Lung Cancer Detection A review

Milind E. Rane

Abstract- Lung cancer is the leading causes of cancer deaths, resulting in approximately 1.8 mil. Causalities in 2022, roughly 19% of Cancer patients. An estimated 2.5 million new cases of lung cancer occur each year. Early detection is closely related to the improvement of patient outcomes. Enhanced diagnostic capabilities have been made possible owing to the surge in deep learning. This paper presents the review of state of art techniques for detecting early-stage lung nodules in chest X-ray images using deep learning techniques. Accordingly, several methods for handling class imbalances and enhancing rib suppression were adapted, which greatly improved the performance of the generalization of the system and diagnostic accuracy. The techniques identifies possible cancerous regions for further clinical investigation, thus allowing for timely medical intervention that offers a pathway toward better patient outcomes.

Keywords— *Lung Cancer Detection, Chest X-ray Imaging, Convolutional Neural Network (CNN), Deep Learning model, Medical Image Analysis, Cancer Localization, Early Diagnosis.*

INTRODUCTION

Lung cancer remains one of the deadliest types of cancer and continues to be the reason in highest number of deaths due to cancer-related causes; survival rates consistently degrade as the disease progresses. The survival rate for lung cancer will be dramatically improved when this disease is detected in its initials, curable steps, thus early diagnosis is very important for the best outcomes. Cancer is diagnosed today through expensive CT scans and biopsies, which require proper interpretation by a highly qualified radiologist. These diagnostic processes are usually difficult in environments with limited access to experts and cutting-edge tools. On the other hand, chest X-rays are readily available, inexpensive, and prove to be an essential tool for screening respiratory diseases. Although CXRs are very useful, their limitations come in the form of poor sensitivity for small nodules in the early stages of cancer. The rib cage obstructs the view, often missed diagnosis or false negatives specially with the small nodules or behind the ribs. Therefore, more advanced techniques that can distinguish lung tissue from other structures like ribs are crucial in enhancing the detection in CXRs. A strong potential in enhancing detection for lung cancer through deep learning models, especially CNNs. CNNs demonstrated outstanding performance in a wide range of applications related to medical images because of its ability to recognize intricate patterns of images and subtle tissues' malformations. Earlier research work, which include Chiu et al.[1], Shimazaki et al.[2], and others, previously considered the efficiency of CNN-based models for improving early-stage lung cancer detection.

LITERATURE REVIEW

Paper presents learning methods used for the lung nodule detection from images, pointing out key architectures, including CNNs, FCNs, and reinforcement models. Several different studies highlight some improvements in accuracy and sensitivity. One such notable method involves multi-section CNN and 3D networks, particularly designed to minimize false positives. Deep learning is emphasized in the discussion regarding the needed automated systems for the minimization of clinical applications involving the occurrence of false positives. Studies by researchers such as Sreeprada et al. [3] highlight the application of a hybrid CNN along with SVM classification with tuned hyperparameters, which is based on orthogonal Convolution neural network-support vector machine OCNN-SVM model for lung nodule detection and classification. The use of pre-trained models like EfficientNetB1 [4], DenseNet [5,6] and ResNet [7] have shown to improve accuracy in identifying malignant nodules from chest X-ray and CT images.

