

ISSN: 1672 - 6553

**JOURNAL OF DYNAMICS
AND CONTROL**

VOLUME 9 ISSUE 5: 301 - 306

**A HYBRID RESNET-U-NET
ARCHITECTURE FOR DETECTION OF
LYMPHANGIOLEIOMYOMATOSIS
(LAM) IN COMPUTED
TOMOGRAPHY LUNG SCANS**

Sithika Seema. S¹, Sumathy. R²

¹Scholar, ²Assistant Professor
Department of Computer science and Engineering,
KIT-Kalaignarkarunanidhi Institute of Technology,
Coimbatore, India

A HYBRID RESNET-U-NET ARCHITECTURE FOR DETECTION OF LYMPHANGIOLEIOMYOMATOSIS (LAM) IN COMPUTED TOMOGRAPHY LUNG SCANS

Sithika Seema. S¹, Sumathy. R²

¹Scholar, ²Assistant Professor

Department of Computer science and Engineering

KIT-Kalaignarkaranidhi Institute of Technology, Coimbatore, India

sithikaseemasyed@gmail.com, sumathykitcbe@gmail.com

Abstract Lymphangioleiomyomatosis (LAM) is a rare and progressive lung disease marked by the abnormal proliferation of smooth muscle-like cells and the formation of numerous thin-walled cysts within the lung tissue. Predominantly affecting women of reproductive age, LAM presents significant diagnostic challenges due to its subtle and diffuse appearance on computed tomography (CT) scans. Early and accurate identification is vital for effective disease management. A novel hybrid deep learning architecture is presented here that combines a Residual Neural Network (ResNet) with a U-Net segmentation model to automate the detection of LAM from CT lung images. In the proposed framework, ResNet functions as the encoder to extract deep semantic features, while U-Net's decoder reconstructs precise spatial representations through skip connections. This Framework increases the effectiveness of segmenting and detecting cystic abnormalities in LAM cases. The resulting segmentation maps offer detailed anatomical insights, which can be leveraged to extract morphological features for auxiliary classification, further distinguishing LAM from other cystic lung pathologies. Extensive experiments were conducted using a curated and annotated dataset of CT lung scans. The hybrid model demonstrated superior segmentation performance, achieving high Dice coefficients and improved classification accuracy. Compared to traditional U-Net and standalone CNN approaches, the ResNet-U-Net architecture yielded significant gains in sensitivity, specificity, and overall robustness. This study highlights the potential of integrating residual learning with encoder-decoder-based segmentation for rare disease detection and illustrates the promise of AI-powered tools in enhancing diagnostic accuracy within radiological workflows.

Keywords: *Lymphangioleiomyomatosis (LAM), Computed Tomography (CT), Deep Learning, Convolutional Neural Networks (CNN), U-Net, ResNet, Medical Image Segmentation, Hybrid Deep Learning Model*

I. INTRODUCTION

Lymphangioleiomyomatosis (LAM) is a unique and rare, chronic pulmonary condition defined by the formation of atypical smooth muscle-like cells (LAM cells), leading to the formation of numerous thin-walled cysts within the lung parenchyma. Predominantly affecting women of reproductive age, LAM presents

with nonspecific symptoms such as shortness of breath, chest pain, or recurrent pneumothorax. These symptoms, along with the diffuse and subtle nature of cystic changes, often lead to misdiagnosis or delayed diagnosis, particularly when differentiating LAM from other cystic lung conditions like emphysema. While high-resolution computed tomography (HRCT) is the most reliable computed imaging approach for detecting LAM, interpretation heavily depends on radiological expertise, which may not be consistently available across all healthcare settings.

The advancement of deep learning has revolutionized biomedical image evaluation offering powerful tools to automate processes such as identifying diseases, classification and segmentation. CNN, have demonstrated exceptional performance in identifying complex patterns within imaging data. U-Net, a widely adopted encoder-decoder architecture, has become a foundational technique in medical image segmentation research for its ability to effectively integrate high-resolution localization with contextual understanding. Concurrently, residual neural networks (ResNet) have shown strong capabilities in training deeper architectures by mitigating vanishing gradient issues and enabling efficient feature extraction through identity-based skip connections.

