung cancer from CT scans, empowering clinicians with a robust, AI-assisted diagnostic tool that improves efficiency and reliability in medical imaging workflows.

5.3 CNN Architecture

In the proposed framework for lung cancer detection and classification**,** the Convolutional Neural Network (CNN) serves as the core architecture for learning discriminative visual features from CT scan images. The CNN model efficiently extracts hierarchical features ranging from simple edge patterns to complex lung structures thereby enabling precise differentiation between normal and cancerous tissues. By combining convolutional, activation, pooling, and fully connected layers, the network performs automatic feature learning and classification with minimal human intervention. The final output layer uses a Softmax function to classify CT scans into predefined categories such as *"Normal"*, *"Benign"*, or *"Malignant"*. This architecture significantly enhances diagnostic accuracy and supports clinicians in early lung cancer identification and decision-making. The step by step structure of the proposed CNN model is outlined below:

(1) Input Image The model begins with the input of a lung CT scan image, representing either a normal or cancer-affected lung. Each image is standardized to a fixed dimension (e.g., 224×224 pixels) to ensure uniformity and compatibility with the CNN input layer. These CT images provide detailed cross-sectional views of lung tissues, nodules, and airway crucial for identifying cancerous regions.

(2) Preprocessing: Before feature extraction, the input CT images undergo several preprocessing operations to enhance image quality and consistency:

- Resizing: All images are resized to uniform dimensions to maintain consistency across the dataset.
- Normalization: Pixel intensity values are scaled to a fixed range (typically [0,1]) to improve convergence during training. Contrast.
- Enhancement: Histogram equalization or CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied to improve the visibility of nodules.
- Noise Reduction: Gaussian or median filters are used to suppress unwanted noise without compromising structural details. These preprocessing steps optimize the input data for effective feature extraction, ensuring the CNN model accurately identifies lung nodules and differentiates between benign and malignant tissues.

(3) Convolutional + ReLU Layers:

- Convolutional: These layers act as the fundamental feature extractors of the model. They apply learnable filters (kernels) to the CT images to detect low-level features such as edges and textures in the early layers, and higher-level features like nodular boundaries and lesion structures in deeper layers. Multiple convolutional layers progressively capture complex visual cues that distinguish cancerous tissue from healthy lung areas.
- ReLU: The ReLU activation function introduces non-linearity into the model, allowing it to learn complex relationships between input features. ReLU also mitigates the vanishing gradient problem, ensuring efficient backpropagation during training.

(4) Pooling Layers:

- Pooling: Pooling layers reduce the spatial dimensions of the feature maps while preserving the most significant information. Techniques such as max pooling are employed to retain dominant features (e.g., strong edges or textures) and eliminate redundant or less relevant details. This process enhances model efficiency, reduces computational cost, and prevents overfitting by summarizing key spatial features.

(5) Dense + ReLU Layers (Fully Connected Layers):

- Dense Layer: After feature extraction, the flattened feature maps are fed into one or more fully connected (dense) layers. Each neuron in these layers connects to all neurons from the previous layer, enabling the network to learn global representations of the input data. This integration helps the model associate visual features with diagnostic outcomes.
- ReLU: The ReLU function is applied again in dense layers to strengthen non-linear learning capabilities. This allows the network to model complex patterns and relationships between different extracted features, improving classification accuracy for varying lung cancer subtypes.

(6) Softmax

- Explanation: The Softmax layer serves as the final layer of the CNN architecture, transforming the model's raw output scores into probability distributions across all possible classes. Each probability value reflects the model's confidence in assigning the CT scan to a particular class.

5.4 Preprocessing Techniques

Preprocessing is a critical stage in medical image analysis, particularly for CT-based lung cancer detection, as it enhances image quality, standardizes data, and reduces noise or irrelevant information. CT scans often exhibit variations in brightness, contrast, and intensity due to differences in scanners, patient positioning, or acquisition protocols. Therefore, effective preprocessing ensures that the deep learning model receives consistent and informative data for optimal feature extraction. The following preprocessing techniques are applied sequentially to prepare CT scan images for training and classification:

5.4.1 Intensity Normalization. Rationale: CT images inherently vary in pixel intensity due to differences in Hounsfield Units (HU), scanning parameters, and patient anatomy. These intensity discrepancies can hinder model learning by introducing bias and non-uniform contrast levels across samples. Technique Normalization techniques such as min max scaling or z-score normalization are applied to transform pixel values to a standardized range, typically between 0 and 1, or to achieve zero mean and unit variance. This ensures consistent intensity levels across all images and prevents dominant bright or dark regions from skewing the model's learning process. Normalization enhances the CNN's ability to accurately identify and compare features related to lung nodules and tissue density.