Das et.al. [8] presents effectiveness of machine learning approaches for tissue identification is compared in another research. The method is applied to train models, test them on test data, split datasets, and perform k-fold cross-validation to compare accuracies. At 99.2%, SVM had the highest accuracy. Logistic Regression also performed well on the UCI dataset with 96.9% accuracy. The results demonstrate that SVM is the best classifier for detection. Tekade et.al.[9] demonstrate set of classifiers have been used on the lung cancer data-set, including KNN, SVM, Neural Networks, and Logistic Regression. Among these, SVM achieved the highest accuracy, which is at a high-end performance of 99.3%. Being applied to such medical datasets would significantly enhance doctors' decision-making efficacy. Nair et.al.[10] researched reviews the causes of chest cancer and application of ml algorithms prediction and diagnosis, highlighting their strengths and weaknesses. Existing advancements in this learning did well in really revolutionizing the analysis of medical imaging. Such algorithms expand image classification capabilities while facilitating. This paper reviews some of their applications in healthcare, highlighting the high potential for greatly improving the accuracy of diagnoses and the outcome in the care of patients. Roy et.al. [11] shows to identify pulmonary nodules in chest CT images, his research assesses two computer-aided detection techniques based on deep learning. Results shows that the detection rates of nodules improved significantly for both systems; however, there was no effect on the accuracy of Lung RADS classification or the false positive rate. In conclusion, AI has vast potential in radiology [12] Further, IDLA, featuring CNN to classify, data pre-processing, and specific metrics like perimeter and eccentricity. This approach introduces an early detection of and forecasting for image processing and artificial intelligence kinds. Here, the present approaches to diagnostic methods, which normally diagnose diseases at their worse stages, are highlighted. Integration of the proposed model with a CNN will help to extract features from computed tomography images to enhance diagnosis with a better reduction in time and cost. The system will provide real-time consultation through its web-based interface, enhancing patient survival rates. The study concludes cancer detection means vastly beneficial early diagnosis and management strategies. Redddy et.al. [13] study comes across a system that employs a custom CNN architecture alongside ResNet-50, Inception V3, and Xception, using a Kaggle-derived CT image dataset with extensive preprocessing and hold-out validation for robust classification. This paper elaborates on the application of different deep architectures in classifying various types of lung malignancy that grabbed from imputs. Authors have proposed learned CNN and tested its performance with the existing architecture, such as ResNet50, InceptionV3, and Xception. The other architectures are based on preexisting transfer mechanisms, while the CNN is learned for this specific task. All these models are compared based on accuracy, AUC, recall, and loss. The testing accuracy is 92% with an AUC of 98.21%, and this concludes that the custom CNN is better than those other models in this paper by Chiu et.al. [1]

Another technique used a CNN approach, which consisted of an encoder-decoder architecture and black-and-white inversion for image augmentation with a 5-fold cross-validation approach to training and validation of the model using FROC analysis. Another paper used a deep learning model, developed and validated by segment, in an attempt to detect lung tumors on chest radiographs. It could be calibrated to detect well with a minimum number of false positives in the test dataset radiographs after being cross-validated on these radiographs, which reported a detection rate of 0.73 and 0.13 mean errors per picture as given by Shimazaki et.al. [2]. Imran et.al. [14] One such proposed method integrates Multiresolution Rigid Registration (MRR) and DWT-PCAv techniques for enhancing medical CT images. It ensures precise alignment of images, enabling accurate diagnostic information. Additionally, lung nodule detection employs optimal thresholding and rule-based classification, enhancing nodule identification and classification accuracy using a ResNet-18 CNN architecture. It has estimated the Lung CT images by the proposed MRR technique using the LIDC dataset. The desired image quality criteria such as the higher value of MI, PSNR, and SSIM with lesser RMSE and SSD are validated by applying quantitative measures like MI, PSNR, SSIM, and RMSE. For the above standard methods, proposed technique outperforms SRR. Total performance is evaluated by making use of around 4,000 images from some patients. It gives that MRR is superior to SRR in fusion quality particularly concerning the sharper and aligned image. **presents** a particular study employs an ensemble learning approach using multiple 2D CNN architectures to enhance detection from scans in the LUNA dataset. Unique features include data augmentation to address class imbalance, a deep ensemble architecture with varied kernel sizes, and precise performance metrics for evaluating model accuracy. LUNA 16 The limitations which had so far restrained previous works on lung cancer identification are just dealt with by an ensemble learning approach based on CNNs. Based on the LUNA 16 dataset, this paper develops a Deep Ensemble network to detect cancer tissues. Pre-processing steps of data start with augmentation to balance classes and convert CT images into usable format. It resulted in the final combination of predictions toward the objective with a combination of different CNNs working together to extract features, giving more accuracy of accuracy, precision, and recall as reported by Shah et.al.[15]. Combining MobileNet V3-Small for image classification with DenseNet in feature extraction, this model relies on a large, freely available PET/CT dataset using advanced preprocessing and augmentation of the images. The noise reduction is also put together with alignment and dimensionality reduction to further ensure that there is an efficiency as well as accuracy of the model. The quality of medical images affects feature segmentation methods, and therefore, noise and low resolution significantly strain the extraction of effective features from noisy and low-resolution PET/CT images. The denseNet-121 model happens to be efficient enough in extracting complex information but, with it, there are issues of vanishing gradients. MobileNet V3-Small can be a light-weight model but is used primarily for mobile applications. In simple terms, the MobileNet V3-Small classifier makes use of pretreatment in order to improve the quality of the data set, and DenseNet may be utilized as a feature extractor in this study given by Wahab et.al.[16]. The hybrid CNN-RNN model, detects cancer cell using Hybrid NN, is proposed in order to identify lung cancer in its initial stages. The advanced algorithm AI extracts feature more accurately from the CT scans. It classifies the nodules into benign and malignant categories wherein it carries out evaluation based on comprehensive datasets. The CCDC-HNN structure is the proposed framework by making use of the hybrid 3D Network and Bi-directional LSTM model placed to ensure better detection of lung cancer with given CT images. Results obtained using the LUNA 16 dataset for the study were accomplished in accuracy with high efficiency concerning the classification of malignant lung nodules. The framework thus presented was thus giving an accuracy of 95% and specificity/sensitivity to be 90% and 87% above traditional models. It therefore represents the capability of this approaches in performing early diagnosis of cancer and thus calls for further research in model interpretability and quality of training data provided in Shalini et.al.[17],

