**Advancements in Pneumothorax Segmentation:**

**A Comprehensive Review of Deep Learning Approaches**

|  |  |  |
| --- | --- | --- |
| Sowmia KR  Department of AI and ML,  Rajalakshmi Engineering College,  Chennai, India  sowmia.kr@rajalakshmi.edu.in | Harshini J  Department of AI and ML,  Rajalakshmi Engineering College,  Chennai, India  harshinijayakumar2908@gmail.com | Harish Nandhan S  Department of AI and ML,  Rajalakshmi Engineering College,  Chennai, India  harishnandhan02@gmail.com |

**Abstract — In recent years, deep learning has made significant advancements in the computer-aided diagnosis for potentially life-threatening pneumothorax, especially with the rise of public pneumothorax diagnosis competitions using thousands of manually annotated chest X-rays. This review demonstrates the quick evolution of deep learning in pneumothorax diagnosis, offering innovative approaches to enhance accuracy, mitigate bias, and advance medical image segmentation. These investigations leverage deep learning, particularly the U-Net architecture with various backbones like ResNet34, achieving notable Dice coefficients up to 0.8574. They also compare deep learning frameworks to human radiologists, revealing similar diagnostic confidence. Innovative techniques like UNet++ improve segmentation accuracy by incorporating change maps and fusing outputs from different semantic levels. Notably, they emphasize AI pneumothorax detection enhancement through in-image annotations targeting the pleural separation, achieving an AUROC rating of 0.877 while mitigating bias from factors like thoracic tubes. This underscores the importance of high-quality in-image localization data for AI algorithm training. Furthermore, on a difficult dataset, the innovative semantic segmentation model Ens4B-UNet (which combines four U-Net architectures with pre-trained backbones) attains a Dice similarity coefficient that is 0.8608. A two-stage deep learning approach secures the second position in a pneumothorax segmentation challenge, leveraging transfer learning and model architecture redesign (PTXNet) for a significant Dice coefficient boost of 18.76%. The Kim-Monte Carlo methodology employs small artificial neural networks for precise pneumothorax localization, outperforming conventional CNNs. Finally, an end-to-end deep learning framework featuring a fully convolutional DenseNet demonstrates competitive segmentation and diagnostic performance.**

***Keywords — Pneumothorax Segmentation - Deep Learning - UNet Architecture - Multi Step Object Fusion - DenseNet- Chest X-rays***

# **introduction**

A serious pulmonary illness with a substantial likelihood of death is pneumothorax, that is characterized by theabnormal buildup of air in the chest wall. Pneumothorax, frequently caused by factors like chest trauma, pulmonary ailments or even smoking, can have severe consequences like dyspnea, shock, and in the most fatal instances, death (A. Tolkachev et al.) [1]. Chest radiographs, a rapid and reasonably priced imaging method, are a crucial component of pneumothorax detection and diagnosis. However, due to the covert nature of pneumothorax, radiologists have a difficult barrier when interpreting chest X-rays for the disease. In X-ray visuals, the disease appears as a region of low-contrast air that can frequently be concealed by thoracic structures. Thus, the ability of radiologists to diagnose pneumothorax accurately is entirely reliant (Wang, Q. et al.) [2].

Ens4B-UNet uses the combined strength of four separate pre-trained backbone networks—ResNet, DenseNet, ResNext, and EfficientNet— to increase the segmentation procedure's resilience and accuracy.The model achieves outstanding pneumothorax segmentation by integrating these networks and using nearest-neighbor up-sampling in the decoder. For enhanced efficiency, the authors also use methods like data augmentation, stochastic weight averaging, and multiple test data augmentations. (Wang, Q. et al.) [2].