This research study presents introducing a hybrid deep learning framework that integrates ResNet as the encoder within a U-Net architecture to automatically detect and segment LAM-related cystic regions in lung CT images. By combining the strengths of both architectures, the model is designed to extract deep semantic features while preserving spatial accuracy, thereby facilitating precise localization of pathological structures. This approach aims to support radiologists in facilitating early and reliable diagnosis of LAM, leading to better clinical decisions and promoting AI-assisted diagnostic tools for rare pulmonary diseases.

II. LITERATURE SURVEY

In this research, the authors describe CSR-Net, a fully convolutional neural network designed for automatic lung segmentation in chest radiographs (CXR), leveraging transfer learning techniques. Recognizing that accurate lung segmentation is a fundamental step for computer-aided diagnosis (CAD)

systems especially for detecting diseases such as lung cancer, infections, and COVID-19 the study integrates ResNet-101 as the encoder to extract deep semantic features and U-Net employed as the core architecture for accurate segmentation. By combining both architectures, this hybrid approach maximizes their respective strengths: ResNet-101 enhances feature extraction through deep residual connections, while U-Net ensures accurate localization via skip connections. The model is evaluated on the JSRT dataset and shows strong performance across multiple metrics including Jaccard Similarity Coefficient (JSC), Precision, Recall, Dice Score, Accuracy, and. The research demonstrates the potential of CSR-Net as a robust and scalable solution for lung segmentation and underlines its value as a foundational component in CAD systems for further clinical image analysis[1]

This study introduces a novel deep learning architecture, “SE-ResNeXt-SA-18” is approached to reliably classify ILD related radiographic patterns derived from computed tomography (CT) scans. The model underscores the critical importance of leveraging volumetric (3D) contextual information of pathological patterns, which was often neglected in previous works relying on two-dimensional CNN inputs. The “SE-ResNeXt-SA-18” architecture combines the multi-path learning of ResNeXt with the SE module and a divided attention mechanism to improve feature representation. The model’s classification efficiency was compared against ResNet-18 and “SE-ResNeXt-18”, showing superior results. Notably, the model recorded an impressive accuracy of 0.991, sensitivity of 0.979, and specificity of 0.994 using a $32 \times 32 \times 16$ input patch. Class activation maps confirmed that the network accurately localized pathological regions. This paper highlights that SE-ResNeXt-SA-18 not only improves classification accuracy but also holds potential in tracking disease progression and evaluating treatment response in ILD patients through reliable pattern recognition[2].

As per this research paper, the authors present a hybrid deep learning model called MRC-TransUNet, designed to enhance the accuracy of medical image segmentation by effectively combining Convolutional Neural Networks (CNNs) with Transformer architectures. Traditional U-shaped models with skip connections often fall short in capturing rich context aware information, which plays a crucial role for clinical interpretation. To overcome this limitation, the proposed method introduces a lightweight Mobile-Residual Vision Transformer (MR-ViT) and a Reciprocal Attention (RPA) module to bridge semantic gaps and retain fine image details. Unlike conventional UNet designs, Skip connections in MRC-TransUNet are limited to the initial layer, with MR-ViT and RPA modules introduced in deeper layers to enhance the extraction of long-range features. The model was evaluated across multiple segmentation tasks involving breast, brain, and lung images, achieving superior

performance over existing cutting-edge methods based on metrics such as the Dice coefficient and Hausdorff distance. This approach shows strong potential for clinical applications requiring precise and context-aware segmentation[3].

As per this research paper, This paper introduces a dual-stage classification framework designed to advance the detection and staging of lung cancer via a hybrid deep learning approach. Recognizing the challenges in early diagnosis due to nonspecific symptoms and overlapping imaging characteristics with other pulmonary diseases, the study presents a novel system that combines segmentation and classification in two phases. Initially, A U-Net model enhanced with dual attention mechanisms and pyramid atrous pooling is applied for accurate tumour segmentation. From these segmented regions, detailed features such as texture, color, and shape are extracted. In the first stage, a hybrid model incorporating Xception and a custom CNN distinguishes between healthy and affected lung images. The next stage employed the hybrid adaptive learning neural network that takes locational features from the abnormalities to accurately classify cancer stages. Validated on multiple datasets including LIDC-IDRI and NSCLC variants, the model demonstrated superior performance compared to existing techniques across multiple evaluation metrics[4].