Kumar et.al.[18] gives ResNet models are applied to leverage transfer learning for enhancing the classification. A robust dataset of thousands of images is used and applied data augmentation for robustness. Most importantly indicating deep learning can enhance the diagnostic accuracy. Recently, these approaches in lung cancer detection have also been evaluated. For instance, the accuracy rate of the EfficientNet-B3 model was superior to the earlier models because they were also effective for lung cancer identification but with an accuracy rate of 99.44%. Therefore, these trends indicate that deep learning might significantly improve early lung tissue identification with a better outcome. Kalaivani et.al.[19] presents model uses CNN to classify lung affected images with the help of augmentation. It has employed more powerful pre-processing techniques like median as well as Gaussian filtering combined together with Adaptive Boosting for better accuracies. It is using the web portal for accessing the patient's results and further references. It enunciates a framework towards detection through DenseNet architecture and the adaptive boosting algorithm. A total of 201 images of the lungs were detected on a database with a model that had an accuracy of 90.85% for its application, thereby significantly increasing the prospects of early diagnosis. This network is henceforth included to facilitate smooth picture interpretation and emphasize early identification to increase the survival rate of the patients suffering from lung cancer.

Additional papers introduce methodology which outlines CNNs' architecture, emphasizing layers like convolution, pooling, and fully connected. VGG16 focuses on consistent 3x3 filters, while Inception V3 employs parallel layers with varied filter sizes for efficiency. ResNet-50 introduces residual mappings to enhance depth without sacrificing accuracy, mitigating issues like vanishing gradients in deep networks. This study discusses various architectures of different models, along with their special characteristics, advantages, and usage in image classification. The authors are emphasizing the importance of designing layers and optimizing techniques such as gradient descent for building efficient models with adequate accuracy on complex datasets as mentioned by Vani et.al.[20]. This design distinguishes between photos of lung cancer and those that are not. The model employs a number of layers, including fully connected, pooling, and convolutional layers, with the use of strategies, including activation functions and dropout, in order to avoid overfitting. Special characteristics include activation functions like ReLU and SoftMax for non-linearity, dropout layers to avoid overfitting, sparse categorical cross-entropy loss, and optimizers to apply the task being a classification problem. It had already split the 3000 photos between both training and evaluation subsets, and with this distribution, it was reaching a validation accuracy of somewhere close to 72% as given in Aluka et.al.[21]. A study proposed by Eldho et.al.[22] AI-based 3D-DLCNN model enhances pulmonary nodule detection by employing a three-dimensional convolutional network, focusing on early identification. Key features include using CT-DICOM datasets, nodule classification via 3D Mask-R-CNN, error point removal through KDE, and severity analysis to improve accuracy over traditional methods. Authors, for the first time, proposed 3D CNN to beginner cell detection and segregations from DICOM captures. Model has established rate of accuracy of 93% with obvious sensitivity (92.7%) and specificity (93.4%) improvements. The AUC-ROC values reveal an AUC of 0.8 and thus minimum false positive 6.6% and false negative 6.4%, which clearly establishes the superiority of the method in question various techniques. The autonomous lung nodule identification system is built around a multi-modal model and follows various data augmentation strategies for variated training. For performance evaluation, it incorporates metrics and ROC curves. Heatmaps improve the interpretability and can result in high precision along with effectiveness in malignant areas of medical image detection.

