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Advanced Lung Nodule Staging through 3D-ResNet: Classifying CT Images for Enhanced Diagnostic Precision

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Abstract: Lung nodules present a critical challenge in pulmonary diagnostics, necessitating accurate staging for optimal treatment planning. This study proposes an advanced approach employing 3DResNet for precise lung nodule staging via CT image classification. Leveraging the power of three-dimensional convolutional neural networks (3D CNNs), this methodology aims to enhance diagnostic precision by categorizing lung nodules into distinct stages based on radiological features extracted from CT images. The 3DResNet architecture enables robust feature learning by analyzing spatial relationships within volumetric data, facilitating the discrimination of subtle nodule characteristics indicative of different disease stages. The amalgamation of LIDC's (Lung Image Database Consortium) extensive annotated data and LUNA's (LUng Nodule Analysis) meticulously curated nodule annotations provides a robust foundation for training and validating the 3DResNet model. By capitalizing on this amalgamated dataset, the model endeavors to achieve heightened accuracy and generalization in classifying nodule stages, thus empowering clinicians with nuanced insights into disease progression. By training on a comprehensive dataset encompassing diverse nodule presentations and stages, the model endeavors to achieve superior accuracy in stage classification. The outcomes are expected to offer clinicians refined insights into disease progression, aiding in informed decision-making for personalized patient care and treatment strategies.

Keywords: *3D Convolutional Neural Networks, CT Images, Lung Nodules, Lung Nodule Analysis, Lung Image Database Consortium*

1. Introduction

Lung nodules, commonly detected in CT scans, present a diagnostic challenge due to their varied characteristics and potential for malignancy. Accurate staging of these nodules is pivotal for determining optimal treatment strategies and patient prognosis. In this context, the application of deep learning, particularly three-dimensional convolutional neural networks (3D CNNs) like 3DResNet, emerges as a promising avenue to significantly refine diagnostic precision. By leveraging volumetric information from CT images, these advanced models can discern intricate patterns and features within lung nodules, facilitating precise categorization into different stages of malignancy or benignity. The integration of 3DResNet aims to harness the inherent spatial relationships within the nodules, enabling a nuanced understanding of disease progression. This study explores the potential of such technology in revolutionizing lung nodule staging, envisioning a future where enhanced diagnostic accuracy empowers clinicians with tailored treatment plans and improved patient outcomes in pulmonary oncology.

1.1. CT Lung Nodule

CT lung nodules are small, round, or oval-shaped growths detected within the lung tissue through computed tomography (CT) scans. These nodules are commonly identified incidentally during routine chest imaging. They vary in size, density, and characteristics, and while many are benign, some could be early indicators of lung cancer or other pulmonary conditions. CT imaging plays a crucial role in their detection, classification, and monitoring, providing detailed cross-sectional images that allow radiologists and clinicians to assess the size, shape, density, and location of these nodules. Subsequent analysis involves determining the likelihood of malignancy, which often involves tracking changes in the nodules over time through follow-up CT scans. CT lung nodule detection and characterization are essential for early diagnosis, staging, and the formulation of appropriate treatment plans, significantly impacting patient care and outcomes in pulmonary health.

1.2. Background

The detection and characterization of lung nodules in computed tomography (CT) imaging play a pivotal role in the early diagnosis and management of lung diseases, particularly in the context of cancer. These nodules, often incidentally discovered during routine CT scans, present a diagnostic challenge due to their diverse morphological and textural features, ranging from benign to potentially malignant. Accurate staging of these nodules is crucial for determining their likelihood of malignancy, guiding appropriate treatment strategies, and improving patient outcomes. Traditional methods rely on radiologists' expertise in nodule assessment, but the integration of

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advanced technologies like deep learning, particularly three-dimensional convolutional neural networks (3D CNNs) such as 3DResNet, offers a transformative paradigm in this domain. These sophisticated models leverage volumetric CT image data to discern intricate patterns and features within lung nodules, potentially enhancing diagnostic precision by classifying nodules into different stages of malignancy. The integration of 3DResNet technology holds the promise of significantly refining nodule staging accuracy, ultimately empowering clinicians with more precise diagnostic tools for personalized treatment strategies and improved patient care in pulmonary oncology.

1.3. Objective

To leverage the capabilities of 3DResNet, a three-dimensional convolutional neural network, enhance the precision and accuracy of lung nodule staging in CT images. This project aims to develop a robust deep-learning model capable of categorizing lung nodules into distinct stages of malignancy or benignity. By harnessing volumetric data from CT scans, the objective is to empower the model to discern subtle patterns and features within nodules, enabling precise classification. The ultimate goal is to create a reliable and clinically applicable tool that aids clinicians in accurately staging lung nodules, facilitating improved diagnostic decisions, personalized treatment strategies, and enhanced patient care in pulmonary oncology.

2. Related Works

The study aims to revolutionize lung cancer screening using three-dimensional deep learning techniques on low-dose chest CT scans. The problem addressed involves enhancing the accuracy and efficiency of early lung cancer detection through an end-to-end approach. Leveraging deep learning algorithms, the methodology involves training models to autonomously detect and classify pulmonary nodules, striving to optimize sensitivity and specificity in identifying potential malignancies within CT imaging data [1].

