Journal of Global Research in Multidisciplinary Studies (JGRMS)
Volume 2 | Issue 7 | July 2026 | Pages 01–07
DOI: 10.5281/zenodo.21129297
e-ISSN: 3049-2963
RESEARCH ARTICLE OPEN ACCESS
Available online: https://saanvipublications.com/journals/index.php/jgrms

U-Net-Based Deep Learning Framework for Automated Lung Nodule Segmentation using CT Images

Neha Thakur[1,*], Pradeep Chouksey[2,] Mayank Chopra[3,] Jatin Sharma[4.]

[1.2.3.4,] Department of Computer Science & Informatics, Central University of Himachal Pradesh, Dharamshala 176206, India
*nehathakur201995@gmail.com, dr.pradeep.chouksey2@gmail.com, mayankchopra.it@gmail.com, sadotramca2k6@gmail.com, jatinsharma2002oct@gmail.com
Corresponding Author: *Neha Thakur(nehathakur201995@gmail.com)

Received: 9 June 2026 | **Revised:** 15 June 2026 | **Accepted:** 29 June 2026

***Abstract*—Lung cancer is a leading cause of cancer-related fatalities globally. Early detection of lung nodules via CT scans is crucial for prompt diagnosis and treatment. This study presents a U-Net-based deep learning framework for automated lung nodule segmentation with the LIDC-IDRI dataset. The CT images and corresponding segmentation masks were preprocessed and used to train the proposed model. U-Net was adopted to identify the spatial features of lung nodules and to produce the masks at pixel level. The experimental results demonstrated learning performance with an accuracy of 99.44% and 99.46% during training and validation phases, respectively. The model yielded Dice Similarity Coefficient of 0.429 and localized the majority of nodule regions in CT images. Further visual comparison of the masks verified the validity of the proposed method. Thus, it can be concluded that the proposed system can aid in automatic localization of the lung nodules and in developing computer-aided diagnosis systems.**

Keywords*—*Lung Nodule Segmentation, U-Net Architecture, Deep Learning, Medical Image Segmentation, Computer-Aided Diagnosis,

I. Introduction

Lung cancer remains one of the most serious health issues in the world, causing the highest number of deaths due to cancer and affecting the survival rates of patients as well as the healthcare system [1]. Despite improvements in medical imaging techniques and treatment modalities, the survival rates of lung cancer patients remain low, and this is attributed to the fact that patients are diagnosed at a late stage, i.e., after the cancer has expanded to beyond the curable stage [2][3]. Early detection is critical for patients with lung cancer [4], as it has been found that a survival rate of over 90% can be achieved within a period of five years for patients with early-stage localized lung cancer, as opposed to less than 20% for those with late-stage cancer [5][6][7]. One of the first signs of lung cancer is the formation of pulmonary nodules, which are abnormal tissue growths in the lungs. Pulmonary nodules are abnormal tissue growths in the lungs, differing greatly in size, shape, and texture. The size of a pulmonary nodule can vary from a few millimetres to a few centimetres. The diagnosis of pulmonary nodules is a challenging task for even experienced radiologists [8]. The detection of small nodules (less than 6 mm) is a challenging task as they are not visually significant on a CT scan image. Computed Tomography (CT) scan images have proved to be the most reliable method of screening for lung cancer, as they allow for a cross-sectional view of the lung structure [9]. The implementation of large-scale screening programs based on low-dose CT scans has resulted in a reduction of mortality rates from lung cancer by enabling early detection of suspicious nodules. However, the rising quantity of CT scans in the clinical environment has created a huge burden on radiologists who have to analyse the hundreds of slices of the image in order to detect any abnormalities [10][11]. This is not only time consuming but also often results in errors due to fatigue. To overcome these issues, Computer-Assisted Diagnosis (CAD) technologies have evolved to aid radiologists in identifying and classifying lung nodules more precisely [12]. The initial systems based on CAD involved the usage of handcrafted features and rule-based systems, which could not generalize their performance on different types of databases and imaging methods. However, since the adoption of deep learning approaches like convolutional neural networks (CNNs), improved outcomes have been reported in the application of deep learning techniques for identifying lung cancer [13]. In spite of these advances, there exist some critical limitations with the available techniques[14]. The lung nodules have different sizes, shapes, and appearances and sometime it is hard to distinguish them from blood vessels and bronchi [15]. Additionally, the importance of developing efficient, scalable, and interpretable systems has gained significant attention as AI-based approaches move from the laboratory environment to real-world applications [6]. In this aspect, there is an increased need to design advanced intelligent systems that can match the needs of the clinical domain while also being very accurate. Some of these requirements include dependability, interpretability, and even real-time processing. Intelligent technologies provide to bridge the gap between research and practice, which enhances the efficiency of lung cancer diagnosis.

