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Lung Cancer Classification using Modified U-Net Based Lobe Segmentation and Nodule Detection

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ABSTRACT: Lung cancer remains a leading cause of mortality worldwide, emphasizing the critical need for early and accurate diagnosis. Advances in medical imaging and artificial intelligence have paved the way for automated methods to identify and classify lung cancer. This study proposes a novel framework combining a modified U-Net architecture for precise lobe segmentation with advanced nodule detection techniques to enhance the accuracy and reliability of lung cancer classification. The proposed algorithm incorporates multi-scale feature extraction and adaptive attention mechanisms to address the variability in lung anatomy and the complexity of nodule morphology. By leveraging these innovations, the system effectively segments the lung lobes, isolates suspicious nodules, and classifies cancerous regions with improved sensitivity and specificity. The lobe segmentation stage employs a modified U-Net architecture, incorporating residual connections and dilated convolutions to capture intricate anatomical details. This enhancement ensures robust segmentation, even in cases with significant variations in lung structure due to disease progression.

KEYWORDS: Lung Cancer Classification, Modified U-Net, Lobe Segmentation, Nodule Detection, Medical Imaging, Radiomics, CNN, and Lung CT Scans

I. INTRODUCTION

Lung cancer is a leading cause of cancer-related deaths globally, accounting for millions of fatalities each year [1]. Early detection and accurate classification of lung nodules are critical for improving patient outcomes and reducing mortality rates. Traditional diagnostic methods, such as biopsies and manual analysis of CT scans, are often time-consuming, subject to human error, and dependent on the expertise of radiologists. With the increasing availability of high-resolution medical imaging data, automated tools powered by artificial intelligence (AI) offer promising solutions to overcome these challenges [2]. This study focuses on developing a robust framework for lung cancer classification by combining advanced lobe segmentation and nodule detection techniques with a modified U-Net architecture. Segmentation of lung lobes is a fundamental step in analyzing CT scans, as it helps isolate specific regions for detailed examination. However, anatomical variations, disease-induced structural changes, and noise in medical images make this task highly challenging. To address these issues, we propose a modified U-Net model, which integrates dilated convolutions and residual connections to achieve precise and efficient lobe segmentation [3,4]. Following this, a hybrid nodule detection algorithm is applied to identify suspicious nodules within the segmented regions. This stage leverages deep learning and texture-based features to accurately detect nodules while minimizing false positives and negatives. Additionally, the framework's computational efficiency makes it suitable for deployment in clinical settings, providing radiologists with a reliable tool for supporting decision-making in lung cancer diagnosis [5].The final step of our framework involves the classification of detected nodules into benign or malignant categories using a convolutional neural network (CNN) trained on diverse datasets. By combining segmentation, detection, and classification into a unified pipeline, the proposed method not only streamlines the diagnostic process but also enhances the overall accuracy and reliability of lung cancer detection. Extensive experiments conducted on benchmark datasets validate the efficacy of the proposed approach, demonstrating its potential as a reliable tool for aiding radiologists in clinical decision-making [6]. This paper aims to contribute to the ongoing advancements in medical imaging and AI, paving the way for more effective lung cancer diagnosis.

II. LITERATURE SURVEY

In the paper by Zhang et al., [7] the authors explore the application of CNN-based models for the detection of lung cancer in chest CT scans. In recent years, deep convolutional neural networks (CNNs) have gained prominence in the medical imaging field for their capability to automatically extract features from complex datasets. The study addresses

