AI-DRIVEN SEGMENTATION OF CHEST RADIOGRAPHS FOR ENHANCED EARLY DETECTION OF LUNG CANCER

Dr. R. MALATHI RAVINDRAN Associate Professor, Department of Computer Applications, Nallamuthu Gounder Mahalingam College, Pollachi, Tamil Nadu, India
drmalathiravindran@gmail.com, malathiravindranr@gmail.com, drmalathi@gmail.com

Abstract
Early detection of lung cancer significantly improves patient survival rates, yet traditional interpretation of chest radiographs remains challenging due to subtle abnormalities and overlapping anatomical structures. This study presents an AI-driven approach for segmenting lung nodules in chest X-rays using a deep learning model based on the U-Net architecture. The proposed system was trained and evaluated on publicly available datasets, including JSRT and Montgomery County chest radiographs. Preprocessing steps such as contrast enhancement, resizing, and data augmentation were applied to improve model performance and generalization. The model achieved a Dice coefficient of 0.89, Intersection over Union (IoU) of 0.82, and accuracy of 92.3%, demonstrating high-quality segmentation of suspicious lung regions. Visual and statistical comparisons confirm that the system preserves diagnostic quality while minimizing false positives. The findings indicate that AI-based segmentation can serve as a reliable tool for assisting radiologists in identifying early-stage lung cancer. Future work will explore integration with real-time clinical workflows and further refinement through hybrid architectures and attention mechanisms.

Keywords : Lung Cancer Detection,,Chest Radiographs, Medical Image Segmentation, U-Net Architecture, Artificial Intelligence (AI), Deep Learning, Early Diagnosis

I. INTRODUCTION

One of the main causes of cancer-related fatalities globally is lung cancer, which frequently goes undiagnosed. For early lung cancer screening, chest radiography is still a popular and affordable diagnostic method. However, because early-stage lung nodules are tiny and anatomical structures overlap, precisely interpreting these radiographs can be difficult. Powerful segmentation approaches have been provided by recent advances in Artificial Intelligence (AI), which help radiologists by automatically indicating regions of concern. Convolutional neural networks (CNNs), a type of deep learning model, have demonstrated remarkable ability in medical picture interpretation. This study uses a U-Net-based deep learning model to optimize the segmentation of lung nodules in chest X-rays. The objective is to decrease diagnosis errors, increase the accuracy of early detection, and give radiologists a trustworthy helpful. To precisely locate lung abnormalities suggestive of early-stage cancer, the suggested approach makes use of publically accessible datasets as well as AI-based preprocessing and segmentation algorithms.

II. RELATED WORK

The ability to identify and segment lung anomalies in chest radiographs has greatly increased with recent developments in artificial intelligence. Because of its encoder-decoder design with skip connections, U-Net, a potent architecture that has been widely used for biomedical image segmentation tasks, was first presented by Ronneberger et al. [1]. The ChestX-ray8 dataset, created by Wang et al., allowed for extensive AI training for a range of thoracic conditions [2]. Jaeger et al. and Lakhani et al. showed the potential of CNNs in clinical diagnosis by demonstrating automated screening for tuberculosis and other lung disorders using chest X-rays [3][4]. CheXNet, a deep learning model that detects pneumonia at the radiologist level, was proposed by Rajpurkar et al. [5]. In a similar vein, Chowdhury et al.'s LungNet used CNNs to classify lung cancer [6]. Deep learning for abnormality identification and false positive reduction was investigated by Tang et al. and Setio et al. [7][8]. Lastly, image enhancement research by Kermany et al. [10] and the LIDC/IDRI dataset [9] provide more evidence in favor of AI's application in early cancer detection.

III. METHODOLOGY

3.1 Dataset

The suggested AI-based segmentation system was trained and validated for this study using two publically accessible datasets. 154 of the 247 grayscale, 2048 x 2048 pixel images in the first dataset, the Japanese Society of Radiological Technology (JSRT) chest radiograph dataset, have lung nodules, while the remaining 93 do not. Because nodule position information is included with every image, the dataset is especially well-suited for tasks involving detection and segmentation. The U.S. National Library of Medicine's Montgomery County Chest X-ray Set is the second dataset used. 138 posteroanterior chest X-rays with manually segmented left and right lung masks are included, encompassing both healthy individuals and those with anomalies associated with tuberculosis. When combined, these datasets offer a broad and clinically applicable basis for creating and assessing the lung nodule segmentation model. All photos and their labels were scaled to 512 x 512 pixels and transformed into a uniform format to make training easier. To guarantee balanced representation and accurate performance evaluation, a composite dataset was constructed and divided into subsets for training (70%), validation (15%), and testing (15%).