This research paper presents A novel architecture, UncertaintyFuseNet, is introduced in this study to enable accurate COVID-19 detection using a combination of chest CT and X-ray imaging. Unlike conventional approaches that focus on a single image modality, UncertaintyFuseNet utilizes a feature fusion strategy to integrate hierarchical features extracted from both CT and X-ray data, thereby improving diagnostic precision. A distinctive contribution of this model is its incorporation of Ensemble Monte Carlo Dropout (EMCD) to quantify prediction uncertainty, a factor typically overlooked in many deep learning studies. By embedding uncertainty awareness into the classification process, the model enhances the reliability and robustness of its predictions, especially when exposed to noisy or unseen data. The authors validated the performance of the proposed model using comprehensive datasets, achieving exceptionally high classification accuracies of 99.08% for CT images and 96.35% for X-ray images. Further evaluation using standard performance metrics precision, recall, F1-score, and ROC curves consistently demonstrated the model’s Strength and accuracy. These results underscore the potential of UncertaintyFuseNet as a dependable tool to support clinical diagnosis and decision-making in COVID-19 detection, with possible applications extending to other thoracic diseases. [5].

In this research paper presents, the authors introduce “LA-ResUNet”, an advanced deep learning model developed for semantic segmentation of pulmonary nodules in chest CT scans. Given that lung cancer often remains

asymptomatic until advanced stages, early identification of potentially malignant pulmonary nodules is crucial. “LA-ResUNet” addresses this need by leveraging the strengths of the ResUNet architecture, enhanced with a linear on focus module to improve focus on relevant features, and the Leaky ReLU activation function to mitigate the “dying ReLU” issue during training. The model employs residual blocks to combat vanishing gradient problems and incorporates skip connections to ensure better feature propagation across layers. By introducing a linear attention module, the model maintains both time and space efficiency, making it practical for high-resolution medical imaging. When evaluated on the LIDC-IDRI dataset, “LA-ResUNet” attained a DSC of 73.11% and an IoU score of 60.62%, reflecting effective segmentation capability. These results validate the model’s potential as a robust, computationally efficient tool for pulmonary nodule segmentation, aiding clinicians in early lung cancer diagnosis and treatment planning [6].

In this research paper, the authors propose an effective two-stage segmentation framework designed to improve the accuracy of lung region segmentation in chest X-ray images. Manual segmentation is not only time-intensive but also susceptible to human error, particularly when reliant on expert interpretation. To overcome these challenges, the proposed approach integrates deep learning with traditional image processing techniques. In the first stage, U-Net and ResU-Net models are used to generate initial lung segmentation masks. These outputs are then fused using a Haar wavelet transform and spatial frequency fusion to integrate the complementary strengths of both networks. In the second stage, the fused image undergoes an inverse Haar transform followed by post-processing techniques to refine the final segmentation output. This hybrid strategy enhances segmentation accuracy, leading to better support for clinical diagnosis. The model’s effectiveness was validated on widely-used public datasets JSRT, Montgomery County (MC), and Shenzhen achieving high accuracy rates of 98.42%, 98.28%, and 98.99%, respectively, showcasing its robustness and potential for real-world application in medical imaging [7].

III. EXISTING SYSTEM

Lymphangioliomyomatosis (LAM) is traditionally diagnosed through the manual evaluation of high-resolution computed tomography (HRCT) scans by experienced radiologists, who look for hallmark features such as diffuse, thin-walled cysts within the lung parenchyma. However, the diagnostic process is often complicated by the rarity of the disease and the visual similarities it shares with other cystic lung conditions, including emphysema and pulmonary Langerhans cell histiocytosis. This reliance on human interpretation introduces subjectivity and inter-observer variability, potentially leading to delayed or inaccurate diagnoses.

Complementary diagnostic tools, such as endothelial growth factor-D (VEGF-D) levels and histopathological analysis via lung biopsy, are sometimes employed, but these methods can be invasive or inaccessible. Semi-automated image processing tools have attempted to aid in cyst quantification, though they often require manual intervention and suffer from limited adaptability. Early computational methods based on classical image processing and machine learning such as texture analysis and support vector machines yielded modest improvements but lacked robustness and generalizability across diverse clinical datasets. In contrast, recent advancements in deep learning, particularly the development of convolutional neural networks (CNNs), have substantially improved the accuracy and reliability of medical image analysis. Notably, U-Net excels in segmentation tasks, while ResNet facilitates deep feature extraction. Yet, these architectures remain underutilized for LAM-specific applications, underscoring the need for a hybrid ResNet-U-Net model tailored to this rare disease.