The design of a two-stage deep learning technique that uses image and pixel level annotations to enhance segmentation accuracy for pneumothorax segmentation in chest radiographs. While the latter stage clearly partitions the affected region, the former stage concentrates on determining whether or not a radiograph contains a pneumothorax. They substantially enhance single-task models in classification accuracy when employing a multi-task training approach (K. Jakhar et al.) [3].They concentrated on how crucial in-image pixel annotations are for increasing the precision of pneumothorax segmentation. It illustrates the difficulties brought on by differences in inflammation form, dimensions, and position in chest radiographs. Through the use of pixel-level annotations, the study presents a training approach containing multiple tasks for Deep Convolutional Neural Networks (DCNNs) that optimizes classification accuracy. This research makes significant improvements to pneumothorax segmentation by providing data that can be used to create accurate and efficient algorithms (Y. Cho et al.) [5]. A segmentation stage for precise region identification and a classification model for determining the existence of pneumothorax. While the segmentation model solely makes use of pneumothorax-positive images, the classification model is trained on both positive and negative samples. They use ensemble learning with a variety of models that utilize different encoding connections to further increase accuracy. On the SIIM-ACR pneumothorax segmentation assessment, this technique succeeds remarkably well, highlighting its potential for clinical applications (Salvaggio K et al.) [4].

Research using Convolutional Neural Networks (CNNs) to identify pneumothorax in chest X-rays led to the creation of a CNN architecture that demonstrated success with GradCAM and saliency maps while consuming less memory and processing resources (A. Patel et al.) [6]. The approach they employ makes use of image pixel annotations of the pulmonary pleura and UNet and MSOF (Multi-Scale Objective Function) to substantially improve performance and minimize biases brought about by embedded thoracic tubes (Z. Li et al.) [7]. Annotations at the pixel level are essential for pneumothorax segmentation. The lack of uniform datasets and the data imbalance are problems that the study addresses. For joint classification and segmentation, it offers a two-stage deep learning strategy that overcomes constraints on data while acquiring more general accuracy (A. Abedalla et al.) [9].

They explore the difficulty of pneumothorax treatment using techniques based on deep learning. They draw attention to the difficulties involved in evaluating chest radiographs because of their low resolution and low contrast. The two-stage deep learning approach described in the study, which combines image-level and pixel-level annotations for improved segmentation efficiency, is the best-performing system for addressing the problem of 2019 SIIM-ACR pneumothorax segmentation. (Rueckel J et al.) [10].

# **Methodology**

* 1. *Artificial Neural Network (Yongil Cho et al.)*

This study used the National Institutes of Health (NIH) Chest radiograph dataset as its basis. This dataset includes radiographs of the chest collected from 30,805 patients, with each image annotated with 14 common thoracic disorders. The labels were created using Natural Language Processing, which means they aren't perfect. So, picking a group of photos that appropriately show pneumothorax is really important. This was achieved by having two qualified emergency medical specialists choose 1,000 grayscale chest X-ray images that contained the illness. Each of these images was then divided into 49 boxes, marking whether the pneumothorax was present or not, forming the basis for the dataset used in the study. The robustness of the models was enhanced by this algorithm's utilization of a randomized optimization approach based on a simulation of Monte Carlo, which iteratively adjusted weights and biases in order to reduce training error. Based on receiver operating characteristic (ROC) curve analysis, the primary statistic used in the evaluation, the area under the curve (AUROC), was calculated. Notably, the top ANN model for pneumothorax diagnosis outperformed CNNs with a substantial 0.882 AUC, 80.6% sensitivity, and 83.0% specificity. The method's advantages are its creative training strategy, the use of board-certified physicians in dataset curation, and a strict evaluation framework built around ROC analysis. The study did recognize, however, that labels created via NLP may have certain limitations and may result in inaccurate data being included in the dataset. [13].

* 1. *U-Net (Karan Jakhar et al.)*

The revolutionary medical image segmentation advances for rapid and accurate identification of pneumothorax have been demonstrated by the implementation of the U-Net framework. The two tier backbone of the U-Net architecture, which accurately encodes complex images into a latent vectors, play a crucial part in allowing medical experts to quickly start therapy [8]. The encoder skillfully minimizes input images while simultaneously grasping significant information, and the decoder creates masks that precisely determine pneumothorax. To effectively prepare different real-world images, standard preprocessing techniques including scaling, color range alteration, and normalization are accomplished [11, 32].