A. Deep Learning in Lung Cancer Diagnosis

Artificial intelligence technology has revolutionized medical imaging in recent times, particularly in the diagnosis of lung cancer using CT scans. Deep learning techniques have

DOI: https://doi.org/10.5281/zenodo.21129297

been found to possess a strong ability to automatically identify intricate patterns from large-scale medical image datasets [16]. Initially, traditional machine learning techniques like Support Vector Machine and Random Forest classifiers were employed [17]. These techniques required feature descriptors like texture and shape features. However, these techniques were found to lack generalizability across different datasets and imaging conditions [18]. Since deep learning emerged, the CNN has been the most popular technique for detecting lung cancer [19]. CNN models can automatically extract features directly from medical images [20]. CNN models have been applied to lung image segmentation, detection, and classification. Even though CNN models have proven successful, they have some limitations. They primarily focus on local features and have limited ability to capture global context. This makes them less effective for detecting nodules with complex shapes or varying sizes. In addition, CNN-based models often struggle with small nodules that are critical for early diagnosis.

To overcome these shortcomings, the recent approach that was suggested in medical imaging is a development of transformer architectures [21]. The Vision Transformer (ViT) architecture uses the self-attention mechanism to deal with long-range dependencies in images. It provides more effective global feature representation in comparison with the CNN model. Additionally, a model known as Swin Transformer employs shifted window attention and hierarchical feature extraction [22]. It is worth noting that this model also achieves good results in detecting and segmenting the lungs nodules [23]. However, the transformer architectures also have some weaknesses. Mostly all of the current techniques use the fixed attention mechanism that is not able to handle the irregular shapes of the tumour. In addition, there are no techniques to model the uncertainty, which is necessary in the decision-making process.

B. *Research Gaps and Novelty*

Despite the remarkable achievements of deep learning-based models in diagnosing lung cancer, several challenges still remain [24]. The models using CNNs have difficulty in handling complicated shapes and sizes of tumours especially the small sized ones which are necessary for early diagnosis [25]. The models using transformers have better capability in learning global features but most of the current models lack uncertainty estimation which is essential in making decisions in clinical practice [26]. In addition, accurately focusing on tumor regions within complex lung structures remains a challenging task [18][19].

To address these limitations, this work proposes a deep learning architecture based on the U-Net model for the automated segmentation of lung nodules. This method is mainly aimed at the accurate localization of lung nodules via pixel-wise segmentation, which facilitates the detection of suspicious regions in CT scans.

C. *Contributions of the Proposed Work*

The main contributions of this work are summarized as follows:

- A deep learning framework based on U-Net is proposed for automatic segmentation of lung nodules in CT scans.
- A pixel-level segmentation approach is developed using the LIDC-IDRI dataset to accurately identify and localize suspicious lung nodule regions.
- The proposed framework is extensively evaluated using quantitative and qualitative analyses which shows its efficiency in lung nodule segmentation.
- The developed model presents an efficient localization method that could be used in computer-aided detection of lung cancer.

II. Related Work

This section provides an overview of the current literature on lung cancer detection, with an emphasis on classical methods, deep learning approaches, and recent advancements in transformer and uncertainty-aware models.

A. *Traditional Machine Learning Approaches*

Early research in the area of lung cancer detection mainly used conventional machine learning methods that made use of handcrafted features such as texture, shape, and intensity of the nodules from CT scans. Some examples of classifiers include SVM (Support Vector Machine), RF (Random Forest), and KNN (K-Nearest Neighbours [27] [28][29].

Despite some successes of this approach, one of the major shortcomings of this method was that the feature selection process could not be automated [30]. The performance of the detection largely depended on how effective the features chosen were, which did not generalize very well from different datasets [31]. Therefore, this approach could not effectively detect tumours of different shapes and sizes [32].

B. *CNN-Based Approaches*

CNNs emerged the most popular technique for detecting lung cancer with the advent of deep learning techniques [33] . Through CNN techniques, hierarchical features can be directly learned from CT images without the requirement of manually engineered features [34]. U-Net, ResNet, and Dense Net are among the most widely used deep learning architectures for classification, segmentation, and detection of lung nodules [35][36]. The performance of these models was found to be superior to that of conventional methods [37]. Among these designs, U-Net has acquired high interest in medical image segmentation due to its encoder-decoder structure and skip connections, which enable exact localization while maintaining spatial information. Its effectiveness in biomedical image analysis has made it a widely adopted model for lung nodule segmentation tasks [28] [38].

Despite their achievements, CNN-based models have certain limitations. The training of the CNN model is largely based on the extraction of local features due to the limited size of the receptive field, which makes it difficult for such models to capture the global context. Hence, it might not be possible for them to detect irregular-shaped nodules of different sizes. Moreover, many CNN algorithms are still unable to detect small-sized lung nodules [39].