IV. MODULES

A. Data Acquisition

This study employs a well-curated dataset of high-resolution computed tomography (HRCT) lung scans to facilitate the development and evaluation of the proposed deep learning framework for the detection and segmentation of Lymphangioliomyomatosis (LAM). The dataset includes volumetric CT images from patients clinically diagnosed with LAM, obtained from open – access medical imaging databases and, where applicable, institutional collaborations. Each image volume is paired with expert-annotated masks that accurately delineate the cystic lesions associated with LAM, serving as ground truth for supervised training. To validate the model’s generalizability and consistent performance, the dataset encompasses a diverse patient cohort, varying in demographics, cyst morphology, and scan quality. All images were anonymized in accordance with ethical standards and data privacy regulations. For robust performance evaluation, the dataset was split into training, validation, and test subsets. This dataset forms a critical foundation for building a clinically applicable LAM detection and segmentation model.

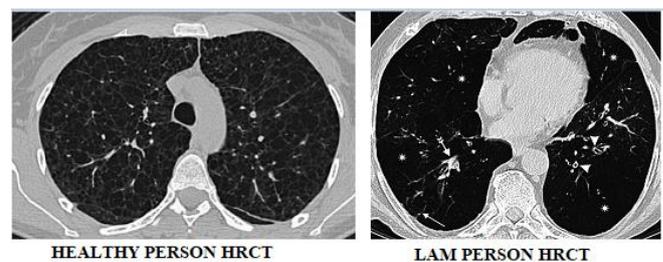


Fig.1. Dataset of Healthy and Lam affected Lung HRCT

B. Data Preprocessing

The module plays a critical role in preparing HRCT lung scan images for deep learning-based analysis. Initially, all CT volumes are resampled to a standardized spatial resolution to mitigate variations introduced by different imaging protocols. Intensity normalization is performed to harmonize pixel value distributions, thereby enhancing contrast consistency across the dataset. Each image is resized or zero-padded to ensure uniform input dimensions suitable for the model architecture. To increase dataset variability and improve model generalization, a range of augmentation techniques including random rotations, horizontal and vertical flips, scaling, and elastic deformations were applied during the training phase. Furthermore, expert-annotated cystic region masks are carefully aligned with the corresponding CT slices to ensure precise ground truth correspondence. This preprocessing pipeline is essential to eliminate data inconsistencies, reduce overfitting risks, and ensure that the model is trained on well-structured, clinically representative inputs for accurate LAM detection and segmentation.

C. Data Augmentation

Data augmentation is essential for improving the performance and generalization capability of deep learning models, especially in medical imaging tasks where annotated datasets are often limited. In this study, data augmentation is employed to synthetically enlarge the training dataset by introducing controlled variability into the high-resolution computed tomography (HRCT) lung scans and their corresponding ground truth masks. A range of geometric and photometric transformations including techniques like random rotations and both horizontal and vertical flipping, scaling, zooming, elastic distortions, and intensity normalization are systematically applied. These techniques simulate diverse imaging conditions and patient anatomical variations, allowing enhancing the model's ability to learn consistent and transferable features. To preserve spatial alignment and semantic accuracy, all transformations are applied identically to both the input image and its annotated mask. By diversifying the training samples, data augmentation helps reduce overfitting and significantly improves the model's performance, making it more resilient and reliable in detecting and segmenting Lymphangiomyomatosis (LAM) across varied clinical scenarios.