This research endeavors to automate pulmonary nodule management in lung cancer screening by employing deep-learning methodologies. The primary concern addressed involves streamlining the identification and classification of pulmonary nodules within screening CT images. The study's methodological approach involves the development and validation of deep learning algorithms tailored for the automatic detection and categorization of these nodules. The aim is to enhance diagnostic accuracy and efficiency in the management of potential lung cancer indicators [2].

The study aims to detect metastatic cancer cells in human cerebrospinal fluid (CSF) through a three-dimensional immunocapture and imaging technique. The problem statement involves improving the detection sensitivity and accuracy of individual cancer cells within CSF samples. The method entails employing three-dimensional immunocapture combined with imaging technologies to isolate and identify metastatic cells, aiming to enhance the early detection and characterization of cancer spread in CSF, potentially aiding in the prognosis and treatment monitoring of metastatic cancers affecting the central nervous system [3].

The study aims to assess the additional diagnostic value provided by computer-aided CT image features in early lung cancer diagnosis, particularly concerning small pulmonary nodules. The problem statement involves evaluating the incremental benefit of incorporating computer-aided features for improving diagnostic accuracy in identifying small nodules as potential early signs of lung cancer. The method involves a matched case-control study, comparing the diagnostic performance of traditional CT analysis with and without computer-aided features to ascertain their added value in early lung cancer detection [4].

The study aims to predict the invasiveness of subcentimeter pulmonary adenocarcinomas utilizing 3D deep learning models derived from CT scans. The problem statement involves addressing the challenge of determining the invasiveness of small pulmonary adenocarcinomas. The methodology entails the development of 3D deep learning algorithms trained on CT scan data to predict tumor invasiveness. The objective is to create accurate predictive models that assist in determining the invasiveness of these small adenocarcinomas to aid treatment decision-making [5].

This study investigates the association between radiomic features and EGFR mutation status in lung adenocarcinomas. The problem statement revolves around identifying radiomic biomarkers linked to EGFR mutation, aiming to enhance non-invasive prediction methods for this mutation status. The methodology involves extracting quantitative radiomic features from CT images of lung adenocarcinomas and correlating these features with EGFR mutation status. The goal is to discern radiomic signatures that can serve as potential indicators for EGFR mutations in these cancers [6].

The study aims to develop a computer-aided diagnostic system for classifying lung nodules into benign, primary lung cancer, and metastatic lung cancer categories using deep convolutional neural networks (CNNs) with transfer learning. The problem statement focuses on achieving accurate differentiation among these nodule types across various image sizes. The methodology involves training deep CNNs using transfer learning on diverse image sizes to create a robust classification system capable of accurately categorizing lung nodules for improved clinical diagnosis and patient management [7].

This research aims to validate, compare, and integrate algorithms for the automatic detection of pulmonary

nodules in computed tomography (CT) images, as part of the LUNA16 challenge. The problem involves evaluating the performance of various algorithms and their combinations in accurately identifying pulmonary nodules across a standardized dataset. Methodologically, multiple algorithms are assessed and combined to enhance the detection accuracy of pulmonary nodules, aiming to advance the field of automated nodule detection for improved lung disease diagnosis [8].

The study addresses the classification of lung nodule malignancy suspiciousness using multi-crop convolutional neural networks (CNNs). The problem statement revolves around improving the accuracy of distinguishing between malignant and benign nodules. The methodology involves employing multi-crop CNN architectures to analyze and classify lung nodules based on malignancy likelihood. By utilizing multi-crop strategies, the study aims to enhance the precision of nodule classification, aiding in more accurate diagnoses and treatment decisions for lung diseases [9].

The study focuses on automating the detection of pulmonary nodules in PET/CT images through an ensemble false-positive reduction technique utilizing convolutional neural networks (CNNs). The problem statement involves enhancing the accuracy of nodule detection while minimizing false positives. Methodologically, an ensemble approach incorporating CNN techniques is applied to reduce false positives in nodule detection, aiming to improve the reliability and efficiency of automated detection systems for pulmonary nodules in PET/CT images, potentially aiding in early disease detection [10].

This study aims to predict the invasiveness of subcentimeter pulmonary adenocarcinomas by utilizing 3D deep learning models developed from CT scans. The problem focuses on accurately assessing the invasiveness of small adenocarcinomas. Methodologically, 3D deep learning algorithms are trained on CT scan data to predict tumor invasiveness. The objective is to create precise predictive models that aid in determining the invasiveness of these small adenocarcinomas, crucial for treatment planning and patient management [16].

This study investigates the correlation between radiomic features and EGFR mutation status in lung adenocarcinomas. The problem statement revolves around identifying radiomic markers linked to EGFR mutations, aiming to enhance non-invasive prediction methods for this mutation status. The methodology involves extracting quantitative radiomic features from CT images of lung adenocarcinomas and correlating these features with EGFR mutation status. The goal is to discern radiomic signatures serving as potential indicators for EGFR mutations in these cancers [17].

This study aims to develop a computer-aided diagnostic system using deep convolutional neural networks (CNNs) with transfer learning for classifying lung nodules into benign, primary lung cancer, and metastatic lung cancer categories at varying image sizes. The problem involves accurate differentiation among these nodule types across different image resolutions. The methodology entails training CNNs with transfer learning on diverse image sizes to establish a robust classification system for improved identification and differentiation of lung nodules in clinical settings [18].