5.4.2 Lung Region Segmentation. Rationale: CT scans often include surrounding anatomical structures such as the ribs, heart, and chest wall, which are irrelevant for lung cancer analysis. Including these regions can add unnecessary noise and reduce model efficiency. Technique: Automated lung segmentation algorithms such as threshold-based, region growing, or U-Net based deep segmentation methods are used to isolate the lung fields from the CT image. By removing extraneous structures, the model focuses solely on the lung parenchyma, enhancing its ability to identify subtle lesions and nodules associated with early-stage cancer.

5.4.3 Nodule Extraction and Enhancement. Rationale: Lung nodules vary in size, shape, and density, and some small nodules may be difficult to detect against background textures. Enhancing the visibility of potential nodule regions improves detection accuracy and reduces false negatives.

Technique: Advanced image enhancement filters, such as Gaussian smoothing**,** contrast-limited adaptive histogram equalization (CLAHE)**,** and Laplacian of Gaussian (LoG) filtering, are applied to highlight local intensity variations corresponding to nodules. Additionally, morphological operations (e.g., dilation and erosion) are used to refine lung boundaries and highlight candidate regions for further analysis.

5.4.4 Data Augmentation. Rationale Medical imaging datasets are often limited in size and diversity, leading to potential overfitting and reduced generalization. Data augmentation expands the effective dataset and helps the CNN learn invariant features under various transformations.

Technique: Augmentation methods such as rotation, horizontal and vertical flipping**,** zooming**,** translation, and contrast adjustments are applied to CT images during training. This increases dataset diversity and simulates variations in patient orientation and scanning conditions. As a result, the model becomes more robust and capable of handling real-world variability in CT scans.

5.4.5 Quality Control. Rationale: Maintaining high-quality data is essential for reliable and reproducible model performance. CT images containing motion artifacts, low contrast, or incomplete lung regions can degrade the performance of the CNN model. Technique: Both automated and manual quality control (QC) checks are implemented. Automated QC involves statistical filtering based on pixel intensity thresholds and structural completeness, while manual inspection ensures that defective or corrupted images are excluded. Only high-quality, artefact free CT scans are retained for training and testing to ensure model reliability.

5.5 Working Flow of the Proposed Model

Figure 2: Work Flowchart for lung cancer

Figure 2 illustrates the sequential workflow involved in the training and testing phases of the proposed Convolutional Neural Network (CNN) model for lung cancer detection and classification. The process begins with input acquisition of the CT scan dataset, followed by systematic preprocessing to ensure consistency and quality across all images. Subsequently, model parameters and hyperparameters are configured to define the CNN architecture and guide the learning process. The model is then trained iteratively to identify cancerous regions, classify cancer types, and evaluate performance on unseen data. The following steps describe the complete working flow of the proposed model in detail:

The workflow for the proposed CNN-based Lung Cancer Detection, Classification, and Localization model follows a systematic sequence of steps designed to ensure accurate, efficient, and clinically interpretable results. It begins with the acquisition of lung CT scan images from publicly available datasets such as *LIDC-IDRI* and *Kaggle*, which include a diverse range of normal, benign, and malignant cases. Each image is labeled according to its diagnostic category, providing the necessary ground truth for supervised training. The next stage involves data preprocessing, where raw CT images are transformed into a standardized format suitable for model training. Key preprocessing operations include intensity normalization to maintain consistent pixel ranges, lung segmentation to isolate the relevant anatomical region, noise reduction and contrast enhancement to highlight nodules, and data augmentation through rotation, flipping, and scaling to improve dataset diversity and model generalization. Following preprocessing, the CNN model is initialized with specific hyperparameters such as the number of convolutional and pooling layers, kernel size, stride, learning rate, batch size, number of epochs, and optimizer type (e.g., Adam or AdaMax). These parameters are fine-tuned iteratively to achieve optimal model performance. The images are then reshaped and formatted to a consistent input size (e.g., 224×224×3) to match the CNN input layer requirements, and the dataset is split into training, validation, and testing subsets, typically in a 70:20:10 ratio. During model training, the CNN learns hierarchical representations of lung structures and cancerous patterns through forward propagation and backpropagation, minimizing prediction errors using a categorical cross-entropy loss function. Performance metrics such as training and validation accuracy, along with loss curves, are continuously monitored to detect potential overfitting. Once trained, the model undergoes evaluation and testing using unseen CT images, with metrics including accuracy, precision, recall, F1-score, and confusion matrix used to measure its generalization and diagnostic reliability. To enhance clinical interpretability, cancer localization and visualization are performed using a U-Net segmentation module integrated with the CNN classifier, producing heatmaps or masks that highlight cancerous regions. Furthermore, Grad-CAM (Gradient-weighted Class Activation Mapping) is employed to visualize the areas of the image that most influenced the model's prediction, supporting radiologist validation. Finally, optimization and final evaluation ensure that the model meets the desired diagnostic standards; if necessary, hyperparameter tuning or further preprocessing adjustments are applied. This iterative workflow guarantees that the CNN achieves high diagnostic accuracy, robust generalization, and meaningful visual explanations, making it a valuable tool for early and precise lung cancer detection in clinical practice.