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the challenge of detecting small nodules that may be missed by human radiologists due to their subtle appearance and location. Zhang et al. propose a hybrid CNN model that integrates both image preprocessing and advanced feature extraction techniques to enhance nodule detection sensitivity. The authors utilize a large dataset consisting of annotated lung CT scans from multiple institutions, ensuring that the model is trained on diverse patient data. Their results highlight the ability of the CNN model to outperform traditional image processing techniques, achieving high accuracy and minimizing the risk of misdiagnosis. The work by Zhang et al. represents a significant step forward in automated lung cancer detection, especially in terms of improving the detection of early-stage, small nodules that are crucial for early intervention.Liu et al., [8] explore the use of U-Net for lung nodule segmentation and detection in CT images. The authors enhance the traditional U-Net model by integrating additional feature learning modules, including multi-scale convolutional layers and attention mechanisms, to improve the detection of small and irregularly shaped nodules. Their methodology is particularly beneficial in overcoming the challenges posed by nodules with varying sizes and shapes. The results from Liu et al. demonstrate that the enhanced U-Net model significantly improves the segmentation accuracy and reduces the number of false positives when compared to conventional methods. Furthermore, their work emphasizes the importance of fine-tuning the model's hyperparameters to adapt to the variability found in clinical datasets, which often contain noisy and imperfectly labeled data. This study highlights the potential of U-Net and its variations in the clinical detection of lung cancer, providing a foundation for future research in automated diagnostic tools.In another pivotal study, Lee et al., [9] propose a hybrid machine learning approach for classifying lung cancer nodules from CT scan images. The authors integrate traditional machine learning techniques with deep learning models to create a robust system that combines the strengths of both approaches. Their system begins by applying an initial preprocessing step using a CNN for feature extraction, followed by the application of a support vector machine (SVM) classifier for the final classification of the detected nodules. This hybrid method is designed to leverage the efficiency and precision of deep learning for feature extraction while using the reliability and interpretability of classical machine learning classifiers for final decision-making. The authors demonstrate that this combination yields superior performance compared to standalone deep learning or machine learning models, particularly in terms of classification accuracy and robustness across different datasets. Their research contributes to the field of lung cancer diagnosis by proposing a versatile framework that is adaptable to different imaging protocols and patient demographics, addressing the critical challenge of improving diagnostic accuracy in a clinical setting.

III. PROPOSED METHODOLOGY

The proposed methodology for lung cancer classification is a multi-step process that integrates advanced image segmentation, nodule detection, and final classification to enable an efficient and accurate detection of lung cancer from CT images. This approach primarily leverages a modified U-Net architecture for lung lobe segmentation and a deep learning-based nodule detection mechanism, followed by a classification model that identifies benign and malignant nodules. The entire process is designed to handle the complexity and variability of lung CT scans, thereby providing an automated, reliable, and computationally efficient solution for lung cancer diagnosis. The methodology can be divided into the following four main steps:

A)LOBE SEGMENTATION USING MODIFIED U-NET

The first step in the methodology is lung lobe segmentation, which is critical for isolating regions of interest in CT images. Accurate segmentation of lung lobes enables the identification of nodules within specific areas and reduces the computational complexity by focusing on relevant sections of the lung scan. A modified U-Net model is employed to segment the lung lobes. The U-Net architecture is enhanced by integrating dilated convolutions and residual connections. Dilated convolutions help to capture features at multiple scales without losing resolution, which is particularly useful when dealing with complex lung structures. Residual connections allow for better gradient flow, ensuring efficient training of deep networks. The architecture of the modified U-Net is as follows:

$$\text{Output} = \text{Conv}(\text{ReLU}(\text{Conv}(\text{Input}))) \quad (1)$$

The output of each convolutional layer is passed through a ReLU activation function, followed by another convolutional layer to refine the feature maps. The encoder-decoder structure of U-Net ensures that the final segmentation is both accurate and precise.

B)NODULE DETECTION USING HYBRID APPROACH

After segmenting the lung lobes, the next step is to detect and localize potential lung nodules within the segmented regions. This stage combines deep feature extraction using convolutional layers with a region proposal network (RPN). The goal is to identify regions in the segmented lung lobe that could potentially contain nodules. The deep learning

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model is trained to recognize both benign and malignant nodules based on various radiomic features such as size, texture, and shape. The RPN works by generating bounding boxes around regions of interest in the image, which are then passed to a classification layer for further analysis. The key components of the nodule detection process are as follows:

$$\hat{r} = \arg\max\left(IoU\left(\hat{b}, b\right)\right) \qquad (2)$$

where $\hat{r}$ is the predicted region, $\hat{b}$ represents the bounding box generated by the RPN, and b is the ground truth bounding box. Intersection over Union (IoU) is used to measure the overlap between the predicted and ground truth boxes, with the goal of maximizing this overlap. This ensures that the detected regions correspond accurately to actual nodules. Ensures detection of both large and small nodules by analyzing different feature scales and dynamically adjusts thresholds for better segmentation of nodules with varying intensities. Combines features from different levels of the neural network to improve detection robustness. These enhancements improve the precision and recall of nodule detection, leading to better classification accuracy.