Getting rid of unwanted boundary noise, which often appears in X-ray images, necessitates using arbitrary cropping alongside filtering out corrupted images. The consequent black and white photographs of masks are artfully designed to bring out the areas of concern. Because the encoder maps images to masks, giving the model the ability to extrapolate this mapping, its ability to downscale images and comprehend latent spaces is crucial [25-28].

Due to this generalization, the model is able to rapidly evaluate any X-ray image and quickly deliver a pneumothorax mask. A blank mask unambiguously indicates the lack of any issue, permitting quick medical assistance. Notably, the addition of a pre-trained ResNet as the encoder and the choice of U-Net, recognized for its compact yet effective architecture, considerably enhance the model's accuracy as well as speed. The vanishing gradient problem is successfully minimized by the addition of skip connections in U-Net along with ResNet's skip connection approach, significantly enhancing the performance of the model [29-30].

The U-Net algorithm has some restrictions despite its exceptional powers. Some users may have resource limitations due to their reliance on sophisticated GPU resources, which is fundamental of deep learning models. The precision of the algorithm is thus closely related to the reliability and consistency of the training data. Consideration should be given to the need for precise threshold calibration during pneumothorax diagnosis, as well as the likelihood of label mistakes that arise from NLP, which may affect the manner in which the algorithm performs [28, 31, 35].

* 1. *UNet++ and MSOF (Zhongzhi Li et al.)*

Pneumothorax segmentation using a novel method that makes use of the UNet++ architecture including nested dense skip routes. A variety of convolution routes are used in combination with UNet++ to obtain multi-scale feature maps, considerably increasing the network's ability to capture fine features in chest X-ray images [12]. By using an extensive connection approach reminiscent of DenseNet, UNet++ breaks away from traditional UNet architectures and revolutionizes skip routes, enabling more effective information transfer. It also uses a multi-level full-resolution feature map technique to create several feature maps, which are essential for later segmentation tasks [27, 33].

Convergence and feature extraction are significantly enhanced by DeepSupervision(DS) by Multiple Side-Outputs Fusion. The proposed model, which draws inspiration from UNet++, is made for segmenting pneumothoraces. It generates multi-scale and varied feature representations utilizing concatenated photographs as inputs and dense skip connections. The method employs multiple-side output fusion (MSOF) to further refine spatial features, and it ends with the creation of a mask using a sigmoid layer [15].

Using the SIIM-ACR dataset, which includes training samples and corresponding masks, this method is thoroughly examined. 20% of the dataset, which is part of the training images, is used for training and testing. The Intersection over Union and Dice score, two common measures of segmentation accuracy, are included in evaluation metrics. The model, which possesses an 86.7 Dice score and an 84.5 IoU score, stands out for its promising performance [12,15].

* 1. *FC-DenseNet with scSE module (Qingfeng Wang et al.)*

Due to the FC-DenseNet architecture's effectiveness in parameter minimization and its resistance to overfitting, an effective fully fledged deep-learning framework for pneumothorax segmentation is proposed. Thisframeworkincludes a reverse-sampling pathway for feature acquisition and a forward-sampling pathway for spatial information restorations with the aid of skipping connections. To efficiently capture changes in objects that are linked to a certain viewpoint, multi-scale convolutional components are laid out. Spatial channel compression and excitation has been integrated into the architecture, allowing for the adaptive adjustment of feature maps and boosting feature utilization [14, 34].

The outcomes show improved segmentation accuracy when compared to a number of previous models, such as DenseASPP, DeepLab v3+,SegNet, U-Net, and FC-DenseNet, as measured by the mean pixel-wise accuracy , Hausdorff distance and dice similarity coefficients . This research offers an innovative approach with promising potential to advance medical image segmentation, particularly in the backdrop of pneumothorax diagnosis, despite potential label errors from natural language processing and the need for empirical threshold setting for pneumothorax diagnosis [28,29].