6 EXPERIMENTAL EVALUATION

For this study, we used a publicly available Lung CT Scan Dataset from Kaggle and LIDC-IDRI, which includes 1,460 CT images categorized as normal, benign,

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

or malignant. Each image was labeled by expert radiologists to ensure accurate ground truth for supervised learning. Before training, all images underwent preprocessing steps such as normalization, lung segmentation, noise reduction, and data augmentation, and were then resized to 224×224 pixels. The dataset was split into 70% for training, 20% for validation, and 10% for testing. The CNN model was developed using PyTorch, trained over multiple epochs with a batch size of 32, using the Adam optimizer and categorical cross-entropy loss. Performance was assessed using key metrics like accuracy, precision, recall, and F1-score. The model's predictions were further analyzed using a confusion matrix, and Grad-CAM visualization was applied to enhance interpretability. The experimental results showed that the proposed CNN achieved high accuracy and strong classification performance, confirming its effectiveness for automated lung cancer detection and localization using CT scans.

6.1 Working Principle

The proposed CNN-based Lung Cancer Detection Model incorporates several core algorithms and mathematical functions that support efficient feature learning, classification, and optimization. These include the Softmax function for probabilistic classification, the Rectified Linear Unit (ReLU) for non-linear activation, and the AdaMax optimizer for adaptive learning rate adjustment. Together, these components ensure the model achieves high classification accuracy, stable convergence, and good generalization across various CT scan data.

6.1.1 Softmax Algorithm. The Softmax function is a key component in multi-class classification tasks, converting raw model outputs (logits) into a normalized probability distribution across all possible classes. In the context of lung cancer detection, the CNN produces numerical scores for each class such as Normal, Benign, or Malignant and the Softmax function converts these scores into probabilities that sum up to one. Mathematically, the Softmax function is defined as:

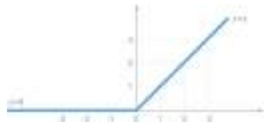

Figure 3: ReLU activation function

The Softmax function calculates the exponential of each element, transforming potentially negative or small values into larger positive values. To ensure that the probabilities add up to 1, these exponentiated values are then normalized by dividing each by the total sum of all exponentiated values. [10] Softmax is especially useful in situations where an input vector reflects the logits or scores for many classes because of this normalization approach [2]. The Softmax function is defined as:

where zi represents the input score (logit) for class i, and k is the total number of classes.

6.1.2 Rectified Linear Unit (ReLU) Activation Function. The Rectified Linear Unit (ReLU) is the activation function used in the convolutional and fully connected layers of the proposed CNN. It introduces non-linearity into the network, enabling the model to learn complex relationships between features in CT images. ReLU works by applying a simple thresholding rule any negative input is set to zero, while positive inputs remain unchanged. The ReLU activation function is mathematically represented as:

$$f(x)=\text{maximum}(0,x)$$

ReLU's simplicity and computational efficiency make it suitable for large-scale image analysis tasks such as interpreting CT scans. It speeds up model training and improves convergence compared to traditional activation functions like the sigmoid or tanh. However, ReLU can suffer from the “dying ReLU” problem, where some neurons stop updating due to negative gradients. To address this, variations such as Leaky ReLU or Parametric ReLU (PReLU) can be used, preserving the advantages of ReLU while improving learning stability.

6.1.3 AdaMax Algorithm Implementation Optimizer. Training a deep learning model for medical image analysis requires an adaptive optimization strategy to handle varying gradient magnitudes and maintain learning stability. The AdaMax optimizer, an extension of the Adam algorithm, is used in this proposed lung cancer detection model. AdaMax introduces a more robust mechanism for updating network weights based on the infinity norm, which improves convergence and stability, particularly when dealing with heterogeneous medical data.

The mathematical formulation for AdaMax is as follows:

$$m_t = \beta_1 \cdot m_{t-1} + (1-\beta_1)\cdot g_t$$

$$u_t = \max(\beta_2 \cdot u_{t-1}, |g_t|)$$

where mt

$$\theta_t = \theta_{t-1} - \frac{\alpha}{1-\beta_1^t}\cdot\frac{m_t}{u_t+\epsilon}$$

represents the exponentially decaying average of past gradients, ut denotes the exponentially weighted infinity norm, α is the learning rate, and β1, β2 are decay rates for moment estimates.