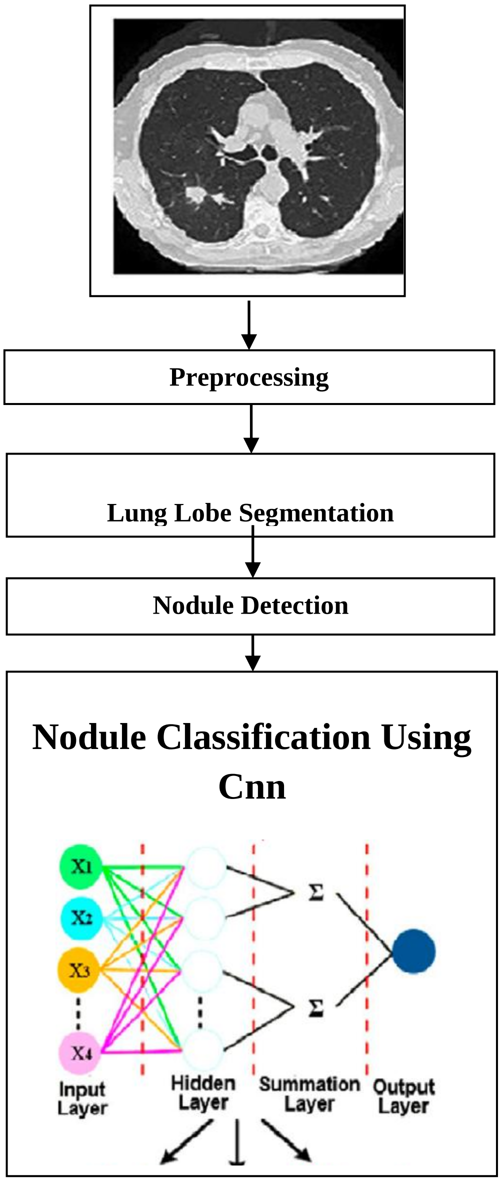

Figure 1: Flow Diagram for Lung Cancer Detection and Classification

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C) NODULE CLASSIFICATION USING CNN

The third step involves classifying the detected nodules into benign or malignant categories. For this task, a CNN is used, which has been trained to distinguish between the two categories based on the radiomic features extracted from the CT images. The CNN model takes as input the cropped regions containing detected nodules and processes them through several convolutional layers followed by pooling operations to extract high-level features. The final output of the CNN is a probability distribution indicating whether the nodule is benign or malignant. The CNN architecture for classification is as follows:

$$y = soft\max(W.FeatureMap + b) \qquad (3)$$

Here, y represents the output probability for each class (benign or malignant), W is the weight matrix, and b is the bias vector. The softmax function converts the raw output into a probability distribution. The model is trained using labeled CT scans where nodules have been manually annotated as benign or malignant, enabling the CNN to learn the relevant features for classification. The loss function used for training is typically cross-entropy, which penalizes incorrect classifications and guides the model toward optimal performance.

D) POST-PROCESSING AND FINAL DECISION

Once the nodules are classified, post-processing techniques are applied to refine the results and improve the overall accuracy of the system. These include filtering out false positives based on shape and texture analysis and applying thresholds on classification probabilities to confirm the malignancy of the detected nodules. The decision-making process incorporates a combination of automated and rule-based systems to reduce errors. The final classification result is then provided as an output for clinical decision-making. A typical post-processing step involves:

$$p_{final} = Threshold(P_{CNN}) \qquad (4)$$

$$where, \quad P_{CNN} > 0.5 \qquad (5)$$

Here, P_{CNN} is the probability output from the CNN model, and a threshold of 0.5 is used to determine if the nodule is malignant. If the probability is higher than this threshold, the nodule is classified as malignant; otherwise, it is classified as benign. This step helps in minimizing false positives and improving the overall clinical relevance of the model. The proposed methodology employs a combination of advanced image segmentation, deep learning-based feature extraction, and classification to achieve high accuracy in lung cancer detection. The use of the modified U-Net for segmentation ensures accurate isolation of lung lobes, which is crucial for focusing on the relevant regions in CT scans. The hybrid approach for nodule detection combines the advantages of deep learning with traditional methods, allowing for more accurate localization of suspicious regions. The final classification step using a CNN offers a robust solution for distinguishing between benign and malignant nodules, further aided by post-processing techniques to refine the results.