D. Hybrid Architecture Design

The Model Architecture Design module forms the backbone of the proposed system, presenting a hybrid deep learning framework specifically engineered for the accurate detection and segmentation of

Lymphangiomyomatosis (LAM) in high-resolution CT lung scans. The model combines the deep feature extraction strengths of Residual Networks (ResNet) with the fine-grained segmentation strengths of U-Net. In this architecture, a modified ResNet-based encoder is employed to capture complex and hierarchical representations of cystic lung structures, while simultaneously addressing vanishing gradient issues through residual learning. The decoder, modeled after the U-Net architecture, reconstructs spatial details through progressive upsampling and employs skip connections to integrate low-level spatial information with high-level semantic features, thereby preserving spatial integrity and enhancing segmentation precision. Batch normalization and dropout layers are incorporated throughout the network to ensure stable training and to reduce overfitting. This architecture achieves a robust trade-off between computational efficiency and clinical performance, enabling reliable, automated LAM segmentation suitable for real-world diagnostic workflows.

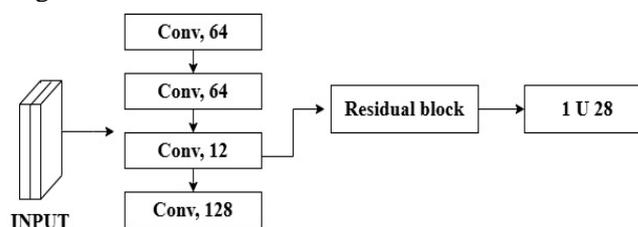


Fig.2.Encoder Section of Hybrid Deep learning

E. Feature Extraction Module (ResNet Encoder)

The Feature Extraction Module employs a modified ResNet-based encoder to extract deep, hierarchical features from high-resolution CT lung scans. Leveraging residual learning and identity skip connections, this architecture ensures effective gradient flow and mitigates the gradient degradation, allowing for the training of deeper, more expressive networks. The encoder captures both fine-grained textures and high-level semantic patterns that are essential for identifying cystic regions characteristic of Lymphangiomyomatosis (LAM). Multiple convolutional and residual layers are stacked to progressively abstract features, creating a robust multi-scale illustration of the input data. These encoded features serve as the foundation for accurate and context-aware segmentation in the U-Net decoder.

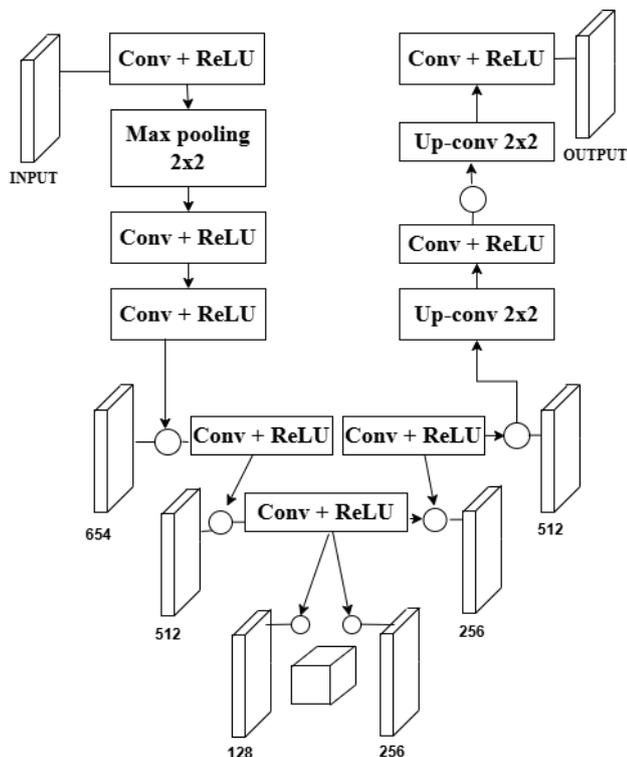


Fig.3. Architecture Diagram for ResNet and U-Net.

F. Segmentation Module (U-Net Encoder)

The Segmentation Module implements a U-Net-inspired decoder that reconstructs high-resolution segmentation maps from the encoded features generated by the ResNet-based encoder. Through a sequence of upsampling and convolutional operations, the decoder restores the spatial dimensions of the input image while preserving critical semantic information. Skip connections from corresponding encoder layers are concatenated at each stage to retain fine-grained anatomical details, enabling the network to accurately localize and delineate LAM-related cystic structures. This architecture ensures that both contextual depth and spatial precision are preserved. The final output is a binary segmentation mask highlighting pathological regions, supporting reliable clinical evaluation and early detection.