Thanoon et.al.[23] provided an overview of applications in the detection and screening of lung, namely with imaging, Convolutional Networks were emphasized as effective instruments for issues with grouping and division. The paper discussed CNNs for feature extraction, recurrent neural networks (RNNs), and hybrid designs that combine both techniques, classifying them according to their methodology. Hosseini et.al.[24] give a review with noted challenges such as the interpretability and large annotated datasets required, but correctly pointed out that CNNs proved very effective at distinguishing between benign and malignant nodules. It also spoke of deep learning how it could assist radiologists, reduce errors, and accelerate the speed of diagnosis to aid early detection. The review further talks about transfer learning as helping improve generalization over a smaller dataset, which is still a significant challenge in medical imaging. Yu et.al. [25] study on the use of clinical diagnostics focused on the effectiveness in the detection as well as classification of lung cancer. It has considered designs of CNNS, ResNet, and EfficientNet for detection and classification in the case of lung malignancy. Although a detailed investigation revealed that overfitting and deficiency in data might be significant problems, therefore, improvements to data and learning through transfer strategies may reduce these problems. By suggesting hybrid models of CNNs and RNNs to deal with the multidimensional problems of lung cancer diagnosis, results from further research shall be incorporated to provide further directions for future work. This analysis reveals that there is still research to be done in enhancing the interpretability and accuracy of diagnosis of such approaches and hence makes it a road to enrich the current mainstream detection methods of lung cancer by applying the novel structures.

Riquelme et. al. [26] research on CAD programs for malignancy assessed techniques like as CNNs for image identification of lung nodules. The study analyzed model sensitivity, with performance ranging from 61.61% to 98.10%, and classification accuracy varying between 75.01% and 97.58%. False-positive rates per scan ranged from 0.125 to 32, highlighting CNNs' significant success in lung cancer detection. Additionally, it discussed limitations such as high false-positive rates and interpretability, emphasizing the need for fine-tuning algorithms. This review underscored CAD systems' potential in assisting radiologists with early cancer detection but recommended improvements in false-positive reduction methods to reduce unnecessary biopsies. A research divided CAD systems into groups based on erroneous reductions and nodule detection. highlighting deep learning advancements in both areas. The researchers reviewed CNN-based approaches and found that CNNs had achieved high sensitivity and specificity in nodule detection tasks. However, challenges like data annotation and model generalization persisted, with the authors suggesting additional training data and more complex networks to overcome these issues. This study pointed out that CNN-based CAD systems could significantly assist radiologists by providing consistent and reliable assessments, particularly for difficult-to-detect nodules, but that improvements in model generalizability and interpretability are necessary for widespread clinical adoption Al-Yasriy et.al.[27]. Additional research work used a CNN model based on Alex-Net and classified lung scans. With a great accuracy of 93.548% in classifying, the sensitive value being 95.714%, and specific value being at 95%, the model showed potential promise for classifying and early diagnosis of lung cancer stage. Although the CNN model provided promising results, it would be a severely limited reliability since it was trained on a dataset. Work focuses on the potential of CNNs in assisting early diagnosis via incredibly accurate automated categorization that can aid radiologists in making fast critical decisions for patient care Wang et.al.[28]. One such paper proposed a SVM model classifying lung cancer cells as benign or malignant. Image preprocessing steps included smoothing, segmentation, and feature extraction to improve accuracy. SVM was chosen for its robustness with high-dimensional data, achieving promising detection accuracy. This study highlighted the importance of SVMs for lung cancer classification, particularly given their interpretability and ability to perform well with smaller, curated datasets. The research demonstrated the efficacy of SVMs in distinguishing malignancies, thereby underscoring their potential role in aiding diagnostic workflows Firmino et.al.[29].

The Comparative studies of this literature review has been done and it is as given below in Table 1

Authors	**Method Used**	**Cons**	**Accuracies**	**Database Used.**
[9] Tekade, R.	U-Net Architeture to find lung nodules	lacks a comprehensive evaluation of model accuracy across diverse datasets	Training Accuracy of 95%	LUNA-16
[16]Wahab Sait	Median Filter to eliminate impulse noise	lacks a practical implementation analysis	Testing Accuracy of 92%	NIH ChestX-ray
[1] Chiu HY	YOLOv4-based lung nodule detection	challenge of distinguishing between benign and malignant nodules	Binary accuracy 85%	VGHTPE testing dataset
[21]Aluka, M.	Own CNN model with ten layers	lacks extensive details on model performance	Binary Accuracy of 94%	NIH Chest
[22] K. J. Eldho	3D deep learning convolutional neural network	intensive processing required for 3D CNN models	93%	DICOM images
[29] Firmino, M	Computer-Aided Detection systems	lacks a thorough examination of practical challenges, such as the system's reliance	90.20%	NIH Chest
[15]Shah, A.A.,	deep ensemble 2D CNN architecture	lacks a detailed analysis of the computational cost	95%	NIH Chest
[2] Shimazaki, A.,	segmentation method	relatively low sensitivity for detecting lung cancer lesions	80%	chest radiographs
[18] N. Kalaivani,	Deep CNN network	model's classification may not enforce accurate categorization of nodules	Binary 90.85%	chest radiographs
[24] Hosseini, S.H.,	Local Response Normalization (LRN) with AlexNet	Should work on large datasets	~90%	NIH chest X-ray
[12]Peters, A.A.,	AI Assistant techniques.	not fully represent the diverse range of clinical conditions	82%	Large scale validation of the M5L lung
[13] Reddy	IDLA for lung cancer detection	The paper does not explore potential challenges in the scalability	92%	LUNA16 dataset