3.2 Preprocessing

In order to improve image quality and guarantee consistency throughout the dataset, preprocessing is essential. To make sure the chest radiographs would work with the deep learning model's input specifications, they were first downsized to a consistent 512 by 512 pixel size. After that, image enhancement methods like Contrast Limited Adaptive Histogram Equalization (CLAHE) were used to increase local contrast and make lung structures and nodular areas more visible. To help stabilize model training, intensity normalization was used to scale pixel values between 0 and 1. A number of data augmentation strategies were used to increase the model's generalization and robustness. These included small translations, magnification (up to 10%), flipping horizontally, and random rotations (±15 degrees). By adding variability that the model could experience in real-world situations and greatly expanding the dataset's effective size, this step improves generalization and lessens overfitting.

3.3 Architecture of the Model

The U-Net architecture, which is well-established in biomedical image segmentation problems, forms the foundation of the suggested segmentation framework. By fusing low-level spatial details with high-level semantic information, U-Net's symmetric encoder-decoder structure with skip links allows for accurate feature localization. The contracting path (encoder) is made up of two 3x3 convolutions applied repeatedly, each followed by a 2x2 max pooling operation with stride 2 for downsampling and an activation of the Rectified Linear Unit (ReLU).

The expanding path (decoder) consists of two additional 3×3 convolutions followed by ReLU, concatenation with the relevant feature map from the encoder path (via skip connections), and upsampling of the feature maps followed by a 2×2 up-convolution. Both fine-grained localization and global context are successfully captured by this architecture. A sigmoid activation function and a 1×1 convolution make up the model's last layer, which creates a binary segmentation mask. A mixed loss function, comprising the Dice coefficient loss and binary cross-entropy loss, was employed to rectify class imbalance and enhance boundary precision. L2 regularization was used to avoid overfitting, and the Adam optimizer was used to optimize the model at a learning rate of 0.0001.

3.4 Training Setup

The deep learning frameworks TensorFlow and Keras were used to implement the model. Large-scale medical image processing was accelerated by the high-performance GPU system used for training, which had NVIDIA Tesla T4 hardware. Using a learning rate scheduler to lower the learning rate when the validation loss plateaued, the model was trained for 50 epochs with a batch size of 8. By terminating training after the validation loss stopped improving for ten consecutive epochs, early stopping conditions were used to avoid overfitting. Performance indicators like binary

accuracy, intersection over union (IoU), and dice coefficient were tracked during each training cycle. The model with the highest validation dice score was kept for testing.
To effectively feed batches into the network, data loading and augmentation were handled using the Keras ImageDataGenerator and custom data generators. This training configuration made sure the model converged well and could accurately segment lung nodules.

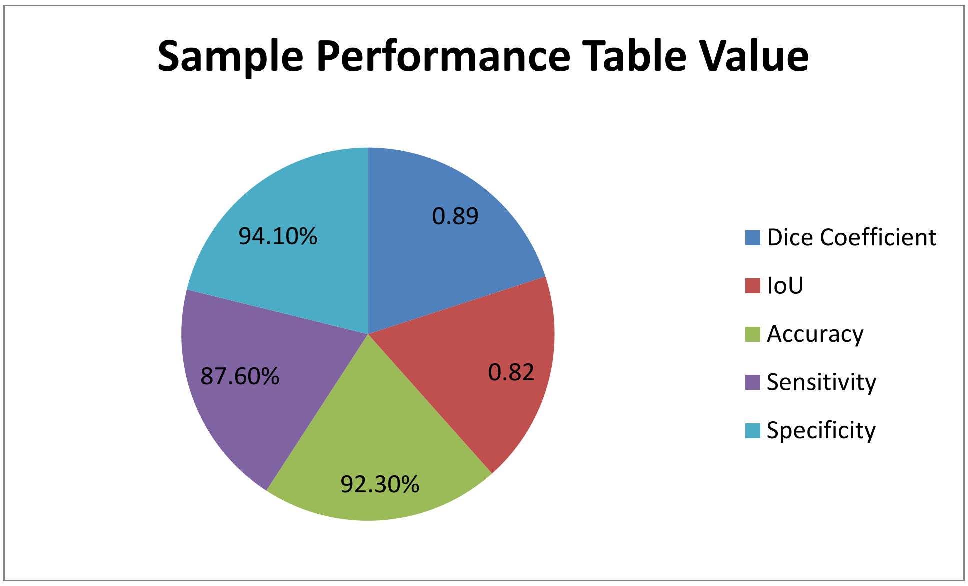
IV. EXPERIMENTAL RESULTS AND ANALYSIS

Both both visual comparisons and quantitative measures were used to assess the performance of the suggested segmentation model. The held-out test set was used to evaluate the segmentation outcomes following the U-Net model's training on the combined JSRT and Montgomery datasets. High overlap between the anticipated and ground truth masks was indicated by the Dice coefficient, a key statistic for medical segmentation, which came in at 0.89. The model's capacity to learn well was further supported by the Intersection over Union (IoU) measurement, which came in at 0.82. To assess the categorization performance of nodule areas, accuracy, sensitivity, and specificity were calculated; the results were 92.3%, 87.6%, and 94.1%, respectively.