* 1. *Two-stage deep learning (ResNet and Efficientnet) (Xiyue Wang et al.)*

The proposed method for segmenting and identifying pneumothoraces consists of two parts. The first step in diagnosing a pneumothorax is analysing an X-ray image with a zero-mean and one-variance. Images with a pneumothorax condition are advanced to the next level of the segmentation network, which generates comprehensive segmentation inside the pneumothorax tract [18]. The data distribution across pneumo-positive and pneumo-negative samples is highly unequal, making it difficult to train a single network to do both detection and segmentation. Consequently, a two-step procedure is employed. Pneumothorax segmentation and picture classification are two of the many output branches employed in the initial step of a multi-task training approach. Be careful to remember that the segmentation branch is only used when training the model and not when testing it [16, 17].

Both the former and later stage networks utilize the encoder for feature extraction and a decoder that generates predictions. Encoder backbones are used to allow flexibility and high performance, incorporating numerous backbone models including ResNet, ResXNet, Squeeze-and-excitation, and EfficientNet. Both steps utilize a model ensemble, which combines the outputs from different models, to further enhance segmentation and classification accuracy [19,30].

A collection of chest X-rays from the SIIM-ACR issue is used as one dataset to evaluate the effectiveness of the suggested approach. AUC, precision, F1-score,accuracy, recall and Dice coefficient are just a few of the metrics that may be utilized to assess how effective the classification and segmentation models are. Ablation research looks into the effects of model preliminary training, augmenting data, multiple task learning, and a two-phase technique on model performance [20].

* 1. *Automated Pneumothorax Detection and Quantification from CT-Scans (Synho Do et al.)*

An automated approach for the segmentation and quantification of pneumothorax from CT scans was developed using a thorough methodology. This technique consists of a pair of vital elements: 2D processing for quick segmentation of thoracic tissue types and 3D processing for air-containing anatomical structures outside the pleural space rectification. First, noise was minimized employing Gaussian smoothing to enhance the visual quality of CT radiographs. Therefore, adaptive thresholding produced a body mask that preserved vital parts of the lungs and thoracic air while eradicating extraneous air from outside the thorax. To ensure the accuracy of pneumothorax segmentation, non-relevant sections which include bronchi and bowel were ruled out through careful morphological analysis. Following that, volumetric measurements were made with the objective to determine the relative pneumothorax volume. On the same datasets, manual segmentation has been carried out by qualified radiologists to determine the accuracy of the automated method. For an in-depth examination, statistical tests which means paired t-tests and Pearson correlation coefficients were used, which validated the algorithm's adaptability and clinical utility [22-24].

When compared to manual approaches, this technology greatly decreases processing time while further enhancing efficiency. It displays incredible efficiency in diagnosing pneumothorax, lessening human error and providing regularity in results across different data sets. The technique, however, might be vulnerable to fluctuations in tissue intensity, thereby overlooking tiny airways and the blood vessels. The efficiency of this intricate algorithm may be dependent on the kind and quality of CT scan data, and its implementation may call for particular proficiency in image processing [35-].

