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Lung Cancer Detection using CNN with Contour Guided Visualization

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***Abstract*— Lung cancer continues to be one of the most common and deadly illnesses globally, with enhanced survival rates largely relying on prompt and precise diagnosis. This research presents an automated system that combines deep learning and conventional image preprocessing methods to provide accurate and understandable diagnostic results. The approach consists of a series of preprocessing actions, such as converting to grayscale, binarizing, applying thresholding, segmenting, and extracting contours. Through contour detection, the system marks the main lung outline in green and additionally accentuates this area with a blue bounding box on the segmented binary image. Although this stage does not specifically isolate the tumor area, it clearly outlines the lung region, making abnormal growths or irregular formations more apparent. In the end, an enhanced VGG16 convolutional neural network is employed to classify the examined areas into three categories: benign, malignant, or normal, ensuring a dependable method for early lung cancer identification. An accuracy of approximately 96% was demonstrated in the experimental evaluation, demonstrating that the combination of CNN-based classification and contour-guided visualization provides a computationally effective and clinically interpretable method. In resource-constrained settings, this method supports initial lung cancer screening and provides a feasible alternative to complex segmentation models.**

***Keywords*— early diagnosis, contour extraction, VGG16, image preprocessing, medical image analysis, lung cancer detection.**

I. INTRODUCTION

A significant portion of cancer-related deaths is due to lung cancer, rendering it one of the most prevalent and lethal forms of cancer globally. As the illness is often identified in its later stages, when there are limited treatment choices and the outlook is grim, early diagnosis is crucial for enhancing survival rates [1]. Conventional diagnostic methods, such as computed tomography (CT) scans, biopsies, and chest radiography, are still useful but come with disadvantages such as significant cost, time commitment, and reliance on skilled radiologists for precise interpretation.

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These drawbacks highlight the necessity of dependable and automated computer-aided diagnostic (CAD) systems [2].
Over the last few years, deep learning has become a revolutionary technology in medical imaging, especially for the detection and classification of lung cancer. Convolutional Neural Networks (CNNs) have shown extraordinary effectiveness in extracting hierarchical characteristics from medical images, facilitating the precise classification of benign and malignant cases [3]. For instance, early stage lung Cancer Detection Using Deep Learning demonstrated the effectiveness of CNNs in improving diagnostic precision relative to traditional methods [1] Comparative evaluations of transfer learning models such as VGG16, InceptionV3, and ResNet50 reveal that VGG16 outperforms others in feature extraction because of its structured convolutional layers and simpler architecture [4].
Many of the researchers have endeavoured to develop lightweight CNN models and efficient frameworks to render lung cancer detection systems computationally viable for extensive implementations. While these methodologies diminish complexity, they frequently compromise interpretability and neglect to emphasize the regions of interest (ROIs) essential for clinical validation [5][6]. Basic methodologies, including shallow CNNs for pulmonary micronodule detection [7] and patch-based nodule classification utilizing centroid cropping [8], offer foundational solutions but exhibit deficiencies in reliably localizing abnormal growths in the lungs.
Regardless the advancements achieved, a substantial research void persists in integrating classical preprocessing methods with deep learning models to attain both precision and interpretability. Lung cancer is still one of the most common causes of cancer deaths around the world. This is mostly because it is hard to find early on and hard to get a precise diagnosis. Traditional methods, such as manually verifying CT scans, are time-consuming and prone to human error. Rapid advances in deep learning for medical imaging have made automated systems more dependable in assisting radiologists [9]. The 3D U-Net architecture has emerged as an effective method for medical image segmentation among the different approaches. By capturing volumetric features from CT scans, 3D U-Net provides a deeper understanding of tumour areas than 2D models that process slices one at a time [9], [11]. Loss functions (such as Dice Loss, Cross-Entropy Loss, or Hybrid Loss) are carefully designed to address the problems of class imbalance between tumour and non-tumor areas in order to further improve performance [10], [12]. Additionally, the model can preserve contextual and spatial details thanks to feature concatenation techniques, which are crucial for accurately segmenting small or irregularly shaped lung nodules [13], [16].
In order to increase the accuracy of lung cancer detection and segmentation, this project focusses on creating a deep learning framework using a 3D U-Net that uses feature concatenation techniques and refined loss functions. The goal is to create a system that helps radiologists make more rapid and reliable clinical decisions in addition to effectively identifying cancerous areas [14], [15].