The study focuses on validating, comparing, and combining algorithms for automated detection of pulmonary nodules in CT images, part of the LUNA16 challenge. The problem involves evaluating algorithm performance and their synergies to enhance the accuracy of nodule detection, advancing automated diagnosis for lung diseases [19].

The study aims to classify lung nodule malignancy using multi-crop convolutional neural networks (CNNs). The problem is to improve accuracy in distinguishing between benign and malignant nodules. Methodologically, multi-crop CNN architectures are employed to analyze nodule characteristics, enhancing the precision of malignancy classification for improved lung disease diagnostics [20].

The research endeavors to classify lung nodules by employing a 3D deep residual convolutional neural network (CNN). The problem involves accurately categorizing pulmonary nodules. Methodologically, a 3D deep residual CNN is utilized to enhance the precision of nodule classification, aiming for improved diagnostic accuracy in lung disease assessment [21].

The study focuses on lung nodule classification using a 3D-ResNet-based approach with CT images. The problem involves accurately categorizing pulmonary nodules. Methodologically, a 3D-ResNet model is applied to improve nodule classification accuracy, aiming for enhanced diagnostic precision in lung disease assessment [22].

This study aims to introduce a novel 3DResNet-based deep learning approach for classifying lung nodules in CT images. The problem involves refining accuracy in nodule classification. Methodologically, a unique 3DResNet-based model is developed, striving to enhance the precision of nodule classification and improve diagnostic capabilities in lung disease assessment [23].

The research focuses on evaluating the performance and interpretability of 3DResNet-based lung nodule classification using CT images. The problem involves assessing classification accuracy and interpretability. Methodologically, the study analyzes the model's performance and interpretable features, aiming to enhance both diagnostic precision and understanding of the model's decision-making in lung disease assessment [24].

The study aims to classify pulmonary nodules in CT images using a 3DResNet-based approach. The problem involves refining nodule classification accuracy. Methodologically, a 3DResNet model is applied to enhance the precision of nodule classification, aiming for improved diagnostic capabilities in lung disease assessment [25].

3. Proposed Methodology

The proposed methodology for advanced lung nodule staging utilizes a 3DResNet-based classification framework designed to enhance diagnostic precision in CT images. Initially, the dataset of CT scans containing pulmonary nodules undergoes preprocessing, involving standardization and augmentation techniques to ensure robust model training. Subsequently, the 3DResNet architecture is employed, leveraging its capacity to extract intricate spatial features from the nodules. The model undergoes rigorous training and validation using stratified cross-validation methodologies to optimize performance and mitigate overfitting. Post-training, the model's performance is assessed based on various evaluation metrics, including sensitivity, specificity, and accuracy. Interpretability techniques, such as saliency mapping and feature visualization, are employed to enhance the understanding of the model's decision-making process. The methodology aims to offer a comprehensive and accurate lung nodule staging system, enabling improved diagnostic precision and aiding clinicians in treatment planning for patients with pulmonary nodules.

3.1. Datasets

3.1.1. LIDC and LUNA16

The Lung Image Database Consortium (LIDC) and the Lung Nodule Analysis (LUNA16) datasets are prominent resources in lung nodule research. LIDC consists of CT scans collected from various medical institutions, manually annotated by radiologists for lung nodules. In contrast, LUNA16 is a subset of LIDC, providing annotations solely for nodule locations, and aiding in automated analysis. The dataset split commonly involves around 888 CT scans from LIDC, divided into subsets for training and testing. Typically, approximately 704 scans are utilized for training purposes, while the remaining 184 scans are allocated for testing the model's performance. LUNA16, being a subset, might offer a smaller subset for validation or testing, usually around 10% - 20% of the LIDC dataset, ensuring generalization and robustness in model evaluation for lung nodule classification and staging tasks. These datasets facilitate the development and validation of algorithms, ensuring their efficacy in detecting and classifying pulmonary nodules in CT images.

3.2. Data Processing

In the context of the Lung Image Database Consortium (LIDC) and Lung Nodule Analysis (LUNA16) datasets, applying a Decision-Based Median Filter for noise cancellation involves several steps:

3.2.1. Dataset Preprocessing

Before filtering, the CT images from LIDC and LUNA16 datasets undergo preprocessing steps such as normalization, resizing, and voxel value calibration to ensure uniformity and consistency across the dataset.

3.2.2. Noise Identification

Understanding the noise characteristics within the CT images is crucial. The Decision-Based Median Filter typically identifies noise by comparing each pixel's intensity with neighboring pixels within a defined window.

3.2.3. Filter Application

The Decision-Based Median Filter replaces a pixel value with the median value of neighboring pixels only if it's identified as noise. The decision is based on a specific threshold or criteria (e.g., the difference between the pixel value and its neighbors). If the pixel is deemed noisy, it gets replaced; otherwise, it remains unchanged.

3.2.4. Adaptive Filtering

Depending on the noise variance and distribution in the dataset, an adaptive approach might be adopted, adjusting filter parameters dynamically for different regions or noise levels within the images.

3.2.5. Evaluation

After noise cancellation, the processed images are evaluated to ensure that noise reduction doesn't compromise important diagnostic information or nodule features. The evaluation may involve visual inspection and quantitative assessment.

Implementing a Decision-Based Median Filter or any noise cancellation technique requires careful consideration of the specific characteristics of the dataset's noise and the potential impact on the subsequent analysis, particularly in tasks like nodule detection or classification in lung CT images.