C. *Transformer-Based Approaches*

Recently, transformer-based methods were widely adopted in the field of medical image analysis owing to their capability of modelling long-range dependencies with self-attention modules [24][33][34][40]. ViT and its various

DOI: https://doi.org/10.5281/zenodo.21129297

extensions were successfully utilized in lung cancer detection by effectively capturing global contextual information [41]. In recent years, Swin Transformers provided hierarchical feature representations along with enhanced computational efficiency [42][36][43]. These methods achieved promising results in both classifications and segmentation processes [44] [37].

However, there are also disadvantages related to transformers. For instance, fixed attention is employed by transformer-based methods and it might fail to model irregular tumor shapes [20]. Furthermore, most of the transformer models do not estimate uncertainties and therefore cannot be used clinically [45] [38].

D. Uncertainty-Aware and Hybrid Approaches

In order to achieve reliable results, some recent studies have tried to develop new strategies for uncertain prediction in medical imaging [46][39]. Some approaches have been developed using Bayesian neural networks and Monte Carlo Dropout to measure the confidence level of predictions[47] [40]. It is expected that such an approach would contribute to better interpretability of medical images. Hybrid approaches combining CNNs with transformers has also been proposed to exploit both local and global feature learning [48][41]. Even though the models demonstrate better accuracy, they add more computational complexity while still lacking adaptability to tumor morphology and multi-scale detection capability [33].

Although transformer-based and hybrid models have shown great potential in analysing medical images, they usually require higher computation resources and complex architecture. Unlike these models, U-Net continues to be one of the primarily used frameworks for segmenting medical images due to its simple design, training efficiency, and capability to precisely detect the target areas on the pixel level. Motivated by these advantages, this study investigates a U-Net-based framework for automatically segmenting lung nodules from CT scan data.

III. Related Work

This section provides an overview of the current literature on lung cancer detection, with an emphasis on classical methods, deep learning approaches, and recent advancements in transformer and uncertainty-aware models.

A. Traditional Machine Learning Approaches

Early research in the area of lung cancer detection mainly used conventional machine learning methods that made use of handcrafted features such as texture, shape, and intensity of the nodules from CT scans. Some examples of classifiers include SVM (Support Vector Machine), RF (Random Forest), and KNN (K-Nearest Neighbours [21][23]. Despite some successes of this approach, one of the major shortcomings of this method was that the feature selection process could not be automated [24]. The performance of the detection largely depended on how effective the features chosen were, which did not generalize very well from different datasets [25]. Therefore, this approach could not effectively detect tumours of different shapes and sizes [26]. CNN-Based Approaches

CNNs emerged the most popular technique for detecting lung cancer with the advent of deep learning techniques [27]. Through CNN techniques, hierarchical features can be directly learned from CT images without the requirement of manually engineered features [28]. U-Net, ResNet, and DenseNet are among the most widely used deep learning architectures for classification, segmentation, and detection of lung nodules [28] [30]. The performance of these models was found to be superior to that of conventional methods [30]. Among these designs, U-Net has acquired high interest in medical image segmentation due to its encoder-decoder structure and skip connections, which enable exact localization while maintaining spatial information. Its effectiveness in biomedical image analysis has made it a widely adopted model for lung nodule segmentation tasks [28] [38].

Despite their achievements, CNN-based models have certain limitations. The training of the CNN model is largely based on the extraction of local features due to the limited size of the receptive field, which makes it difficult for such models to capture the global context. Hence, it might not be possible for them to detect irregular-shaped nodules of different sizes. Moreover, many CNN algorithms are still unable to detect small-sized lung nodules [32].

B. Transformer-Based Approaches

Recently, transformer-based methods were widely adopted in the field of medical image analysis owing to their capability of modelling long-range dependencies with self-attention modules [33][34]. ViT and its various extensions were successfully utilized in lung cancer detection by effectively capturing global contextual information [35]. In recent years, Swin Transformers provided hierarchical feature representations along with enhanced computational efficiency [36][43]. These methods achieved promising results in both classifications and segmentation processes [37].

However, there are also disadvantages related to transformers. For instance, fixed attention is employed by transformer-based methods and it might fail to model irregular tumor shapes [20]. Furthermore, most of the transformer models do not estimate uncertainties and therefore cannot be used clinically [38].

C. Uncertainty-Aware and Hybrid Approaches

In order to achieve reliable results, some recent studies have tried to develop new strategies for uncertain prediction in medical imaging [39]. Some approaches have been developed using Bayesian neural networks and Monte Carlo Dropout to measure the confidence level of predictions [40]. It is expected that such an approach would contribute to better interpretability of medical images. Hybrid approaches combining CNNs with transformers has also been proposed to exploit both local and global feature learning [41].Even though the models demonstrate better accuracy, they add more computational complexity while still lacking adaptability to tumour morphology and multi-scale detection capability [33].