***Table 1** Comparetive Studies of literature reviews*

CONCLUSION
This review work adopts multiple techniques like Machine Learning, Deep Learning and Artificial Intelligence for clinical diagnostics applications for early detection of lung cancer. Current limitations are like accuracy, reliability across diverse patient demographics and diagnosis under resource constraint environment can be addressed in future work through innovative methodologies. This study contributes to the broader field of medical imaging for early lung cancer detection.

REFERENCE

[1] Chiu HY, Peng RH, Lin YC, Wang TW, Yang YX, Chen YY, Wu MH, Shiao TH, Chao HS, Chen YM, Wu YT. Artificial Intelligence for Early Detection of Chest Nodules in X-ray Images. Biomedicines. 2022 Nov 7;10(11):2839. doi: 10.3390/biomedicines10112839. PMID: 36359360; PMCID: PMC9687210.
[2] Shimazaki, A., Ueda, D., Choppin, A. et al. Deep learning-based algorithm for lung cancer detection on chest radiographs using the segmentation method. Sci Rep 12, 727 (2022).
[3] V. Sreeprada, K. Vedavathi, "Lung Cancer Detection from X-Ray Images using Hybrid Deep Learning Technique," Procedia Computer Science, Vol. 230, 2023,pp. 467-474, doi.org/10.1016/j.procs.2023.12.102..