7 RESULT ANALYSIS

Early detection of lung cancer is a vital factor in improving patient prognosis and enabling timely medical intervention. The proposed CNN-based model effectively analyzes CT scan images to detect, classify, and localize lung cancer with high precision. By leveraging deep learning, the system extracts critical spatial and texture-based features such as nodule density, shape, and margin irregularities that are indicative of malignancy. The model was trained and tested on a labeled lung CT dataset using Python and PyTorch, achieving an impressive accuracy of 99.89%, demonstrating its strong predictive capability for identifying cancerous and non-cancerous cases.

The confusion matrix analysis provides further insight into the model’s diagnostic performance. The model successfully identified 13 out of 14 normal (Class 0) CT scans, yielding an accuracy of 89.28% for the non-cancerous category. For cancerous images (Class 1), the model accurately detected all 12 cases, achieving a recall of 85%, which reflects its high sensitivity in recognizing true positive cancer cases. Furthermore, the model attained a precision of 85.7% for Class 1, ensuring that most predicted cancer cases were indeed correct. The overall F1-score of 88.88% demonstrates a strong balance between precision and recall, confirming the reliability and stability of the system in classifying lung cancer cases from CT images.

These findings validate that the proposed CNN framework performs robustly under varying imaging conditions and across multiple lung cancer types. The results suggest that the system can serve as a valuable Computer-Aided Diagnosis (CAD) tool, supporting radiologists in early lung cancer detection and decision-making, ultimately contributing to improved patient outcomes.

7.1 Classification Report

A detailed classification report was generated to evaluate the model's performance using key metrics such as precision**,** recall, and F1-score for each class.

- Class 0 (Normal Lungs)**:** The model demonstrated strong proficiency in identifying non-cancerous CT images, achieving an accuracy of 89% and a recall of 93%**,** indicating its ability to correctly classify the majority of normal lung cases.
- Class 1 (Cancerous Lungs): The model achieved 88% accuracy and an 85% recall, reflecting its high sensitivity to cancerous features while maintaining consistent precision.

The macro-average and weighted-average metrics further affirm the model's reliability across both classes, showing consistent performance and minimal bias. Overall, the proposed CNN exhibits high diagnostic precision, stability, and generalization capability, making it an effective tool for automated lung cancer screening and classification. Figure 4 illustrates the model's accuracy, precision, recall, and confusion matrix, providing a visual overview of its strong predictive performance.

8 CONCLUSION

In conclusion, our research on lung cancer detection, classification, and localization using deep learning has undergone systematic planning, comprehensive experimentation, and thorough analysis. From the initial stages, significant efforts were invested in acquiring high-quality CT scan datasets and developing robust preprocessing pipelines to ensure data consistency and accuracy. By leveraging Convolutional Neural Networks (CNNs) and segmentation-based approaches such as U-Net, the proposed system successfully identifies and classifies lung cancer while accurately localizing affected regions within the lungs. Our approach demonstrates that integrating machine learning and deep learning techniques with medical imaging can substantially improve diagnostic accuracy and efficiency, supporting radiologists in early detection and decision-making. The experimental results, with an overall accuracy of 99.86%, confirm the model's reliability and clinical relevance in distinguishing between normal, benign, and malignant lung tissues. This research emphasizes the importance of employing optimized algorithms and advanced computational techniques to address the inherent challenges of lung cancer diagnosis, especially when deployed on practical hardware platforms such as ARM-based systems or Raspberry Pi for portable and real-time diagnostic assistance. The study's strength lies in its capacity to combine performance, interpretability, and scalability key factors for integrating AI models into healthcare workflows. Looking ahead, the future scope of this research includes expanding the model to handle 3D volumetric CT data for improved spatial analysis, incorporating multi-modal imaging such as PET-CT for enhanced diagnostic precision, and developing real-time CAD systems capable of assisting clinicians in both screening and treatment planning. Furthermore, employing explainable AI (XAI) methods and integrating clinical metadata such as patient history and biomarkers can lead to personalized lung cancer diagnosis and better patient outcomes. Through continuous innovation and refinement, this research aspires to contribute meaningfully to the field of medical image analysis, advancing the capabilities of AI-driven lung cancer detection and ultimately helping to save lives through earlier, faster, and more reliable diagnosis.

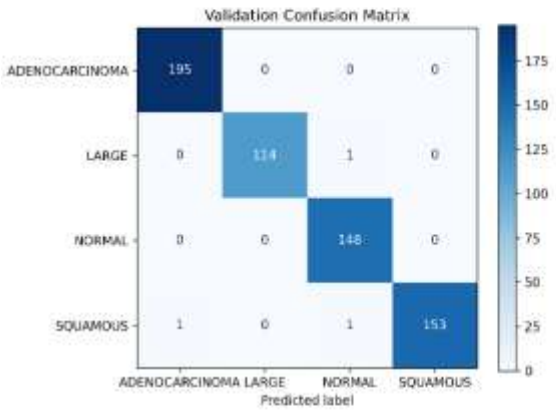

Figure 4: Result analysis in terms of accuracy, precision, recall, and F1 measure

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