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COMPREHENSIVE REVIEW OF CAD-BASED LUNG CANCER DETECTION TECHNIQUES

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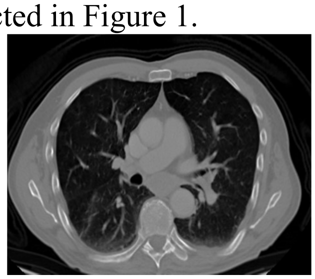
ABSTRACT :
Lung cancer originates in the tissues lining the airways of the lungs and is a primary cause of demise for both men and women. It is categorized into two types: small cell lung cancer and non-small cell lung cancer. Each type exhibits unique growth patterns and requires specific treatments. Signs of lung cancer include tireless coughing, coughing up blood, habitual chest infections, squatness of breath, fatigue and pain when breathing or coughing. Lung cancer often spreads to areas such as the brain and bones, leading to additional symptoms like headaches and nausea. The objective of this research is to provide an in-depth analysis of Computer-Aided Design (CAD) systems, their processing methods, and their role in lung cancer detection and classification. This study reviews published research over a ten-year period, offering valuable insights for researchers interested in CAD systems and lung cancer.
Keywords: Computer-Aided Diagnosis (CAD), Artificial Intelligence (AI), Deep Learning (DL), Neural Network (NW), Lung Cancer, Nodules.

INTRODUCTION:

Lung cancer is the most frequently diagnosed cancer globally and is especially prevalent in developing countries. It accounts for a significant number of new cancer cases and fatalities among both genders. Smoking is a major risk factor, contributing to 85% of male cases and 75% of female cases, while non-smokers represent 15% of cases due to factors such as genetics, radon gas exposure, asbestos, passive smoking, and air pollution. Early detection of lung cancer through CT imaging can increase the ten-year survival rate to 90%. Computer-aided detection (CAD) systems assist radiologists by analyzing CT images and highlighting potential abnormalities, helping reduce false negatives. CAD systems play a vital role in radiology by providing a second opinion and improving diagnostic accuracy. They should minimize false positives, deliver fast results, and require low maintenance and training costs. Despite the benefits, lung cancer screening faces challenges such as limited accessibility and the risk of over diagnosis, often due to false positives. Developing an accurate lung cancer risk prediction model and improving screening strategies can enhance detection effectiveness.

Medical imaging is a well-known research area in healthcare engineering, which aims to assist physicians in diagnosing diseases. After ten years, the candidates' survival rate can increase to 90% when lung cancer is detected early by CT imaging [2]. Therefore, our approach uses CT images. Computer assisted detection refers to a system that tests problematic elements on the images and notifies the radiologist of them so as to minimize false negative results. A healthy lung and a lung with cancer are depicted in Figure 1.



a) Cancerous Lung Image

b) Normal Lung Image

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Figure 1: Lung CT Contrast image of normal person and a person with cancer

Computer-aided diagnostic (CAD) systems are a great device for identifying and classifying various lesions in the context of lung cancer diagnosis. The primary objectives of such organizations are to support the radiologist throughout the entire inquiry process and to offer a second view on his results. One essential component of medical radiography technology is the CAD system. However, many systems lack the components that radiologists find most helpful for identifying and diagnosing disease. The methods listed below will help radiologists perform better by offering high diagnostic sensitivity. The formula for calculating sensitivity, as shown in the system's sensitivity chart, is TP/(TP+FN), where TP stands for true positive and shows the results obtained when a sample of patients had a positive response from the system. False positive results when the sample was infected are indicated by the symbol FN, which stands for false result. Few false positives (FP) should be generated by the system. FP will be the result each time a disease persists despite the sample showing none. In addition to prolonging the radiologist's detection time, more false positive results, or FP results, will result in incorrect disease diagnosis. The system must operate quickly. When a request for detection is made, it should react promptly. It should emphasize the low cost of system training, support, maintenance, and deployment. Tiny nodules, like those that are 3 mm in size or attached to the sides of the lung, should be picked up by it.