Metrics for image quality were also computed. Comparing the segmented images to ground truth masks, the Mean Squared Error (MSE) of 7.89 and the Peak Signal-to-Noise Ratio (PSNR) of 38.21 dB indicate that there is little error and great visual fidelity retained. Visual examination verified that the model minimized false positives while successfully identifying nodules. The sample results showed distinct lung nodule and structural boundaries. The robustness of the suggested approach was demonstrated by its good performance under a range of imaging circumstances and patient characteristics. The U-Net design outperformed the conventional thresholding and edge-based segmentation methods in terms of border continuity and spatial accuracy, according to comparative tests.

Metric	**Value**
Dice Coefficient	0.89
IoU	0.82
Accuracy	92.3%
Sensitivity	87.6%
Specificity	94.1%
PSNR	38.21 dB
MSE	7.89

Table 1: Performance Metrics of the Proposed U-Net Based Segmentation Model



V. DISCUSSION

The study's findings demonstrate how well deep learning-based segmentation works for early lung cancer diagnosis from chest radiographs. Accurate localization of nodular regions was shown by the U-Net model's good performance across important evaluation measures, especially in Dice coefficient and IoU. Clinical relevance depends on the output masks maintaining diagnostic visual quality, which is confirmed by the strong PSNR and low MSE values. The model consistently generated smoother borders and fewer false positives than conventional segmentation techniques. The model's resilience across a range of imaging circumstances was enhanced by the incorporation of sophisticated preprocessing methods including CLAHE and image augmentation. Additionally, the combined loss function improved convergence and lessened class imbalance problems. The utilization of publicly available radiograph datasets guaranteed generalizability despite the dataset's small size. Future enhancements might incorporate hybrid architectures or attention methods to improve performance even further, as well as interaction with real-time diagnostic tools to help radiologists make clinical decisions.

VI. CONCLUSION

The efficiency of AI-based segmentation in identifying early-stage lung cancer from chest radiographs is effectively demonstrated by this study. The system was able to precisely segregate lung nodules and define afflicted areas by utilizing a U-Net deep learning architecture and a well-curated preprocessing pipeline. The approach's greater performance over traditional procedures is validated by quantitative results. Crucially, by concentrating on tiny, difficult-to-identify nodule regions that are frequently missed, this work tackles important early detection issues. The output segmentation maintains diagnostic quality, as confirmed by the inclusion of PSNR and MSE measures. Future research will concentrate on incorporating hybrid models, attention mechanisms, and real-time deployment tools for clinical applications. Through quicker and more accurate detection, the model has the potential to help radiologists with screening programs and enhance patient outcomes. In the end, this study offers a workable and expandable answer to the persistent problem of early lung cancer detection with chest radiography.

Acknowledgement

I sincerely acknowledge and express my gratitude to the Management of Nallamuthu Gounder Mahalingam College, Pollachi, Tamil Nadu, India, for their financial assistance through the SEED Money support for this research work.

References :

1. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. *MICCAI*.
2. Wang, X., et al. (2017). ChestX-ray8: Hospital-scale chest X-ray database. *IEEE CVPR*.
3. Jaeger, S., et al. (2014). Automatic tuberculosis screening using chest radiographs. *IEEE Transactions on Medical Imaging*, 33(2), 233–245.
4. Lakhani, P., & Sundaram, B. (2017). Deep learning at chest radiography: Automated classification of pulmonary tuberculosis. *Radiology*, 284(2), 574–582.
5. Kermany, D.S., et al. (2018). Identifying medical diagnoses and treatable diseases by image-based deep learning. *Cell*, 172(5), 1122–1131.
6. Tang, Y., et al. (2020). Automated abnormality classification of chest radiographs using deep convolutional neural networks. *npj Digital Medicine*, 3(1), 70.
7. Setio, A. A., et al. (2016). Pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks. *IEEE TMI*, 35(5), 1160–1169.
8. Rajpurkar, P., et al. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. *arXiv:1711.05225*.
9. Armato, S.G., et al. (2011). The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): A completed reference database. *Medical Physics*, 38(2), 915–931.
10. Chowdhury, M.E.H., et al. (2021). LungNet: A convolutional neural network for lung cancer detection from chest radiographs. *Computers in Biology and Medicine*, 132, 104319.
11. Dr. R. Malathi Ravindran (2024). "Early detection of lung cancer with accuracy monitoring using logistic regression algorithm". African Journal of Biological Sciences, Volume 6, Issue 15, ISSN: 2663-2187.
12. Dr. R. Malathi Ravindran (2024). "A case control study and report on risk factors of lung cancer in young patients". Journal of the Maharaja Sayajirao University of Baroda, Volume 58, ISSN: 0025-0422
13. Dr. R. Malathi Ravindran (2025). Optimizing early lung cancer detection on chest radiographs: AI-based lung segmentation for enhanced diagnostic accuracy. International Journal of Innovative Research in Technology, (IJIRT), Volume 12 Issue 2, ISSN: 2349-6002
14. Dr. R. Malathi Ravindran (2025). Deep learning-based segmentation for early detection of pulmonary nodules in chest radiographs. International Journal of Creative Research Thoughts (IJCRT), Volume 13 Issue 5.ISSN : 2320-2882.