Although transformer-based and hybrid models have shown great potential in analysing medical images, they usually require higher computation resources and complex architecture. Unlike these models, U-Net continues to be one of the primarily used frameworks for segmenting medical images due to its simple design, training efficiency, and capability to precisely detect the target areas on the pixel level. Motivated by these advantages, this study investigates a U-Net-based framework for automatically segmenting lung nodules from CT scan data.

DOI: https://doi.org/10.5281/zenodo.21129297

$$Dice = \frac{2|A \cap B|}{|A|+|B|} \quad (1)$$

where (B) is the ground-truth region and (A) is predicted segmentation region. Consequently, effective segmentation and agreement between the predicted and actual lung nodule locations are indicated by a high Dice Score. Through the combination of encoder-decoder feature learning and pixel-level prediction, the U-Net architecture successfully performs lung nodule segmentation.

IV. Experimental Setup

This section presents the experimental settings used to evaluate the proposed U-Net-based lung nodule segmentation framework. The implementation environment, training configuration, and evaluation metrics are described in detail.

A. Implementation Environment and Training Configuration

This model was built by utilizing Python and TensorFlow/Keras libraries. Training, testing, and developing the model was done using GPU support for fast learning process. NumPy, OpenCV, Matplotlib, and Scikit-learn are other scientific computation libraries that were used for data handling, analysis, and visualization purposes. Training of the U-Net segmentation model was done using CT scan images and their ground-truth masks from LIDC-IDRI data set. Image dimensions were resized to 128×128 pixel format before feeding them into the model. The model was trained using supervised learning method for 10 epochs for spatial characteristics learning of the lung nodules.

Both training and validation sets were used during the learning period to check the learning behaviour of the network. It can be seen from the training and validation loss curves that the model converged well. Similarly, both training and validation accuracies improved gradually during the training phase. Both sets for training and validation were used during the learning period to monitor the learning behaviour of the network.

B. Performance Evaluation Metrics

The performance of the proposed system was evaluated by applying parameters such as accuracy, loss, and DSC. The metric of accuracy assesses the rate of pixels that were classified correctly, while the loss is an assessment of prediction errors during training.

The suggested model achieved the Dice score of around 0.429, which means there is reasonable overlapping of predicted and ground-truth annotations of lung nodule regions. Besides quantitative assessment, qualitative one was conducted through the comparison of CT scans, ground-truth masks, and predicted masks.

V. Results and Discussion

This section presents the performance analysis of the proposed U-Net-based lung nodule segmentation framework. Both quantitative and qualitative analysis were conducted to analyse the efficacy of the framework in detecting and segmenting the lung nodules.

A. Training Performance Analysis

The training and validation curves indicate the training behaviour of the model for the entire training process. The proposed U-Net model achieved a final training accuracy of 99.44% and a validation accuracy of 99.46%. Similarly, the training and validation loss values converged to 0.0162 and 0.0160, respectively. These results indicate stable learning behaviour and good generalization capability of the model. In Figure 1 below, we can observe that both training loss and validation loss decrease progressively, indicating successful optimization and efficient convergence of the model. The model's effective feature learning without overfitting is implied by the close proximity of these two curves.

$$Dice = \frac{2|A \cap B|}{|A|+|B|} \quad (2)$$

where (B) is the ground-truth region and (A) is predicted segmentation region. Consequently, effective segmentation and agreement between the predicted and actual lung nodule locations are indicated by a high Dice Score. Through the combination of encoder-decoder feature learning and pixel-level prediction, the U-Net architecture successfully performs lung nodule segmentation.

VI. Experimental Setup

This section presents the experimental settings used to evaluate the proposed U-Net-based lung nodule segmentation framework. The implementation environment, training configuration, and evaluation metrics are described in detail.

A. Implementation Environment and Training Configuration

This model was built by utilizing Python and TensorFlow/Keras libraries. Training, testing, and developing the model was done using GPU support for fast learning process. NumPy, OpenCV, Matplotlib, and Scikit-learn are other scientific computation libraries that were used for data handling, analysis, and visualization purposes. Training of the U-Net segmentation model was done using CT scan images and their ground-truth masks from LIDC-IDRI data set. Image dimensions were resized to 128×128 pixel format before feeding them into the model. The model was trained using supervised learning method for 10 epochs for spatial characteristics learning of the lung nodules.

Both training and validation sets were used during the learning period to check the learning behaviour of the network. It can be seen from the training and validation loss curves that the model converged well. Similarly, both training and validation accuracies improved gradually during the training phase. Both sets for training and validation were used during the learning period to monitor the learning behaviour of the network.

B. Performance Evaluation Metrics

The performance of the proposed system was evaluated by applying parameters such as accuracy, loss, and DSC. The metric of accuracy assesses the rate of pixels that were classified correctly, while the loss is an assessment of prediction errors during training.