The lack of increased use of lung cancer screening techniques can be attributed to two important factors. Accessibility is one of the problems since radiology's capacity might not be able to meet demand [3]. Given the requirement for comprehensive and efficient training for the medical professionals assessing the images, over diagnosis is another significant issue that is commonly linked to false positive cases [4]. Previous studies' findings [5,6] that the benign incidence for a diagnostic procedure following nodule discovery can reach 40% emphasize the significance of comprehensive nodule surveillance before beginning any long-term treatments in order to reduce post-operative risk and avoid needless complexity or pulmonary function destruction.

An accurate lung cancer risk prediction model and a likelihood-customized approach are expected to increase the efficacy of lung cancer screening. The ideal CAD would mimic all three steps of a radiologist's examination of a chest CT scan in order to detect lung cancer. The first step is to identify an irregularity in the 3D image set that indicates the presence of one or possibly more Regions of Interest (ROI). An The first step is to identify an irregularity in the 3D image set that indicates the presence of one or possibly more regions of interest (ROI). A nodular opacity is an example of such an irregularity. A nodular opacity is an example of such an irregularity.

The next step is to extract all pertinent data about those ROIs, such as their dimensions, textures, and any connections to nearby regions. The collected features would then be used to classify the ROIs according to their likelihood of developing hate, often using established criteria [7]. Based on the results of the previous stage, the next step in patient management is chosen. CADs usually need to perform feature extraction in order to identify the voxels of interest in the ROI.

LITERATURE REVIEW:

Several automated and semi-automated techniques for detecting lung nodules have been proposed, typically following four stages: preprocessing, candidate extraction, false-positive reduction, and classification. Preprocessing techniques include various filtering methods such as bilateral filtering, Wiener filtering, Gaussian filtering, and high-pass filtering to remove noise and enhance image quality. Segmentation methods help isolates lung regions from surrounding structures. Threshold segmentation and region-based methods are commonly used, while texture-based techniques and statistical approaches

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like Expectation-Maximization (EM) provide additional precision. Advanced segmentation approaches include 3D morphological filtering, deformable models, and clustering algorithms.

The literature has proposed a number of approaches for the automatic and semi-automated exposure of lung nodules [8]. To find the pulmonary nodule, each of these investigations had to go through four steps: pre-processing, nodule candidate extraction, false positive reduction, and classification. These stages are explained in greater detail in Figure 2.

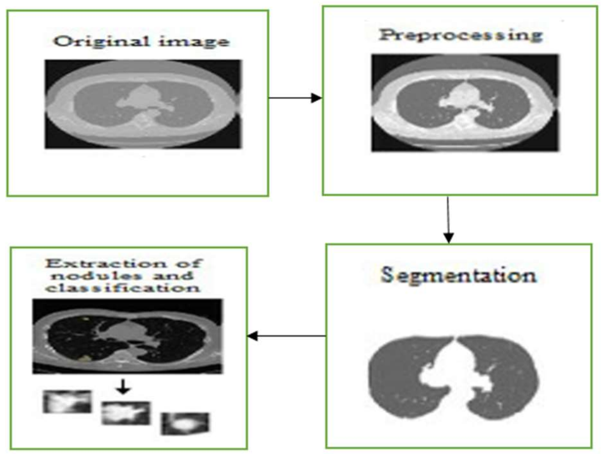

Figure 2. The Pipeline of lung nodule recognition system

The following section emphases on the various research involving these actions preprocessing, segmentation and extraction.

One of the finest techniques for identifying pulmonary nodules is computed tomography (CT) [9]. X-rays are used to collect structural and functional information about the human body. Nonetheless, the radiation dose significantly affects the quality of the CT image. A significant radiation dose improves image quality [10], but at the same time, more x-rays are caught by the lungs. As it shields the human body from all dangers, radiologists are grateful for the reduction in radiation dose, which impairs image quality and increases noise in lung CT scans.

A pre-processing procedure is employed to reduce the noise in these photos. Numerous filtering techniques, including bilateral filtering, wiener filtering, Gaussian filtering, and a particular high-pass filter, were proposed in the literature to eliminate these disturbances. Numerous other works chain median filters and Laplacian filters using a differential procedure that involves subtracting a nodule-suppressed image from a signal-improved image. Getting a differential image with nodule enhanced signal is the next stage [11].