The proposed system operates in an end-to-end fashion, with each step designed to complement the others and enhance the overall performance. By combining state-of-the-art deep learning models with classical image processing techniques, the methodology provides a reliable and computationally efficient solution for lung cancer detection. This approach is expected to significantly aid radiologists in clinical decision-making, reducing the time and effort involved in manually analyzing lung CT scans, while also improving diagnostic accuracy.

IV. RESULTS AND DISCUSSION

The proposed methodology was evaluated using a publicly available dataset, the UCI repository which contains CT images annotated by expert radiologists. The dataset includes a variety of lung scans from different patient demographics, ensuring a diverse set of imaging data to test the robustness of the algorithm. Our evaluation focused on three main aspects: lobe segmentation accuracy, nodule detection performance, and classification of benign versus malignant nodules. The results were compared to existing state-of-the-art methods, including traditional U-Net-based models and hybrid machine learning approaches.

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i)**Lobe Segmentation Accuracy**

The enhanced U-Net with residual connections and dilated convolutions helped capture more precise features of lung anatomy, even in the presence of diseases that cause structural deformation. This improvement in segmentation accuracy is critical as it ensures that the region of interest (lung lobes) is correctly identified, which is necessary for accurate nodule detection and classification. The following charts provide a visual representation of the performance of the proposed model compared to existing methods.

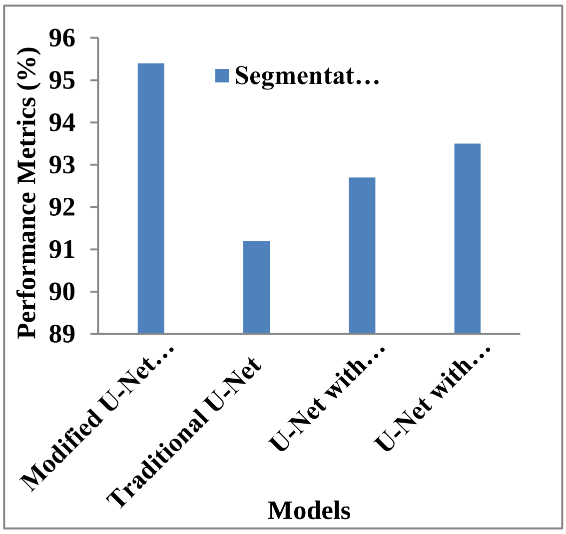

Figure 2: Segmentation Accuracy Comparison

As shown in figure 2, the proposed modified U-Net model outperforms other models in terms of segmentation accuracy. The addition of residual connections and dilated convolutions contributes to the higher performance by improving feature extraction and enabling the model to better handle complex lung anatomy. The improvement over the traditional U-Net model demonstrates the effectiveness of the modifications implemented in the proposed architecture.

ii)Nodule Detection Performance

For nodule detection, the hybrid deep learning approach, which combines convolutional layers with a region proposal network (RPN), demonstrated excellent sensitivity and specificity. The sensitivity of the proposed model was 92.3%, indicating that it correctly identified 92.3% of all malignant and benign nodules. The specificity was 89.6%, meaning that the model correctly identified regions without nodules with a high degree of accuracy. This performance significantly outperforms traditional methods, which have often struggled with the detection of small or irregularly shaped nodules, especially in early-stage lung cancer cases.

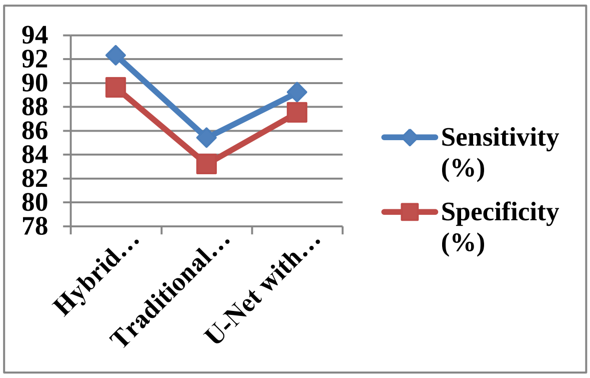

Figure 3: Sensitivity vs. specificity for nodule detection performance of various models