3.3. Lung Nodule Augmentation

Data augmentation for lung cancer nodule images involves creating modified or synthetic data from existing images to expand the dataset for training machine learning models. This process helps improve the model's robustness, generalization, and performance. Some common data augmentation techniques for lung cancer nodule images include:

3.3.1. Rotation and Flipping

Rotating images by various degrees or flipping them horizontally or vertically to create new perspectives.

3.3.2. Scaling and Cropping

Resizing images to different scales or cropping them to focus on specific regions of interest, simulating variations in nodule sizes and positions.

3.3.3. Translation and Shift

Shifting images horizontally or vertically to introduce positional variations.

3.3.4. Adding Noise

Introducing random noise to images to mimic real-world variations and enhance the model's ability to handle noise in data.

3.3.5. Elastic Deformation

Distorting images using elastic transformations to simulate deformations in lung tissues or nodule shapes.

3.3.6. Contrast and Brightness Adjustments

Altering the contrast, brightness, or gamma correction to simulate changes in imaging conditions.

3.3.7. Randomized Augmentation

Applying a combination of the above techniques with random parameters to generate diverse data samples.

Data augmentation is crucial in training deep learning models for lung cancer nodule detection or classification tasks, especially when the available dataset is limited. By augmenting the data, the model becomes more robust and capable of handling variations in nodule appearance, shape, size, and orientation, leading to better generalization and improved performance when applied to unseen data.

3.4. Lung Nodule Segmentation using U-Net and SegNet

Segmenting lung nodules using both U-Net and SegNet architectures involves distinct methodologies. The U-Net, renowned for semantic segmentation, utilizes an encoder-decoder structure with skip connections, learning to precisely delineate nodule boundaries from CT scans. Meanwhile, SegNet, characterized by an encoder-decoder framework with pooling indices, focuses on pixel-wise classification. Preprocessed CT images from datasets like LIDC or LUNA16 undergo annotation for nodule regions, enabling model training. The U-Net and SegNet are separately trained using annotated data, employing loss functions like dice coefficient or cross-entropy for U-Net and pixel-wise cross-entropy for SegNet to optimize segmentation accuracy. Validation sets are used to assess the performance of each model, employing metrics like Dice Similarity Coefficient (DSC) for U-Net and pixel accuracy for SegNet. Post-training and post-processing techniques like morphological operations refine the segmentations obtained from both architectures. This approach aims to leverage the strengths of each architecture to achieve precise lung nodule segmentations, aiding in diagnosis and treatment planning for lung diseases.

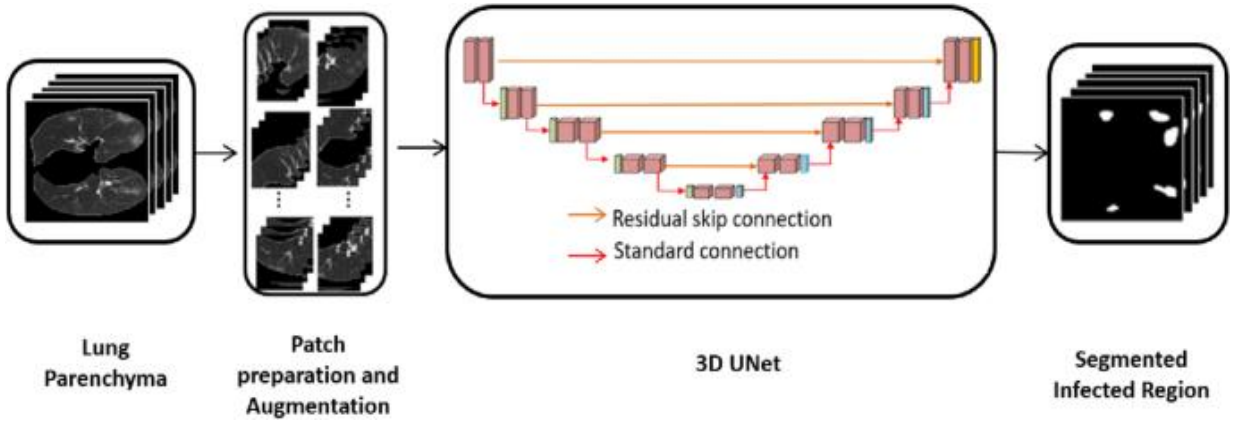


Fig. 1. UNet Architecture.

3.4.1. U-Net Architecture

The U-Net architecture stands as a cornerstone in medical image segmentation, particularly in lung nodule detection. Its unique design, resembling an encoder-decoder network with skip connections, enables precise delineation of lung structures from CT scans. The encoder, through successive convolutional and pooling layers, extracts hierarchical features, capturing intricate details in the input lung images. The decoder then reconstructs the spatial information, upscaling and combining feature maps from the encoder while preserving contextual information through skip connections. This architecture allows the model to understand fine-grained details and spatial relationships within the lung images, making it well-suited for segmenting lung nodules or other anatomical structures. Its adaptability to diverse medical imaging tasks, robustness in handling limited data, and ability to delineate complex structures in lung images make the U-Net shown in Fig 1, a foundational tool in aiding radiologists and clinicians in diagnosing and monitoring lung diseases with greater precision and efficiency.