The suggested model achieved a Dice score of around 0.429, which means there is reasonable overlapping of predicted and ground-truth annotations of lung nodule regions. Besides quantitative assessment, a qualitative one was conducted through the comparison of CT scans, ground-truth masks, and predicted masks.

DOI: https://doi.org/10.5281/zenodo.21129297

VII. Results and Discussion

This section presents the performance analysis of the proposed U-Net-based lung nodule segmentation framework. Both quantitative and qualitative analyses were conducted to analyse the efficacy of the framework in detecting and segmenting the lung nodules.

A. *Training Performance Analysis*

The training and validation curves indicate the training behaviour of the model for the entire training process. The proposed U-Net model achieved a final training accuracy of 99.44% and a validation accuracy of 99.46%. Similarly, the training and validation loss values converged to 0.0162 and 0.0160, respectively. These results indicate stable learning behaviour and good generalization capability of the model. In Figure 1 below, we can observe that both training loss and validation loss decrease progressively, indicating successful optimization and efficient convergence of the model. The model's effective feature learning without overfitting is implied by the close proximity of these two curves.

Fig. 1. Training and Validation Loss Curves of the Proposed U-Net Model.

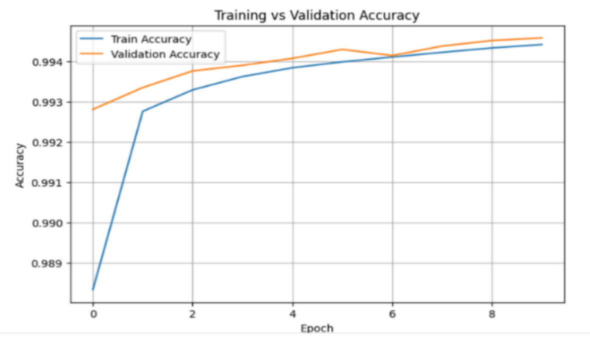

Fig. 2. Training and Validation Accuracy Curves of the Proposed U-Net Model.

Likewise, training and validation accuracies in Figure 2 are shown to improve progressively in the training process. Accuracies gradually increase and then reach high levels, suggesting that the U-Net model is capable of learning features from CT scan images for lung nodules. The minimal difference in the training and validation accuracies implies good generalization ability of the model on test data.

B. *Segmentation Performance Evaluation*

The segmentation performance was evaluated using the Dice Similarity Coefficient, which evaluates the degree of overlap of the prediction masks and ground truth annotations. For the proposed network, the obtained Dice Score of 0.429 shows that the framework was suitable for localize lung nodules; however, accurate delineation of small nodule boundaries remains challenging. Despite the high pixel-wise precision of the framework, the value of the Dice Score proves that the precise border detection of small lung nodules still represents a difficult task for the framework. This action is characteristic of most medical imaging segmentation tasks, when the area of interest constitutes a relatively small part of the image.

C. *Qualitative Analysis of Segmentation Results*

Representative segmentation masks obtained using the proposed approach are depicted in Figure 3. In the figure, one can see the visualization of the original CT image, the expert-annotated ground-truth mask, and the segmentation mask predicted by the U-Net architecture.

Fig. 3. Comparison of the Original CT Image, Ground-Truth Mask, and U-Net Predicted Segmentation Mask.

This figure demonstrates that the proposed method was able to accurately localize most lung nodule regions and provide segmentations similar to those done by experts. The segmentation masks obtained by our method were capable of representing the location and morphology of the nodules. However, slight discrepancies can be observed on the borders of the nodules, which affect the moderate Dice Score value due to high pixel-level accuracy. Such qualitative analysis shows the possibility of using the proposed model for computer-aided detection.

D. *Discussion*

The results from the experiment show the efficiency of the U-Net framework for the lung nodule segmentation. This was made possible by the utilization of the encoder-decoder architecture and skip connections which helped in preserving the spatial properties as well as learning higher level semantic features, which played a big role in identifying the location of the lung nodules in different CT images. From the loss and accuracy graphs shown in Figures 1 and 2, one can conclude that the model had stable convergence and good generalization capacity during training. Additionally, Figure 3 shows that the model was able to successfully identify suspicious areas of the lung region and provide segmentation masks that correspond to the expert annotations.

Despite the encouraging results, the Dice Score indicates that the model still has to be improved in terms of segmenting small nodules and strengthening the borders. The qualitative results demonstrate the effectiveness of the suggested method in identifying and locating most of lung nodules, even with the comparatively low Dice Score. These findings demonstrate the efficiency of U-Net for lung nodule localization, while also highlighting the need for further optimization of boundary segmentation. Future research can include the use of attention mechanisms, more advanced U-Net models, data augmentation techniques, and hybrid deep learning architectures.