II. Literature Survey

Lung Cancer detection through deep learning based techniques has been one of the most attractive fields in medical imaging as they can assist radiologists to automatically detect, classify and analyse the pulmonary nodules. Being able to detect cues is important, as it greatly improves the chances of an effective treatment and the survival chances of the patients.
Hussein et al. [1] introduced a framework for the early detection of lung cancer utilizing deep learning, demonstrating that these models considerably surpass conventional CAD (Computer-Aided Detection) systems by enhancing sensitivity and specificity in analyzing CT scans. Shen et al. [2] showed the efficacy of multi-scale deep learning frameworks in classifying lung nodules, indicating that deep learning models can autonomously learn hierarchical features from CT scans and lessen reliance on manually crafted descriptors.
Sasikala and Kumaravel [3] presented a comprehensive review of deep learning methods for detecting, classifying, and predicting lung cancer, highlighting prevalent issues like elevated false-positive rates, insufficient annotated data, and a lack of interpretability in models. Reddy and Divya [4] conducted a comparative analysis of various deep learning architectures and found that simpler, well-defined models tend to provide consistent performance across medical imaging datasets.
Sujatha et al. [5] proposed a computationally efficient deep learning framework suitable for real-time lung cancer detection. However, they also noted limitations in interpretability and precise region localization, which remain crucial for clinical adoption. Agarwal et al. [6] developed a lightweight, end-to-end deep learning approach for lung cancer identification in histopathological images, achieving faster inference with reduced model complexity, but lacking proper region-of-interest visualization needed for clinical validation.
Setio et al. [7] applied a multi-view deep learning strategy to differentiate between pulmonary micro-nodules and non-nodules, which improved sensitivity for detecting small nodules. However, the approach was limited by

insufficient contextual lung information. Similarly, Kumar et al. [8] proposed a patch-based deep learning framework for pulmonary nodule classification using CT scans, achieving promising results, though still highly dependent on the availability of large annotated datasets.

Expanding on these foundations, scientists have investigated more sophisticated deep learning models. Çiçek et al. [9] developed the 3D U-Net to enhance the U-Net model for volumetric biomedical segmentation. Their research showed that acquiring spatial context across various slices greatly enhances the segmentation of irregular tumor areas. Milletari et al. [10] presented V-Net, utilizing Dice loss to tackle the challenge of class imbalance in medical image segmentation, resulting in significant enhancements in tumor detection precision.

Isensee et al. [11] introduced nnU-Net, a self-adjusting framework that autonomously configures itself for different biomedical segmentation applications, demonstrating the adaptability and strength of U-Net-based models. Zhou et al. [12] investigated hybrid loss functions integrating Dice and cross-entropy losses, demonstrating better performance than individual loss functions when addressing highly imbalanced medical datasets.

Zhao et al. [13] highlighted the importance of multi-level feature fusion and concatenation in improving deep network performance. Their results emphasized that integrating characteristics from various phases of the model enhances segmentation precision and resilience. Myronenko [14] presented a 3D U-Net featuring encoder-decoder pathways and residual connections, reaching top performance in lung tumor segmentation at the MICCAI Lung Nodule Challenge.

Tang et al. [15] incorporated attention mechanisms into U-Net architectures to enhance the learning of important features, resulting in a notable increase in the accuracy of lung cancer detection. In a similar manner, Chen et al. [16] developed a 3D deep learning model that employed multi-scale feature concatenation, allowing for the identification of global structures as well as intricate local features. This method was particularly successful in detecting small and intricate nodules in CT images

III. METHODOLOGY

The lung dataset encompasses of patients with non-small cell lung cancer publicly available through The Cancer Imaging Archive (TCIA) and it was previously used to create a radiogenomic signature. The following acquisition and reconstruction parameters were considered for 96 preoperative thin-section CT scans and the parameters are as follows:

Section-Thickness<1.5mm; 120 kVp; 100-700 mA automatic the current modulation range, tube rotation speed 0.55; helical pitch 0.9-1.0 and a sharp reconstruction kernel.