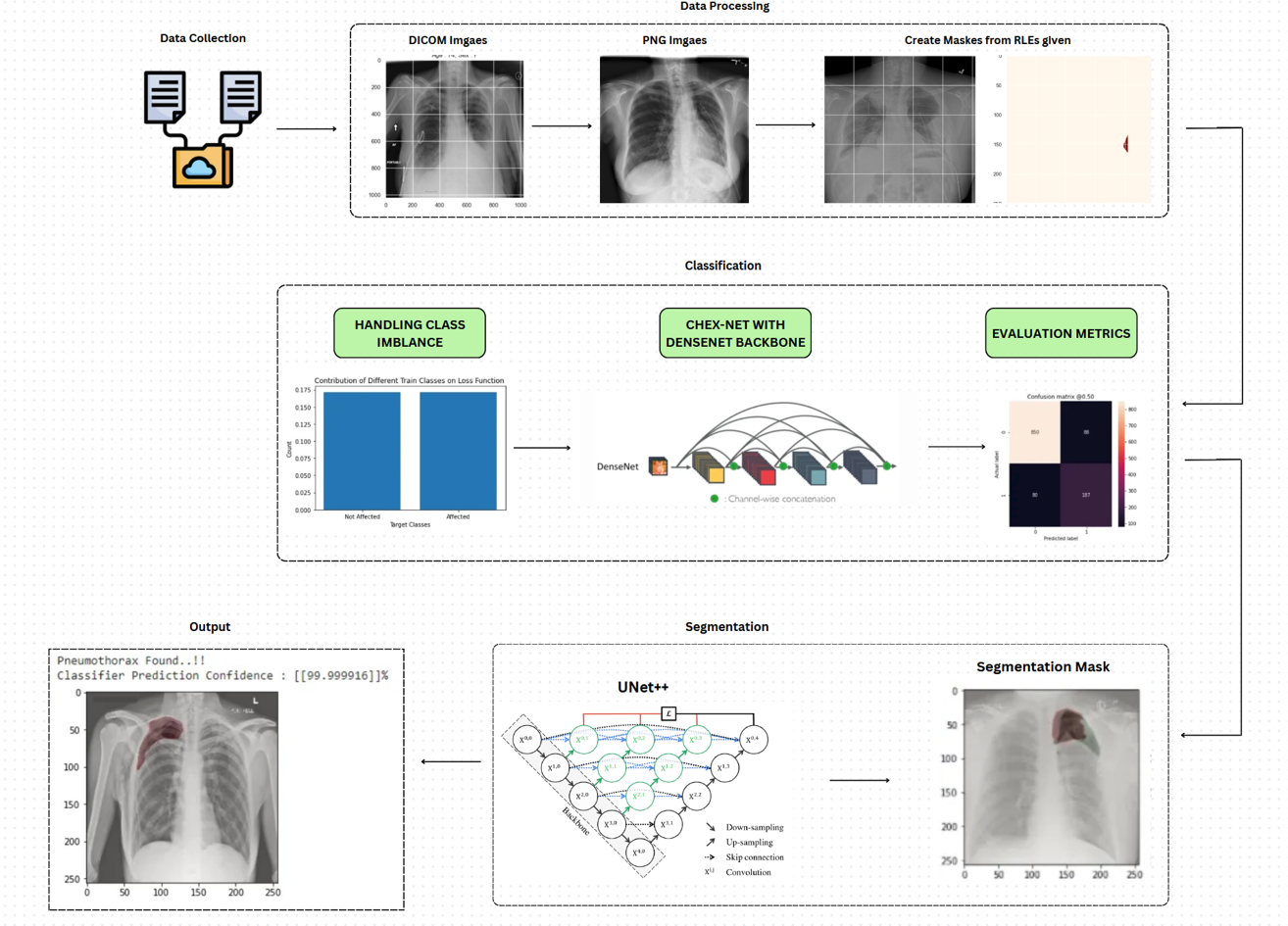


Fig. 1. Schematic representation of Pneumothorax classification and Segmentation

1. **proposed system**

A comprehensive architectural diagram illustrating the pneumothorax classification and segmentation workflow is shown in Figure1. The procedure starts with a chest radiograph input. Since these radiographs usually come in the dicom format, the picture must first be converted to the png format in order to be further examined. After the image is preprocessed, the system's emphasis turns to recognizing the Run-Length Encoding (RLE) masks in photographs of pneumothorax cases. Classification, segmentation, and modeling are the next steps. The technique addresses pneumothorax classification in the modeling stage. The system addresses the classification of pneumothorax at the modeling stage. It uses probabilistic functions and metrics to determine definitively whether or not pneumothorax is present in the image, addressing the problem of class imbalance. To categorize the images, CheXNet, a 121-layer DenseNet model that has been improved using chest X-ray data, is used. The architecture makes use of UNet++, an efficient algorithm for Biomedical Image segmentation, during the segmentation stage. The main function of it is to precisely identify and highlight the pneumothorax regions in the image. An image indicating the presence or absence of pneumothorax is the end outcome. The segmented part is highlighted if pneumothorax is discovered, giving healthcare professionals vital visual information. This process demonstrates a thorough method for segmenting and diagnosing pneumothorax, which could transform medical imaging by providing more precise and effective tests for diagnosis.