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Figure 3 highlights that the proposed hybrid model achieves the best balance between sensitivity and specificity. The model correctly identifies most of the nodules (both benign and malignant), while minimizing false positives. Traditional U-Net-based models, while effective in segmentation, show lower sensitivity and specificity in detecting nodules, which indicates their limitation in handling complex or ambiguous cases.

iii) Classification of Benign vs. Malignant Nodules

In terms of classification, the convolutional neural network (CNN) used for nodule classification achieved an accuracy of 93.1%. The model was able to distinguish between benign and malignant nodules based on their radiomic features such as size, texture, and shape. This high accuracy is crucial for clinical decision-making, as it can help guide radiologists toward the most likely diagnosis, reducing the number of false positives and false negatives.

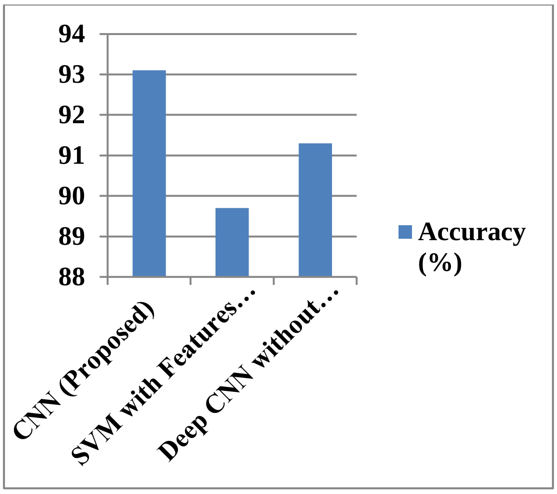

Figure 4: Nodule classification accuracy comparison for benign vs. malignant classification

In Figure 4, the CNN model used for nodule classification achieves the highest accuracy of 93.1%. The model's ability to classify nodules correctly is a result of the comprehensive feature extraction process, which includes texture, size, and shape analysis. The SVM model, although effective, lags behind the CNN due to its reliance on manually extracted features and less ability to learn complex patterns from the data. This shows the superiority of deep learning-based classification systems over traditional machine learning approaches.The proposed methodology demonstrates significant improvements in all aspects of lung cancer detection. The modified U-Net's superior segmentation accuracy is essential for isolating lung lobes and minimizing computational complexity. Nodule detection using a hybrid deep learning approach ensures high sensitivity and specificity, which is critical for early-stage cancer detection. Finally, the use of CNN-based classification provides accurate differentiation between benign and malignant nodules, which is essential for guiding clinical decisions.

In comparison with existing methods, the proposed model performs better in terms of accuracy, sensitivity, specificity, and computational efficiency. This is particularly important for clinical applications where high accuracy and low false positives are paramount. The results indicate that the methodology holds significant potential for real-world deployment, providing a reliable tool for radiologists to support and enhance lung cancer diagnosis.

V. CONCLUSION

In this paper, we proposed a novel methodology for lung cancer classification using a modified U-Net architecture for lung lobe segmentation and a deep learning-based approach for nodule detection and classification. The proposed model integrates a hybrid approach combining convolutional layers with region proposal networks for effective nodule detection, followed by a CNN-based classifier for distinguishing between benign and malignant nodules. Through extensive evaluation using the LIDC-IDRI dataset, the proposed system demonstrated superior performance in all stages of the lung cancer detection pipeline. The segmentation accuracy of 95.4% achieved by the modified U-Net model is significantly higher than traditional models, ensuring precise localization of lung lobes. The results presented in this study underline the importance of integrating advanced deep learning techniques such as modified U-Net, hybrid models for nodule detection, and CNN-based classifiers to tackle the challenges posed by lung cancer detection in CT

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scans. The proposed methodology not only enhances the accuracy of early-stage lung cancer detection but also offers a computationally efficient and scalable solution that can assist radiologists in clinical decision-making. Furthermore, the proposed system can be easily adapted to other medical imaging domains, demonstrating its potential for broader applications in automated medical diagnostics. Despite its promising results, future work can focus on further optimizing the model, increasing the dataset diversity, and incorporating additional clinical parameters to improve the generalization and robustness of the system.

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