VIII. CONCLUSION

This study proposed a U-Net-based framework for automated lung nodule segmentation utilizing CT images from the LIDC-IDRI dataset. The model was designed to detect and localize lung nodules by segmenting the corresponding pixels. The results of the experiment proved stable convergence of the model and showed that its training and validation accuracy were 99.44% and 99.46%, respectively. The obtained Dice Score of 0.429 demonstrated reasonable agreement between the predicted masks and expert annotations. The visual evaluation also confirmed that the model successfully identified most lung nodule regions. The proposed model can be used as an effective tool for pre-processing and localization in computer-assisted lung cancer diagnosis systems.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The author declares no conflict of interest.

How to cite this article:

N. Thakur, P. Chouksey, M. Chopra, and J. Sharma, "U-Net-Based Deep Learning Framework for Automated Lung Nodule Segmentation using CT Images," Journal of Global Research in Multidisciplinary Studies (JGRMS), vol. 2, no. 6, pp. 1–7, Jul. 2026 doi:10.5281/zenodo.21129297

REFERENCES

[1] C. Gao *et al.*, "Deep learning in pulmonary nodule detection and segmentation: a systematic review," *Eur. Radiol.*, vol. 35, no. 1, pp. 255–266, Jul. 2024, doi: 10.1007/s00330-024-10907-0.

[2] H. M. Cheo, C. Y. G. Ong, and Y. Ting, "A Systematic Review of AI Performance in Lung Cancer Detection on CT Thorax," *Healthcare*, vol. 13, no. 13, p. 1510, Jun. 2025, doi: 10.3390/healthcare13131510.

[3] V. Chaturvedi, "Disease Diagnostic Systems based on AI-Applications in Healthcare: Models, Challenges, and Future Directions," *Int. J. Emerg. Res. Eng. Technol.*, vol. 6, no. 4, pp. 207–217, Dec. 2025, doi: 10.63282/3050-922X.IJERET-V6I4P125.

[4] S. Mukherjee, "Performance Evaluation of Deep Learning Models for Early Detection of Infectious Diseases in Healthcare Systems," in *SoutheastCon 2026*, IEEE, Feb. 2026, pp. 1–6. doi: 10.1109/SoutheastCon63549.2026.11475977.

[5] L. J. Crasta, R. Neema, and A. R. Pais, "A novel Deep Learning architecture for lung cancer detection and diagnosis from Computed Tomography image analysis," *Healthc. Anal.*, vol. 5, p. 100316, Jun. 2024, doi: 10.1016/j.health.2024.100316.

[6] B. S. Sambit Ranjan Pattanayak, Janmejaya Mishra, VNLN Murthy, Abhilash Pati, Amrutanshu Panigrahi, "Harnessing Grey Wolf Optimization for Early Thyroid Cancer Prediction," in *2025 International Conference on Responsible, Generative and Explainable AI (ResGenXAI)*, Bhubaneswar, India: IEEE, 2025, pp. 10–12, September. doi: 10.1109/ResgenXAI64788.2025.11344005.

[7] R. V. S. S. B. R, S. S. Harakannanavar, Z. A. Alsalami, M. S, and G. Vijayakumari, "Early Detection of Sepsis by using Attention based Recurrent Neural Networks with Shapley Additive Exp lanations," in *2024 International Conference on Integrated Intelligence and Communication Systems (ICIICS)*, IEEE, Nov. 2024, pp. 1–5. doi: 10.1109/ICIICS63763.2024.10860199.

[8] L. Salhi, K. Moussa, and R. Ben Salah, "Enhanced Pulmonary Nodule Detection and Classification Using Artificial Intelligence on LIDC-IDRI Data," *Explor. Res. Hypothesis Med.*, vol. 11, no. 1, p. e00032, Jan. 2026, doi: 10.14218/ERHM.2025.00032.

[9] X. Yang *et al.*, "Segmentation and Classification of Lung Cancer Images Using Deep Learning," *Appl. Sci.*, vol. 16, no. 2, p. 628, Jan. 2026, doi: 10.3390/app16020628.

[10] M. Abumohsen, E. Costa-Montenegro, S. García-Méndez, A. Y. Owda, and M. Owda, "Machine Learning and Deep Learning in Lung Cancer Diagnostics: A Systematic Review of Technical Breakthroughs, Clinical Barriers, and Ethical Imperatives," *AI*, vol. 7, no. 1, p. 23, Jan. 2026, doi: 10.3390/ai7010023.

[11] S. K. Chandrappa, S. Paheding, A. A. Reyes-Angulo, and A. Essa, "Attention-Based Spectral Profile Representation for Hyperspectral Image Classification," in *NAECON 2025 - IEEE National Aerospace and Electronics Conference*, Dayton, OH, USA: IEEE, 2025, pp. 1–6, November. doi: 10.1109/NAECON65708.2025.11235401.

[12] M. K. Faizi *et al.*, "Deep learning-based lung cancer classification of CT images," *BMC Cancer*, vol. 25, no. 1, p. 1056, Jul. 2025, doi: 10.1186/s12885-025-14320-8.