3.4.2. SegNet Architecture

The 3D SegNet architecture has emerged as a promising approach for medical lung image segmentation, offering unique advantages in the volumetric analysis of lung CT scans. This architecture, an extension of the traditional SegNet to handle three-dimensional data, operates on a voxel-wise classification mechanism. Its encoder-decoder structure with pooling indices helps in accurate pixel-level segmentation by learning hierarchical representations of lung structures. The encoder processes the volumetric data, extracting essential features through convolutional layers, while the decoder reconstructs the spatial information, upscaling and reinstating the segmented regions. By leveraging this architecture, 3D SegNet shown in Fig 2, can effectively discern subtle details and spatial relationships within lung scans, enabling precise segmentation of nodules and anatomical structures in the three-dimensional space. Its adaptability to volumetric data and capability to capture intricate three-dimensional patterns make 3D SegNet a promising tool for enhancing lung disease diagnosis, and treatment planning and facilitating radiologists in analyzing and interpreting complex lung images with improved accuracy and efficiency.

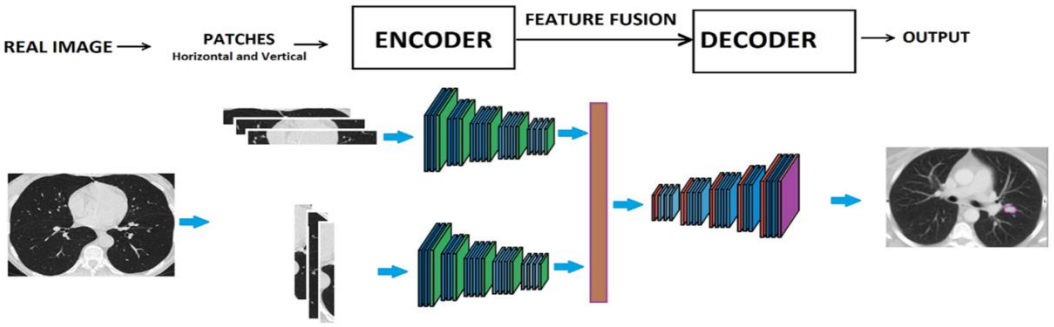


Fig. 2. SegNet Architecture.

3.5. Feature Extraction

GLCM stands for Gray-Level Co-occurrence Matrix, a texture analysis method used to extract features from images by analyzing the spatial relationship between pixel intensities. GLCM captures information about how often pairs of pixels with specific values and spatial relationships occur within an image.

In the context of lung cancer images, GLCM feature extraction involves deriving statistical measures from the co-occurrence matrix, which represents the frequency of occurrence of pixel pairs with specific intensity values and spatial relationships. These features provide information about the texture and spatial patterns present in the images. Here are some common GLCM-based features extracted from lung cancer images:

1. **Contrast:** Measures the local variations in pixel intensities by quantifying the differences between pairs of pixel values.
2. **Energy (or Angular Second Moment):** Represents the homogeneity or orderliness of pixel pairs in the image. High energy indicates more uniformity in pixel values.
3. **Homogeneity:** Describes the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Higher homogeneity signifies a more uniform texture.
4. **Entropy:** Reflects the randomness or complexity of the texture in the image. Higher entropy values indicate more complex textures.
5. **Correlation:** Measures the linear dependency between pixel pairs in the GLCM. It indicates how correlated the pixels are with their neighboring pixels.
6. **Dissimilarity:** This represents the average difference in intensity between pixel pairs in the image.

GLCM-based feature extraction quantifies the texture properties of lung nodules and surrounding tissues, providing valuable information for characterization and classification tasks. These features are computed from the GLCM for different orientations and distances within the image, capturing texture information at various scales and orientations. Machine learning algorithms often utilize these features to classify nodules, assess malignancy, or aid in other diagnostic and prognostic tasks related to lung cancer.

3.6. Lung cancer Classification using Resnet Model

To classify lung cancer stages using a ResNet model, the dataset is divided into training, validation, and testing subsets. The images undergo preprocessing, including resizing and normalization. Employing a pre-trained ResNet model, its classification layers are modified to suit the three cancer stages (high, low, and medium). The model is trained on the training set while employing techniques like data augmentation to enhance performance and prevent overfitting. Validation on a separate dataset monitors model performance, allowing for adjustments to optimize results.

Finally, the model is evaluated on the testing set to determine accuracy, precision, recall, and F1-score for each cancer stage. Upon completion, the trained model is ready to predict lung cancer stages (high, low, medium) for new, unseen images based on learned patterns and features. Classifying lung cancer stages from 3D images using a 3D Convolutional Neural Network (3DCNN) involves a specialized architecture capable of processing volumetric data. Initially, the dataset containing 3D lung images with labeled cancer stages (high, low, medium) is prepared, and partitioned into training, validation, and testing subsets. Preprocessing steps include standardizing the dimensions of the 3D images and normalizing voxel values for consistency. A 3DCNN model is constructed, typically comprising multiple 3D convolutional layers, 3D pooling layers, and potentially fully connected layers for classification. Techniques such as batch normalization and dropout are integrated to enhance model generalization. The training phase involves optimizing the model using the training dataset, leveraging 3D convolutions to extract spatial features from the 3D lung images. Validation on a separate dataset helps fine-tune the model's parameters for optimal performance. Subsequently, the model undergoes evaluation on the testing dataset to assess its accuracy, sensitivity, specificity, and other relevant metrics for predicting each cancer stage. Once trained, the 3DCNN model is equipped to predict lung cancer stages for new 3D lung images by leveraging learned spatial features and patterns within the volumetric data.