1. **Conclusion**

Deep learning architectures like U-net and scSE-DenseNet exhibit great promise in accurately identifying and segmenting pneumothorax in chest X-rays. These models often achieve commendable diagnostic accuracy and align well with human radiologists, even though they may face challenges in complex cases. The adoption of advanced techniques, including multi-scale modules and ensemble learning, significantly enhances segmentation performance, effectively addressing the intricacies of pneumothorax detection. Furthermore, these models enable swift and precise diagnoses, greatly assisting healthcare professionals in timely treatment decisions. Future research should focus on the scalability and generalizability of these models across diverse clinical scenarios, patient demographics, and data sources. Leveraging the combination of various CNN architectures through stacking methods offers a potent avenue for enhancing model robustness and performance. There is a growing imperative to explore weakly supervised or semi-supervised learning approaches to reduce the dependency on labor-intensive manual annotations thereby enhancing the adaptability and accessibility of these deep learning models for broader clinical applications. The combined results highlight the revolutionary potential of deep learning in pneumothorax diagnosis, with future research focused on enhancing scalability and minimizing data annotation constraints to maximize real-world clinical impact.

##### **Acknowledgment**

##### The Pneumothorax Dataset is used in this work. We are grateful for the augmented annotations provided by the American College of Radiology (ACR) and the Society of Imaging Informatics in Medicine (SIIM) on the National Institutes of Health (NIH) public chest radiograph dataset.