[13] M. Hammad, M. ElAffendi, A. A. A. El-Latif, A. A. Ateya, G. Ali, and P. Plawiak, "Explainable AI for lung cancer detection via a custom CNN on CT images," *Sci. Rep.*, vol. 15, no. 1, p. 12707, Apr. 2025, doi: 10.1038/s41598-025-97645-5.

[14] B. Jeganathan, "Exploring the Power of Generative Adversarial Networks (GANs) for Image Generation: A Case Study on the MNIST Dataset," *Int. J. Adv. Eng. Manag.*, vol. 7, no. 1, pp. 21–46, Jan. 2025, doi: 10.35629/5252-07012146.

[15] T. Hu, Y. Lan, Y. Zhang, J. Xu, S. Li, and C.-C. Hung, "A lung nodule segmentation model based on the transformer with multiple thresholds and coordinate attention," *Sci. Rep.*, vol. 14, no. 1, p. 31743, Dec. 2024, doi: 10.1038/s41598-024-82877-8.

[16] L. Zhi, W. Jiang, S. Zhang, and T. Zhou, "Deep neural network pulmonary nodule segmentation methods for CT images: Literature review and experimental comparisons," *Comput. Biol. Med.*, vol. 164, p. 107321, Sep. 2023, doi: 10.1016/j.compbiomed.2023.107321.

[17] J. Wu and T. Qian, "A survey of pulmonary nodule detection, segmentation and classification in computed tomography with deep learning techniques," *J. Med. Artif. Intell.*, vol. 2, pp. 8–8, Apr. 2019, doi: 10.21037/jmai.2019.04.01.

[18] G. K. Subramanyam, K. Srinivas, V. V. R. Indugu, D. S. Gondi, and S. K. G. Subbammagari, "Segmentation-Guided Hybrid Deep Learning for Pulmonary Nodule Detection and Risk Prediction from Multi-Cohort CT Images," *Diseases*, vol. 14, no. 1, p. 21, Jan. 2026, doi: 10.3390/diseases14010021.

[19] B. Sahu *et al.*, "Harnessing TLBO-Enhanced Cheetah Optimizer for Optimal Feature Selection in Cancer Data," *Comput. Model. Eng. Sci.*, pp. 1–26, 2025, doi: 10.32604/cmes.2025.069618.

[20] A. G. Akintola *et al.*, "Integrated deep learning paradigm for comprehensive lung cancer segmentation and classification using mask R-CNN and CNN models," *Franklin Open*, vol. 11, p. 100278, Jun. 2025, doi: 10.1016/j.fraope.2025.100278.

[21] R. F. Khan, B.-D. Lee, and M. S. Lee, "Transformers in medical image segmentation: a narrative review," *Quant. Imaging Med. Surg.*, vol. 13, no. 12, pp. 8747–8767, Dec. 2023, doi: 10.21037/qims-23-542.

[22] H. Jin, C. Yu, J. Zhang, R. Zheng, Y. Fu, and Y. Zhao, "Multitask Swin Transformer for classification and characterization of pulmonary nodules in CT images," *Quant. Imaging Med. Surg.*, vol. 15, no. 3, pp. 1845–1861, Mar. 2025, doi: 10.21037/qims-24-1619.

[23] L. Lei and W. Li, "Transformer-based multi-task model for lung tumor segmentation and classification in CT images," *J. Radiat. Res. Appl. Sci.*, vol. 18, no. 3, p. 101657, Sep. 2025, doi: 10.1016/j.jrras.2025.101657.

[24] R. Azad *et al.*, "Advances in medical image analysis with vision

DOI: https://doi.org/10.5281/zenodo.21129297

Transformers: A comprehensive review," *Med. Image Anal.*, vol. 91, p. 103000, Jan. 2024, doi: 10.1016/j.media.2023.103000.

[25] K. He *et al.*, "Transformers in medical image analysis," *Intell. Med.*, vol. 3, no. 1, pp. 59–78, Feb. 2023, doi: 10.1016/j.imed.2022.07.002.

[26] B. Lambert, F. Forbes, S. Doyle, H. Dehaene, and M. Dojat, "Trustworthy clinical AI solutions: A unified review of uncertainty quantification in Deep Learning models for medical image analysis," *Artif. Intell. Med.*, vol. 150, p. 102830, Apr. 2024, doi: 10.1016/j.artmed.2024.102830.

[27] M. Firmino, A. H. Morais, R. M. Mendoça, M. R. Dantas, H. R. Hekis, and R. Valentim, "Computer-aided detection system for lung cancer in computed tomography scans: Review and future prospects," *Biomed. Eng. Online*, vol. 13, no. 1, p. 41, 2014, doi: 10.1186/1475-925X-13-41.