Architecture: The model consists of the 3D U-Net architecture which is designed to handle volumetric(3D) image segmentation. The architecture consists of the Encoder path (Contracting path), the Decoder path (Expanding path) and the bottleneck layer. The Encoder path is the left side of the U-Net that progressively downsamples the input volume. The 3D convolution blocks consists of 3D convolution with kernel size 3x3x3, Batch Normalization and ReLU activation and downsampling is achieved with a stride of 2x2x2. The Expanding path is the right side of the U-Net architecture that progressively upsamples back to original resolution and the upsampling is done via transposed 3D Convolutions and skip connections to concatenate features from corresponding encoder level to provide spatial context. And, the bottleneck layer connects the Encoder and Decoder containing the most abstract features.

The loss function, optimizer and the training process decides how the U-Net actually learns The Dice Loss function is used in this work, which is based on the Dice Similarity Coefficient (DSC). The DSC calculates the overlapping region between the Prediction and the ground truth. The Dice Score is given by:

$$Dice = \frac{2 \cdot |Prediction \cap GroundTruth|}{|Prediction| + |GroundTruth|}$$

Because, segmentation often suffers from class imbalance (e.g. lung area small compared to background) and the Dice Loss focusses directly on region overlap rather than pixel-by-pixel probability making it ideal for medial image segmentation. And, since the model outputs raw logits applying sigmoid squashes them to [0,1] probabilities. Further, for optimization of the model the Adam optimizer is used which combines momentum and Adaptive learning rate, thus updating with its own learning rate, adapting to how steep or flat the loss landscape is. The update rule is given by:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{m_t}{\sqrt{v_t} + \epsilon}$$

Mt = Moving average of gradient(momentum)
Vt = Moving average of squared gradient (Adaptive scaling)
Eta = learing rate
And, also the metric used is DiceMetric which measures the segmentation quality during validation. Thus, the training of the model alternates between learning on train set and checking performance on the validation set and hence saving the best model. The plots of training Vs Validation loss and Dice Score per epoch is illustrated in the below figures:

Fig 1: Training vs Validation Loss curves

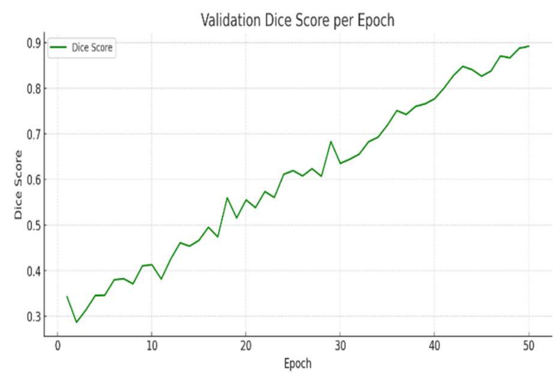

Fig 2: Validation Dice Score per Epoch

IV. Results and Discussion

The proposed model obtained a dice score of 0.75. The model adapted the Adam optimizer with momentum. The ReLU activation function is used for the U-Net architecture. The proposed model yielded a competitive dice score.

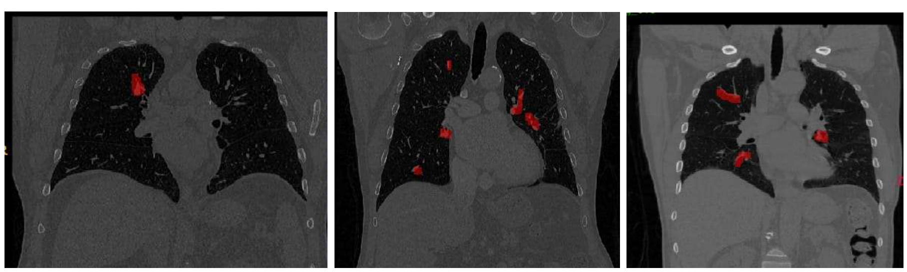

Fig 3

V. Conclusion

Further, the model will be enhanced to Vision Transformers, which yields more robust Dice scores. The HD95 metric will also be implemented and the Vision Transformer model will be compared with different architectures dice score and the non-parametric statistical analysis will also be performed.

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