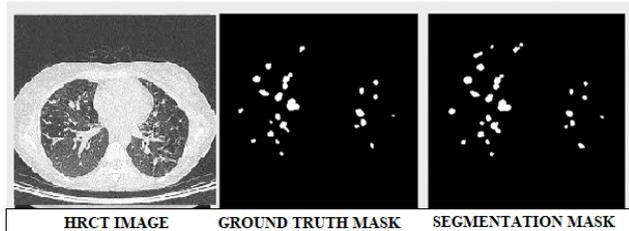


Fig.4. Predicted Segmented mask image

G. Evaluation and Performance Metrics

The Evaluation and Performance Metrics module represents the concluding phase of the proposed

framework, dedicated to rigorously assessing the model's effectiveness in identifying and segmenting Lymphangioliomyomatosis (LAM) in HRCT lung scans. To ensure a comprehensive and unbiased evaluation, the model is tested on an independent test dataset and assessed using standard performance metrics, including Dice Similarity Coefficient (DSC), Intersection over Union (IoU), sensitivity, precision, and overall accuracy. These metrics collectively quantify segmentation performance by measuring spatial overlap with ground truth annotations and the model's ability to minimize classification errors. The structured dataset is divided into training, validation, and testing subsets to promote generalizability and reduce the risk of overfitting. Additionally, the proposed framework is benchmarked against baseline deep learning models to validate its improvements. Consistently high scores across all metrics demonstrate the model's robustness, clinical reliability, and potential integration into real-world computer-aided diagnostic (CAD) systems for early and accurate LAM detection.

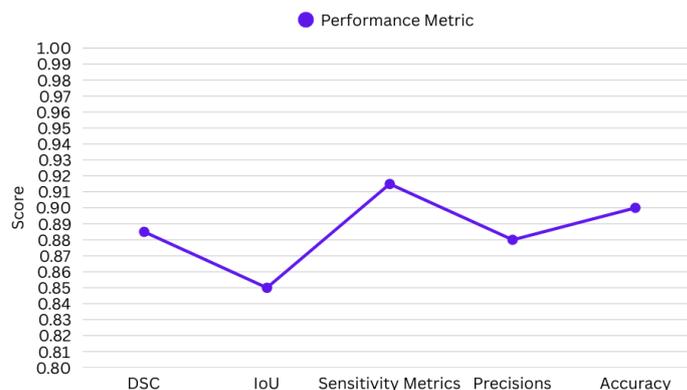


Fig.5. Performance Metrics of LAM Detection Model

CONCLUSION

This study introduced a hybrid deep learning framework that integrates the capabilities of Residual Networks (ResNet) and U-Net architectures to automate the detect and segment of Lymphangioliomyomatosis (LAM) in high-resolution CT lung scans. The proposed model efficiently captures both abstract semantic features and precise spatial information, enabling accurate identification of LAM-related cystic regions. Key components such as residual connections, batch normalization, dropout layers, and robust data augmentation techniques contributed to improved training stability, reduced overfitting, and enhanced generalization. Quantitative evaluation using metrics including Dice Similarity Coefficient (DSC), Intersection over Union (IoU), sensitivity, and precision confirmed the model's high performance and clinical relevance. These findings demonstrate the model's capability as a reliable and efficient computer-aided diagnostic (CAD) tool to support radiologists in early LAM detection. Future efforts will focus on expanding the dataset, enhancing interpretability, and facilitating real-world deployment within clinical diagnostic workflows.