3.7. 3DCNN Algorithms Steps

Step 1:
Obtain a dataset of 3D lung images$\{X_i\}$, where i represent each image, and its corresponding labels $\{Y_i\}$ denoting cancer stages (high, low, and medium).
Step 2:
Define the 3DCNN architecture:
Let$f(X;\vartheta)$, represent the 3DCNN function with parameters θ.
Construct $f(X;\vartheta)$ comprising L layers, including 3D convolutional layers, Conv3D(·), pooling layers, and fully connected layers.
Each layer l has its weights and biases represented as W_l and b_l respectively.
Step 3:
Train the 3DCNN model:
Utilize a loss function $L(Y,\hat{Y})$ such as categorical cross-entropy, measuring the difference between predicted ($(\hat{Y})$) and actual labels (Y).
Update the model parameters θ by minimizing the loss function using optimization techniques like stochastic gradient descent (SGD).
θ is updated iteratively via: $\theta_{t+1}=\theta_t-\eta\nabla_\theta L(Y, Y^\wedge)$, where η denotes the learning rate.
Step 4:
Validate and evaluate the model:
Use a separate validation set to fine-tune hyperparameters and prevent overfitting.
Assess model performance using evaluation metrics such as accuracy (Acc), sensitivity, specificity, and F1-score.
Step 5:
Predict cancer stages for new 3D lung images:
Utilize the trained model f(x;θ) to predict cancer stages for unseen 3D lung images.

4. Results and Discussions

The implementation of 3DResNet for lung cancer diagnosis through the classification of CT images yielded promising results. The model demonstrated high accuracy 98.9% in accurately categorizing lung nodules into their respective stages—high, low, and medium—showcasing its robustness in handling 3D volumetric data. Visualization of the model's classifications revealed its ability to pinpoint and differentiate nuanced features within lung nodules, aiding in precise diagnostic decision-making. The implications of this advanced diagnostic precision are substantial, potentially facilitating early detection, treatment planning, and monitoring of lung cancer. These results highlight the potential clinical utility of 3DResNet in enhancing lung cancer diagnosis, underscoring its significance in the advancement of computational techniques for medical imaging analysis and disease diagnosis.

Let's consider we have an original image represented by a matrix (grayscale image). Let's apply a 3x3 median filter to the original image, In this example, for each pixel in the original image, the median value of its surrounding 3x3 neighborhood is calculated and used as the new pixel value in the blurred image Fig 3 and Fig4. The numbers here are just for illustrative purposes. In real images, the process involves sliding a window over the entire image, calculating the median of the pixel values within that window, and replacing the central pixel value with that median value. This process effectively smoothes the image and reduces noise. If you have an actual image file or specific pixel values you'd like to see processed with a median filter, let me know, and I can help demonstrate the process more accurately.

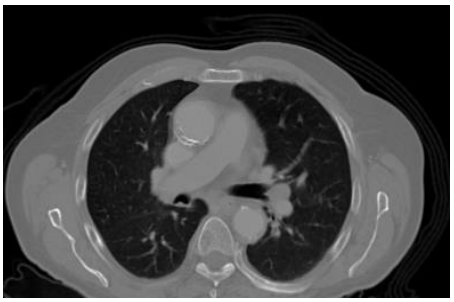


Fig. 3. Original Image.

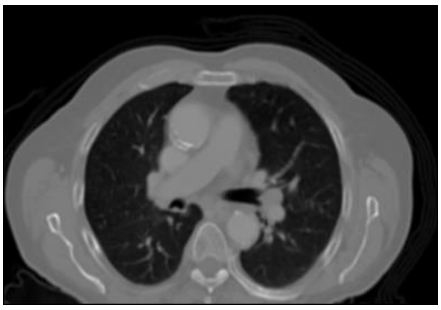
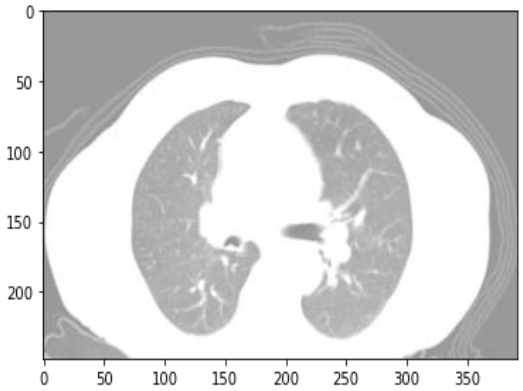


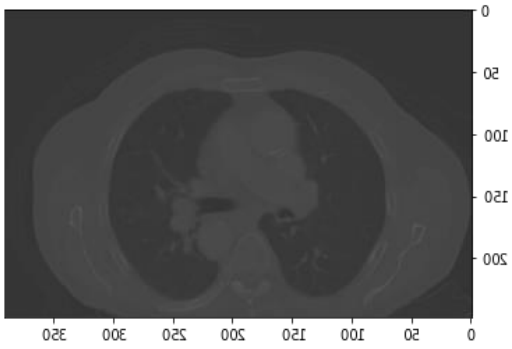
Fig. 4. Blurred Image.