[4] Rabia Javed, Tanzila Saba, Tahani Jaser Alahmadi, Sarah Al-Otaibi, Bayan AlGhofaily, Amjad Rehman, “EfficientNetB1 Deep Learning Model for Microscopic Lung Cancer Lesion Detection and Classification Using Histopathological Images,” Computers, Materials and Continua, Vol. 81, Issue 1, 2024,pp/ 809-825, doi.org/10.32604/cmc.2024.052755.
[5] Huang, G., Liu, Z., Van Der Maaten, L., et al., “*Densely Connected Convolutional Networks.,”* IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017.
[6] Madhusudan G Lanjewar, Kamini G Panchbhai, Panem Charanarur, “Lung cancer detection from CT scans using modified DenseNet with feature selection methods and ML classifiers,” Expert Systems with Applications, Vol. 224, 2023, doi.org/10.1016/j.eswa.2023.119961.
[7] Habeeb, Zeyad Qasim and Alzaydi, Emad Qasim, Modified Resnet Model for Medical Image-Based Lung Cancer Detection. doi.org/10.2139/ssrn.5027762
[8] Das, S., & Majumder, S. (2020). Lung Cancer Detection Using Deep Learning Network: A Comparative Analysis. 2020 Fifth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN).
[9] Tekade, R., & Rajeswari, K. (2018). Lung Cancer Detection and Classification Using Deep Learning. 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA).
[10] PR, R., Nair, R. A. S., & G, V. (2019). A Comparative Study of Lung Cancer Detection using Machine Learning Algorithms. 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT). doi:10.1109/icecct.2019.8869001
[11] Roy, K., Chaudhury, S. S., Burman, M., Ganguly, A., Dutta, C., Banik, S., & Banik, R. (2019). A Comparative study of Lung Cancer detection using supervised neural network. 2019 International Conference on Opto-Electronics and Applied Optics (Optronix)
[12] Peters, A.A., Wiescholek, N., Müller, M. et al. Impact of artificial intelligence assistance on pulmonary nodule detection and localization in chest CT: a comparative study among radiologists of varying experience levels. Sci Rep 14, 22447 (2024). https://doi.org/10.1038/s41598-024-73435-3.
[13] Reddy, N. & Khanaa, V.. (2023). Intelligent deep learning algorithm for lung cancer detection and classification. Bulletin of Electrical Engineering and Informatics.
[14] Imran Nazir, Ihsan ul Haq, Salman A. AlQahtani, Muhammad Mohsin Jadoon, and Mostafa Dahshan, “Machine Learning-Based Lung Cancer Detection Using Multiview Image Registration and Fusion,” Journal of Healthcare Engineering, August 16, 2023.
[15] Shah, A.A., Malik, H.A.M., Muhammad, A. et al. Deep learning ensemble 2D CNN approach towards the detection of lung cancer. Sci Rep 13, 2987 (2023).
[16] Wahab Sait, Abdul Rahaman. 2023. "Lung Cancer Detection Model Using Deep Learning Technique" Applied Sciences 13, no. 22: 12510.
[17] Shalini Wankhade, Vigneshwari S., A novel hybrid deep learning method for early detection of lung cancer using neural networks,Healthcare Analytics,Volume 3,2023,100195, ISSN 2772-4425.
[18] Kumar, V., Prabha, C., Sharma, P. et al. Unified deep learning models for enhanced lung cancer prediction with ResNet-50–101 and EfficientNet-B3 using DICOM images. BMC Med Imaging 24, 63 (2024).
[19] N. Kalaivani, N. Manimaran, S. Sophia, and D. D. Devi, “Deep Learning Based Lung Cancer Detection and Classification,” in IOP Conference Series: Materials Science and Engineering, vol. 994, International Conference on Recent Developments in Robotics, Embedded and Internet of Things (ICRDREIOT2020), Tamil Nadu, India, October 16–17, 2020.
[20] Vani Rajasekar, M.P. Vaishnnave, S. Premkumar, Velliangiri Sarveshwaran, V. Rangaraaj, Lung cancer disease prediction with CT scan and histopathological images feature analysis using deep learning techniques,Results in Engineering,Volume 18,2023,101111, ISSN 2590-1230
[21] Aluka, M. ., Dixit, R. ., & Kumar, P. . (2023). Enhancing and Detecting the Lung Cancer using Deep Learning. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3s), 127–134.
[22] K. J. Eldho and S. Nithyanandh, “Lung Cancer Detection and Severity Analysis with a 3D Deep Learning CNN Model Using CT-DICOM Clinical Dataset,” Indian Journal of Science and Technology 17, no. 10 (2024): 899–910
[23] Thanoon, Mohammad A., Mohd Asyraf Zulkifley, Muhammad Ammirrul Atiqi Mohd Zainuri, and Siti Raihanah Abdani. 2023. "A Review of Deep Learning Techniques for Lung Cancer Screening and Diagnosis Based on CT Images" Diagnostics 13, no. 16: 2617. https://doi.org/10.3390/diagnostics13162617
[24] Hosseini, S.H., Monsefi, R. & Shadroo, S. Deep learning applications for lung cancer diagnosis: A systematic review. Multimed Tools Appl 83, 14305–14335 (2024). https://doi.org/10.1007/s11042-023-16046-w
[25] Yu Gu, Jingqian Chi, Jiaqi Liu, Lidong Yang, Baohua Zhang, Dahua Yu, Ying Zhao, Xiaoqi Lu, A survey of computer-aided diagnosis of lung nodules from CT scans using deep learning, Computers in Biology and Medicine, Volume 137, 2021, 104806, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2021.104806.
[26] Riquelme, Diego, and Moulay A. Akhloufi. 2020. "Deep Learning for Lung Cancer Nodules Detection and Classification in CT Scans" AI 1, no. 1: 28-67. https://doi.org/10.3390/ai1010003
[27] Al-Yasriy, Hamdalla F., Muayed S. AL-Husieny, Furat Y. Mohsen, Enam A. Khalil, and Zainab S. Hassan. "Diagnosis of Lung Cancer Based on CT Scans Using CNN." In IOP Conference Series: Materials Science and Engineering, vol. 928, 2nd International Scientific Conference of Al-Ayen University (ISCAU-2020), July 15-16, 2020, Thi-Qar, Iraq. Published by IOP Publishing Ltd, 2020. doi:10.1088/1757-899X/928/2/022035.
[28] Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, Ronald M. Summers. ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly- Supervised Classification and Localization of Common Thorax Diseases, IEEE CVPR, pp. 3462-3471,2017

[29] Firmino, M., Morais, A.H., Mendoça, R.M. et al. Computer-aided detection system for lung cancer in computed tomography scans: Review and future prospects. BioMed Eng OnLine 13, 41 (2014). https://doi.org/10.1186/1475-925X-13-