##### **References**

1. Tolkachev, Alexey, IlyasSirazitdinov, MaksymKholiavchenko, TamerlanMustafaev, and BulatIbragimov. "Deep learning for diagnosis and segmentation of pneumothorax: The results on the Kaggle competition and validation against radiologists." IEEE Journal of Biomedical and Health Informatics 25, no. 5 (2020): 1660-1672.
2. Wang, Qingfeng, Qiyu Liu, GuotingLuo, Zhiqin Liu, Jun Huang, Yuwei Zhou, Ying Zhou, WeiyunXu, and Jie-Zhi Cheng. "Automated segmentation and diagnosis of pneumothorax on chest X-rays with fully convolutional multi-scale ScSE-DenseNet: a retrospective study." BMC Medical Informatics and Decision Making 20, no. 14 (2020): 1-12.
3. Jakhar, Karan, AvneetKaur, and Dr Meenu Gupta. "Pneumothorax segmentation: deep learning image segmentation to predict pneumothorax." arXiv preprint arXiv:1912.07329 (2019).
4. Do, Synho, Kristen Salvaggio, Supriya Gupta, MannudeepKalra, Nabeel U. Ali, and Homer Pien. "Automated quantification of pneumothorax in CT." Computational and Mathematical methods in Medicine 2012 (2012).
5. Cho, Yongil, Jong Soo Kim, Tae Ho Lim, Inhye Lee, and Jongbong Choi. "Detection of the location of pneumothorax in chest X-rays using small artificial neural networks and a simple training process." Scientific Reports 11, no. 1 (2021): 13054.
6. Patel, Aarya, and AnkitVidyarthi. "PTXNet: An extended UNet model-based segmentation of pneumothorax from chest radiography images." Expert Systems 39, no. 3 (2022): e12807.
7. Li, Zhongzhi, JiankaiZuo, Chunhong Zhang, and Yifan Sun. "Pneumothorax image segmentation and prediction with UNet++ and MSOF strategy." In 2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE), pp. 710-713. IEEE, 2021.
8. Abedalla, Ayat, Malak Abdullah, Mahmoud Al-Ayyoub, and ElhadjBenkhelifa. "Chest X-ray pneumothorax segmentation using U-Net with EfficientNet and ResNet architectures." PeerJ Computer Science 7 (2021): e607.
9. Rueckel, Johannes, Christian Huemmer, Andreas Fieselmann, Florin-CristianGhesu, AwaisMansoor, BalthasarSchachtner, Philipp Wesp et al. "Pneumothorax detection in chest radiographs: optimizing artificial intelligence system for accuracy and confounding bias reduction using in-image annotations in algorithm training." European radiology (2021): 1-13.
10. Wang, Xiyue, Sen Yang, Jun Lan, Yuqi Fang, Jianhui He, Minghui Wang, Jing Zhang, and Xiao Han. "Automatic segmentation of pneumothorax in chest radiographs based on a two-stage deep learning method." IEEE Transactions on Cognitive and Developmental Systems 14, no. 1 (2020): 205-218.
11. Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18, pp. 234-241. Springer International Publishing, 2015.
12. Zhou, Zongwei, MdMahfuzurRahmanSiddiquee, NimaTajbakhsh, and Jianming Liang. "Unet++: A nested u-net architecture for medical image segmentation." In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support: 4th International Workshop, DLMIA 2018, and 8th International Workshop, ML-CDS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 20, 2018, Proceedings 4, pp. 3-11. Springer International Publishing, 2018
13. Goel, Akash, Amit Kumar Goel, and Adesh Kumar. "The role of artificial neural network and machine learning in utilizing spatial information." Spatial Information Research 31, no. 3 (2023): 275-285.
14. Girdhar, Nancy, AparnaSinha, and Shivang Gupta. "DenseNet-II: An improved deep convolutional neural network for melanoma cancer detection." Soft computing 27, no. 18 (2023): 13285-13304.
15. Yuan, Yirong, Jianyong Cui, Yawen Liu, and Boyang Wu. "A Multi-Step Fusion Network for Semantic Segmentation of High-Resolution Aerial Images." Sensors 23, no. 11 (2023): 5323.
16. Rajendran, SowmiaKanakam, Dennise Mathew, BabuRajendiran, and Vijay Kandasamy. "Diabetic retinopathy detection using deep learning techniques." In AIP Conference Proceedings, vol. 2790, no. 1. AIP Publishing, 2023.
17. Latha, G. C. P., S. Sridhar, S. Prithi, and T. Anitha. "Cardio-vascular disease classification using stacked segmentation model and convolutional neural networks." Journal of Cardiovascular Disease Research 11, no. 4 (2020): 26-31.
18. Babu, R., Prithi Samuel, and K. Jayashree. "Cognitive Authentication for Smart Healthcare System." Deep Learning for Cognitive Computing Systems: Technological Advancements and Applications 7 (2022): 149.
19. Wang, Xiyue, Sen Yang, Jun Lan, Yuqi Fang, Jianhui He, Minghui Wang, Jing Zhang, and Xiao Han. "Automatic segmentation of pneumothorax in chest radiographs based on a two-stage deep learning method." IEEE Transactions on Cognitive and Developmental Systems 14, no. 1 (2020): 205-218.
20. Manikandan, J., Sterlin Rani Devakadacham, M. Shanthalakshmi, Y. Arockia Raj, and K. Vijay. "An Efficient Technique for the Better Recognition of Oral Cancer using Support Vector Machine." In 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1252-1257. IEEE, 2023.