[28] X. Wang, K. Mao, L. Wang, P. Yang, D. Lu, and P. He, "An Appraisal of Lung Nodules Automatic Classification Algorithms for CT Images," *Sensors*, vol. 19, no. 1, p. 194, Jan. 2019, doi: 10.3390/s19010194.

[29] S. G. Armato *et al.*, "The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): A completed reference database of lung nodules on CT scans," *Med. Phys.*, 2011, doi: 10.1118/1.3528204.

[30] D. Kumar, A. Wong, and D. A. Clausi, "Lung Nodule Classification Using Deep Features in CT Images," in *2015 12th Conference on Computer and Robot Vision*, IEEE, Jun. 2015, pp. 133–138. doi: 10.1109/CRV.2015.25.

[31] W. Shen, M. Zhou, F. Yang, C. Yang, and J. Tian, "Multi-scale Convolutional Neural Networks for Lung Nodule Classification," 2015, pp. 588–599. doi: 10.1007/978-3-319-19992-4_46.

[32] J. L. Causey *et al.*, "Highly accurate model for prediction of lung nodule malignancy with CT scans," *Sci. Rep.*, 2018, doi: 10.1038/s41598-018-27569-w.

[33] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Med. Image Anal.*, vol. 42, pp. 60–88, Dec. 2017, doi: 10.1016/j.media.2017.07.005.

[34] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," 2015, pp. 234–241. doi: 10.1007/978-3-319-24574-4_28.

[35] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778. doi: 10.1109/CVPR.2016.90.

[36] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Jul. 2017, pp. 2261–2269. doi: 10.1109/CVPR.2017.243.

[37] M. A. Thanoon, M. A. Zulkifley, M. A. A. Mohd Zainuri, and S. R. Abdani, "A Review of Deep Learning Techniques for Lung Cancer Screening and Diagnosis Based on CT Images," *Diagnostics*, vol. 13, no. 16, p. 2617, Aug. 2023, doi: 10.3390/diagnostics13162617.

[38] S. Mukherjee, "An Effective System for Medical Image Diagnosis Using Deep Convolutional Networks (CNNs) in Healthcare Sector," in *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, IEEE, Mar. 2026, pp. 01–06. doi: 10.1109/ISDFS69419.2026.11459010.

[39] A. A. A. Setio *et al.*, "Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: The LUNA16 challenge," *Med. Image Anal.*, vol. 42, pp. 1–13, Dec. 2017, doi: 10.1016/j.media.2017.06.015.

[40] S. Khan, M. Naseer, M. Hayat, S. W. Zamir, F. S. Khan, and M. Shah, "Transformers in Vision: A Survey," *ACM Comput. Surv.*, vol. 54, no. 10s, pp. 1–41, Jan. 2022, doi: 10.1145/3505244.

[41] N. Thakur, P. Chouksey, A. Sharma, M. Chopra, P. Sadotra, and S. Kumar, "Binary classification of lung cancer using vision transformer models on CT images," *Discov. Comput.*, vol. 29, no. 1, p. 66, Feb. 2026, doi: 10.1007/s10791-026-09931-z.

[42] Y. Tang *et al.*, "Self-Supervised Pre-Training of Swin Transformers for 3D Medical Image Analysis," in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Jun. 2022, pp. 20698–20708. doi: 10.1109/CVPR52688.2022.02007.

[43] S. K. Chandrappa, S. Paheding, and A. A. Reyes-Angulo, "Unraveling Patch Size Effects in Vision Transformers: Adversarial Robustness in Hyperspectral Image Classification," *MDPI*, vol. 18, no. 4, pp. 656, February, 2026, doi: https://doi.org/10.3390/rs18040656.

[44] A. Hatamizadeh *et al.*, "UNETR: Transformers for 3D Medical Image Segmentation," in *2022 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, IEEE, Jan. 2022, pp. 1748–1758. doi: 10.1109/WACV51458.2022.00181.

[45] M. Abdar *et al.*, "A review of uncertainty quantification in deep learning: Techniques, applications and challenges," *Inf. Fusion*, vol. 76, pp. 243–297, Dec. 2021, doi: 10.1016/j.inffus.2021.05.008.

[46] J. Gawlikowski *et al.*, "A survey of uncertainty in deep neural networks," *Artif. Intell. Rev.*, vol. 56, no. S1, pp. 1513–1589, Oct. 2023, doi: 10.1007/s10462-023-10562-9.

[47] J. Chen *et al.*, "TransUNet: Rethinking the U-Net architecture design for medical image segmentation through the lens of transformers," *Med. Image Anal.*, vol. 97, p. 103280, Oct. 2024, doi: 10.1016/j.media.2024.103280.

[48] A. Lin, B. Chen, J. Xu, Z. Zhang, G. Lu, and D. Zhang, "DS-TransUNet: Dual Swin Transformer U-Net for Medical Image Segmentation," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–15, 2022, doi: 10.1109/TIM.2022.3178991.