REFERENCES

- [1] P. Kumar, L. Raja, and P. K. Soni, "CSR-NeT: Lung Segmentation from Chest Radiographs Using Transfer Learning Technique," *SN Computer Science*, vol. 3, no. 4, pp. 1–10, Jul. 2022. DOI: [10.1007/s42979-022-01294-8](https://doi.org/10.1007/s42979-022-01294-8).
- [2] J.-X. Chen, Y.-C. Shen, S.-L. Peng, Y.-W. Chen, H.-Y. Fang, J.-L. Lan, and C.-T. Shih, "Pattern Classification of Interstitial Lung Diseases from Computed Tomography Images Using a ResNet-Based Network with a Split Transform-Merge Strategy and Split Attention," *SN Computer Science*, vol. 5, no. 1, pp. 1–14, Jan. 2024, doi: [10.1007/s42979-023-02115-7](https://doi.org/10.1007/s42979-023-02115-7).
- [3] Z. Zhang, H. Wu, H. Zhao, Y. Shi, J. Wang, H. Bai, and B. Sun, "A Novel Deep Learning Model for Medical Image Segmentation with Convolutional Neural Network and Transformer," *SN Computer Science*, vol. 5, no. 1, pp. 1–13, Sep. 2023, doi: <https://doi.org/10.1007/s12539-023-00585-9>.
- [4] J. Subash and S. Kalavani, "Dual-stage classification for lung cancer detection and staging using hybrid deep learning techniques," *SN Computer Science*, vol. 5, no. 4, pp. 1–12, Mar. 2024, doi: <https://doi.org/10.1007/s00521-024-09425-3>.
- [5] M. Abdar, S. Salari, S. Qahremani, H.-K. Lam, F. Karray, S. Hussain, A. Khosravi, U. R. Acharya, V. Makarenkov, and S. Nahavandi, "UncertaintyFuseNet: Robust uncertainty-aware hierarchical feature fusion model with Ensemble Monte Carlo Dropout for COVID-19 detection," *Computers in Biology and Medicine*, vol. 152, p. 106400, 2023, doi: <https://doi.org/10.1016/j.inffus.2022.09.023>.
- [6] P. C. S. Prithvika and L. J. Anbarasi, "LA-ResUNet: An Efficient Linear Attention Mechanism in ResUNet for the Semantic Segmentation of Pulmonary Nodules," in *IEEE Access*, vol. 12, pp. 75361–75370, 2024, doi: <https://doi.org/10.1109/ACCESS.2024.3386162>.
- [7] C. Sumathi and Y. A. V. Phamila, "Efficient Two Stage Segmentation Framework for Chest X-Ray Images With U-Net Model Fusion," in *IEEE Access*, 2024, doi: <https://doi.org/10.1109/ACCESS.2024.10649560>.
- [8] B. Shirokikh et al., "Deep Learning for Brain Tumor Segmentation in Radiosurgery: Prospective Clinical Evaluation," in *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, A. Crimi and S. Bakas, Eds., *Lecture Notes in Computer Science*, Springer, 2020, . doi: https://doi.org/10.1007/978-3-030-46640-4_12
- [9] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, N. Navab, J. Hornegger, W. Wells, and A. Frangi, Eds., *Lecture Notes in Computer Science*, 2015, doi: https://doi.org/10.1007/978-3-319-24574-4_28
- [10] Z. Huang et al., "CCNet: Criss-Cross Attention for Semantic Segmentation," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 6, pp. 6896–6908, 1 June 2023, doi: <https://doi.org/10.1109/TPAMI.2020.3007032>
- [11] R. Zhao et al., "Structure-Enhanced Attentive Learning For Spine Segmentation From Ultrasound Volume Projection Images," in *Proceedings of the 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Toronto, ON, Canada, 2021, pp. 1195–1199, doi: <https://doi.org/10.1109/ICASSP39728.2021.9414658>
- [12] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," in *Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, 2016, pp. 770–778, doi: <https://doi.org/10.1109/CVPR.2016.90>
- [13] A. Hosny, C. Parmar, T. P. Coroller, P. Grossmann, R. Zeleznik, A. Kumar, J. Bussink, R. J. Gillies, R. H. Mak, and H. J. W. L. Aerts, "Deep learning for lung cancer prognostication: A retrospective multi-cohort radiomics study," *PLoS Med.*, Nov. 2018, doi: <https://doi.org/10.1371/journal.pmed.1002711>
- [14] V. Chouhan, S. K. Singh, A. Khamparia, D. Gupta, P. Tiwari, C. Moreira, R. Damaševičius, and V. H. C. de Albuquerque, "A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images," *Appl. Sci.*, Jan. 2020, doi: <https://doi.org/10.3390/app10020559>
- [15] Nazir, I. ul Haq, S. A. AlQahtani, M. M. Jadoon, and M. Dahshan, "Machine Learning-Based Lung Cancer Detection Using Multiview Image Registration and Fusion," *Journal of Healthcare Engineering*, Aug. 2023, doi: <https://doi.org/10.1155/2023/6683438>