21. Wang, Yunpeng, Kang Wang, XueqingPeng, Lili Shi, Jing Sun, ShibaoZheng, Fei Shan, Weiya Shi, and Lei Liu. "DeepSDM: Boundary-aware pneumothorax segmentation in chest X-ray images." Neurocomputing 454 (2021): 201-211.
22. Vong, Khai-My, and Tien Ba Dinh. "Pneumothorax Segmentation In Chest X-Rays Using UNet++ And EfficientNet." In 2021 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI), pp. 1-4. IEEE, 2021.
23. Kannan, E., S. Ravikumar, A. Anitha, Sathish AP Kumar, and M. Vijayasarathy. "Analyzing uncertainty in cardiotocogram data for the prediction of fetal risks based on machine learning techniques using rough set." Journal of Ambient Intelligence and Humanized Computing (2021): 1-13.
24. Jakhar, Karan, AvneetKaur, and Dr Meenu Gupta. "Pneumothorax segmentation: deep learning image segmentation to predict pneumothorax." arXiv preprint arXiv:1912.07329 (2019).
25. Manikandan, J., S. AdolphineShyni, R. Dhanalakshmi, S. V. Akshaya, and S. Dharshini. "Segmentation and Detection of Pneumothorax using Deep Learning." In 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 468-473. IEEE, 2023.
26. Shreyas, M. S., Ashish M. Bhat, Aman Singh, and V. ShubhaRao. "Pneumothorax Segmentation." In 2020 IEEE International Conference for Innovation in Technology (INOCON), pp. 1-6. IEEE, 2020.
27. Groza, Vladimir, and ArturKuzin. "Pneumothorax segmentation with effective conditioned post-processing in chest X-ray." In 2020 IEEE 17th International Symposium on Biomedical Imaging Workshops (ISBI Workshops), pp. 1-4. IEEE, 2020.
28. Niu, Hongwei, Zhengyuan Lin, Xuan Zhang, and TianzhiJia. "Image Segmentation for pneumothorax disease Based on based on Nested Unet Model." In 2022 3rd International Conference on Computer Vision, Image and Deep Learning & International Conference on Computer Engineering and Applications (CVIDL & ICCEA), pp. 756-759. IEEE, 2022.
29. Li, Zhongzhi, JiankaiZuo, Chunhong Zhang, and Yifan Sun. "Pneumothorax image segmentation and prediction with UNet++ and MSOF strategy." In 2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE), pp. 710-713. IEEE, 2021
30. BousiasAlexakis, E., and C. Armenakis. "Evaluation of UNet and UNet++ architectures in high resolution image change detection applications." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 43 (2020): 1507-1514.
31. Kandasamy, Vijay, RevathyPadmanabhan, Priya Vallinayagam, and Sowmia KanakamRajendran. "Survey on chaos RNN–A root cause analysis and anomaly detection." In AIP Conference Proceedings, vol. 2790, no. 1. AIP Publishing, 2023.
32. Al Jowair, Hamdan, Mansour Alsulaiman, and Ghulam Muhammad. "Multi parallel U-net encoder network for effective polyp image segmentation." Image and Vision Computing 137 (2023): 104767.
33. Li, Pengyu, Wenhao Wu, Lanxiang Liu, Fardad Michael Serry, Jinjia Wang, and Hui Han. "Automatic brain tumor segmentation from Multiparametric MRI based on cascaded 3D U-Net and 3D U-Net++." Biomedical Signal Processing and Control 78 (2022): 103979.
34. Zhou, Tao, XinYu Ye, HuiLing Lu, XiaominZheng, Shi Qiu, and YunCan Liu. "Dense convolutional network and its application in medical image analysis." BioMed Research International 2022 (2022).
35. Yin, Xiao-Xia, Le Sun, Yuhan Fu, Ruiliang Lu, and Yanchun Zhang. "U-Net-Based medical image segmentation." Journal of Healthcare Engineering 2022 (2022).
36. Gupta, Meenu, Karan Jakhar, Avneet Kaur, and Fadi Al-Turjman. "Deep learning-based segmentation and analysis of pneumothorax using chest X-ray images." In AIP Conference Proceedings, vol. 2555, no. 1. AIP Publishing, 2022.
37. Eguchi, Takashi, Toshihiko Sato, and Kimihiro Shimizu. "Technical advances in segmentectomy for lung cancer: a minimally invasive strategy for deep, small, and impalpable tumors." Cancers 13, no. 13 (2021): 3137.
38. Malhotra, Priyanka, Sheifali Gupta, and Deepika Koundal. "Comparative Analysis of Deep Learning Based Automated Segmentation of Pneumothorax on Chest X-Ray Images." ECS Transactions 107, no. 1 (2022): 8905.
39. Upasana, C., Anand Shanker Tewari, and Jyoti Prakash Singh. "An Attention-based Pneumothorax Classification using Modified Xception Model." Procedia Computer Science 218 (2023): 74-82.
40. Moses, Daniel A. "Deep learning applied to automatic disease detection using chest x‐rays." Journal of Medical Imaging and Radiation Oncology 65, no. 5 (2021): 498-517.
41. Anis, Shazia, Khin Wee Lai, Joon Huang Chuah, Shoaib Mohammad Ali, Hamidreza Mohafez, Maryam Hadizadeh, Ding Yan, and Zhi-Chao Ong. "An overview of deep learning approaches in chest radiograph." IEEE Access 8 (2020): 182347-182354.
42. Agrawal, Tarun, and Prakash Choudhary. "Segmentation and classification on chest radiography: a systematic survey." The Visual Computer 39, no. 3 (2023): 875-913.