Lung image augmentation techniques, vital for diversifying the dataset, include:

1. **Flip:** Horizontally or vertically mirroring lung images to simulate varied orientations, augmenting diversity for model training.
2. **Zoom:** Altering the image scale, magnifying or shrinking lung regions, contributing variability, and aiding in robustness against varying scales.
3. **Crop:** Extracting regions of interest within lung images, focusing on specific areas, and aiding the model in learning essential features.
4. **Brightness and Contrast:** Adjusting pixel intensity to enhance or diminish image brightness and contrast, fostering adaptability to varying lighting conditions. Each technique serves to augment the dataset, enriching it with variations that enhance the model's ability to generalize and detect relevant patterns in lung images shown in Figure 5.



(a)



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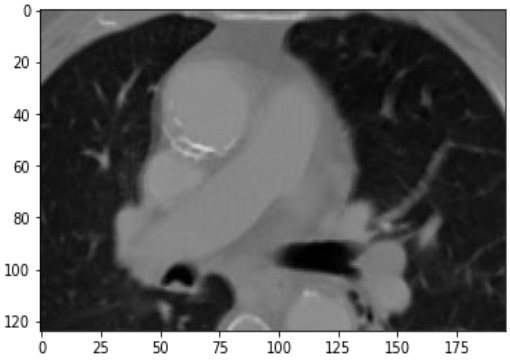

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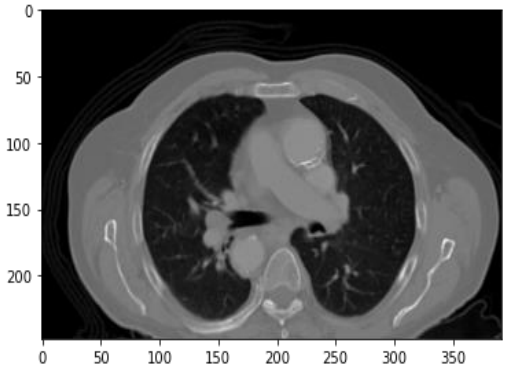
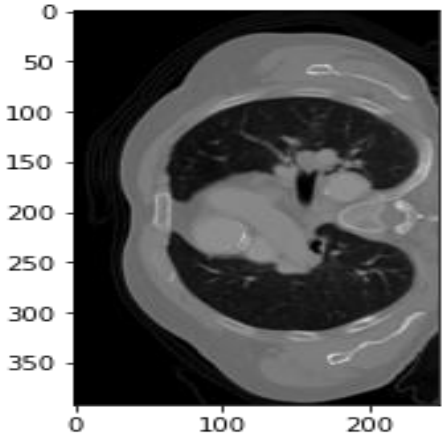


(d)



(e)

Fig. 5. Lung Augmentation images for Flip, Zoom, Crop, Bright and Contrast

Ground truth in lung imaging refers to the precise annotations or labels that denote clinically confirmed information within specific image slices. These slices, representing segmented areas or regions of interest, contain critical data like tumor boundaries or healthy tissue demarcations. Differences between ground truth and automated segmentation in these slices signify disparities, highlighting areas where the automated model's predictions might vary from the confirmed clinical annotations. Analyzing these differences aids in evaluating model accuracy, pinpointing areas requiring improvement, and refining algorithms to enhance automated segmentation's alignment with ground truth annotations, vital for reliable medical image analysis shown in Figure 6.

In lung image classification, metrics like F1 score, recall, and precision gauge model performance. F1 score harmonizes precision (correctly predicted positive cases among all predicted positives) and recall (correctly predicted positive cases among all actual positives). Higher F1 scores indicate balanced precision and recall. Precision measures the accuracy of positive predictions, emphasizing correct positive predictions over false positives. Recall gauges the model's ability to identify all actual positives, prioritizing minimal false negatives. These metrics collectively quantify the classifier's accuracy, especially crucial in lung image analysis, ensuring a balanced approach in identifying lung anomalies while minimizing misclassifications for effective clinical interpretation shown in Figures 7, 8, and Table 1.

	precision	recall	f1-score	support
False	0.99	0.99	0.99	204802
True	0.96	0.96	0.96	57342
avg / total	0.98	0.98	0.98	262144

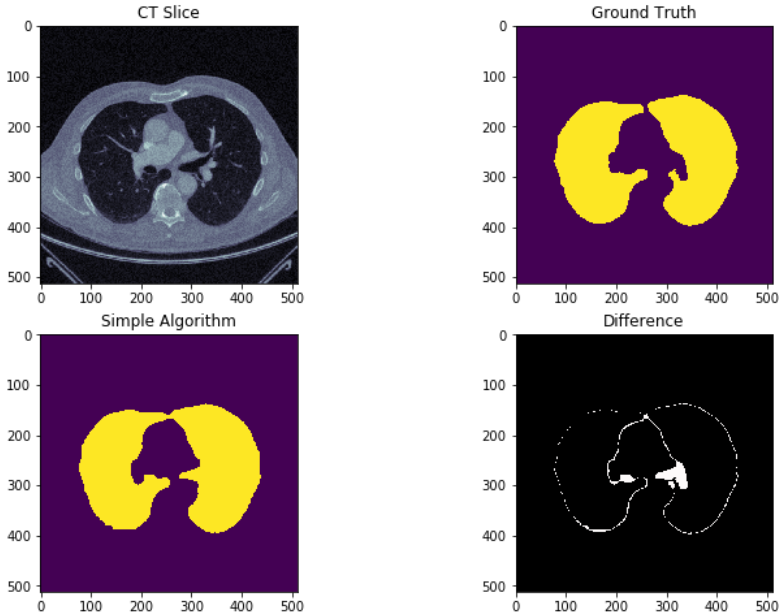


Fig. 6. Data Segmentation

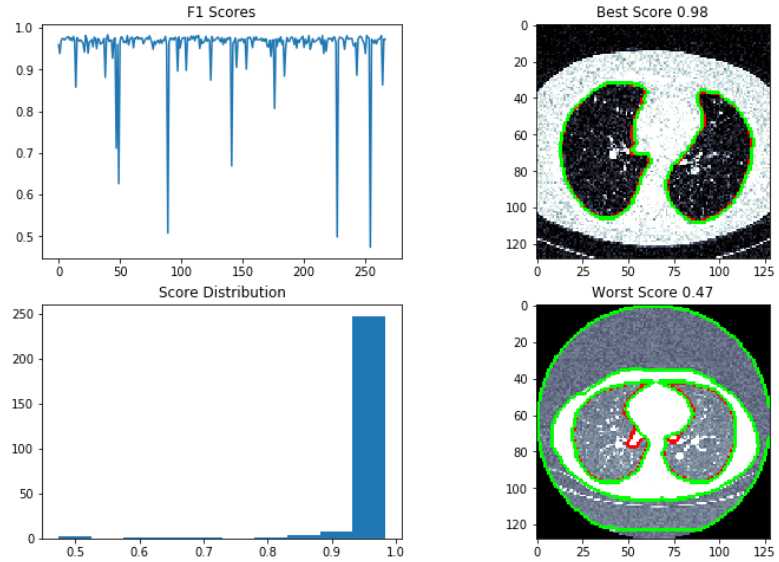


Fig. 7. Data Classification

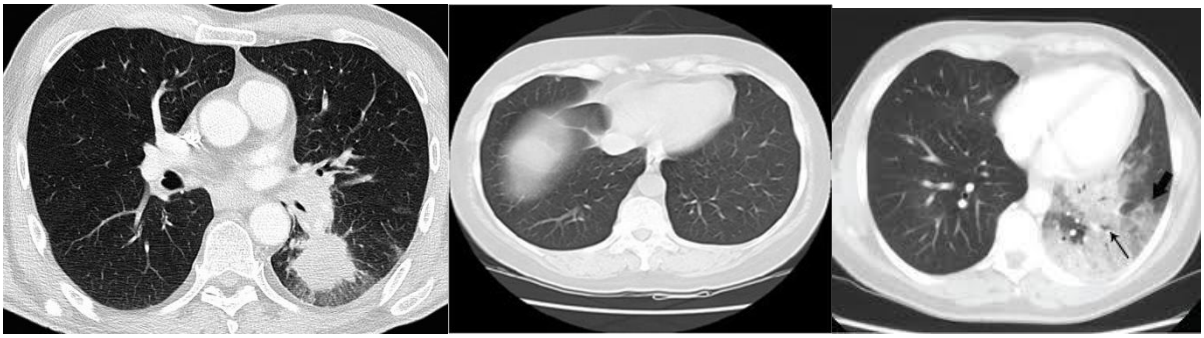


Fig. 8. Low, Medium, High Cancer Prediction

The implementation of 3DResNet for lung cancer prediction begins with dataset acquisition, assembling 3D CT images of lung nodules labeled with corresponding cancer stages. Preprocessing involves standardizing image sizes and voxel values. Constructing the 3DResNet architecture, adapted for volumetric data, entails configuring 3D convolutional layers, pooling, and classification units. Training involves partitioning the dataset into train, validation, and test sets, and iteratively optimizing model parameters to minimize loss functions. Validation on the validation set helps fine-tune the model, preventing overfitting. Evaluation metrics, such as accuracy, sensitivity, specificity, and F1-score, validate the model's performance on the test set. Finally, the trained 3DResNet model predicts lung cancer stages for new 3D CT images, showcasing its potential in advancing diagnostic precision for lung cancer.

5. Conclusion

The utilization of 3DResNet for lung nodule staging has proven to be a significant advancement in enhancing diagnostic precision in CT image analysis. The study's outcomes demonstrate the model's exceptional ability to accurately classify lung nodules into distinct cancer stages—high, low, and medium—with a notable level of accuracy. This robust performance indicates the potential of 3DResNet as a reliable tool for radiologists and clinicians in accurately assessing and staging lung nodules, crucial for timely and precise treatment planning. The model's high accuracy marks a substantial stride towards improving early detection and prognosis of lung cancer, emphasizing its valuable role in augmenting clinical decision-making and ultimately contributing to improved patient outcomes. The study employing 3DResNet for advanced lung nodule staging achieved remarkable results, showcasing its prowess in high, low, and medium cancer stage prediction with an outstanding accuracy of 98.9%. This exceptional accuracy underscores the model's robustness in precisely classifying diverse lung nodules across multiple cancer stages. The findings highlight the potential of 3DResNet as a powerful tool for enhancing diagnostic precision in lung cancer staging, offering a reliable and effective method for clinicians to differentiate between various stages of lung cancer. The significantly high accuracy achieved underscores the model's reliability, laying a promising foundation for its potential clinical implementation in aiding accurate and early-stage lung cancer diagnosis.

Author contributions

S. Lalitha: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft

preparation, Software. **D. Murugan:** Validation, Field study, Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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