Ochs et al. [12] proposed several pre-processing methods for processing medical images. Furthermore, whereas Paik et al. [13] used a spherical enhancement filter to increase the nodule-like arrangement in CT images and Bae et al. [14] employed a morphological filter to develop the image region,

According to the authors of [15], insufficient lighting during image acquisition results in poor contrast, which must be corrected by an adaptive median filtering. They created a low frequency image by substituting the median value calculated over a 5x5 pixel square for each pixel value. The distinction limited adaptive histogram equalization (CLAHE) method is then used to increase the dissimilarity of the CT pre-processed image.

However, in [16], Farag et al. contend that the filtering method should successfully reduce noise in synchronized physical regions, preserve object borders and fine structures, and sharpen discontinuities to enhance morphological features. The Wiener filter and an isotropic diffusion filter were both employed by the authors in their study.

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Additionally, a number of filters have been created to improve 3-D lung architecture photos. In order to improve vessels, Frangi et al. developed a 3D multi-scale structural improvement filter based on the Hessian matrix's eigenvalues [17]. Numerous research that employed filters based on the Hessian matrix's eigenvalues have previously employed this strategy [18]. More precisely, Rikxoort et al. [19] suggested the first supervised improvement technique based on single phase and multi-phase algorithms. The authors of [20] used a number of 3D morphological filters to separate the nodule from its environments, as well as nearby edifices like arteries and bronchi.

Segmenting the lung portions is the second step in the system for processing procedures. To distinguish the pixels that represent lung tissue from the surrounding structure, the pre-processed CT image is divided into various regions.

By designating all pixels as background and those that are greater than a certain value as foreground, the threshold segmentation method transforms a gray scale image into a binary image. In [21], the authors use gray level thresholding and mathematical morphology to select possible nodule candidates from CT data. To segment candidate nodule regions, the image is first histogram to establish two threshold values, and then it undergoes a multilayer thresholding step and a connected-component labeling phase. Farag et al. also used a simple thresholding technique to establish the strength characteristics of lung CT scans. [14] Seeded segmentation was used to eliminate the nodule candidates from the background picture [22], and thresholding was used to differentiate the juxtapose-pleural nodule from other structures.

In order to accomplish the initial segmentation of the pulmonary parenchyma, Shao et al. twice applied the adaptive iteration threshold method in the same scenario. Region-based segmentation methods are a unique subset of lung CT segmentation techniques. When determining object borders, these techniques often concentrate on the homogeneity of the image. The method that is most frequently utilized is region growing. By examining the subsequent pixels of the primary seed points, it regulates if the pixel neighbor should be included to the section and, if so, iterates on that choice. The homogeneity criterion requires that an object of interest have nearly constant or gradually changing intensity values, which is true for images of CT scans.

Further techniques tying together textural features, aside from the method for regions to expand, were put into practice in [8][10][16] last year, employed local binary patterns as textural characteristics and intensity histograms to create regions of interest (ROIs). Devaki et al. created the features that characterize the texture of common lung nodules by combining the SURF and the LBP descriptors. [10].

Statistics are used by stochastic approaches to establish the differences between the visible structures in lung pictures. In an effort to match the circulation of concentration values in an image to a set of statistical mathematical equations, numerous approaches have been developed. Each function defines a class and determines the probability that a concentration value belongs to that class based on its result. This methodology was used by Guo et al. when they established a lung segmentation method by fusing expectation-maximization (EM) analysis with morphological processes [28]. The authors use the (EM) algorithm to estimate the proper threshold value for lung segmentation after computing the image's histogram.

El-Baz et al. proposed the alternative segmentation method [22]. It uses Gibbs Markov Random Field (GMRF) to separate the lungs from the surrounding structures. The next step is to identify lung abnormalities using adaptive template matching and an inherited algorithm.

Using contour-based methods, the boundaries of a CT scan image are identified. Contour-based strategies can be regarded as into two groups: gradient-based approaches and deformable models. In [29] and [30], nodule images were segmented using deformable models. To identify the lung region, Kim et al. [49] used segmentation techniques such as thresholding, mathematical morphology, and

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deformable models. Bellotti et al. [31] engaged area expanding with form following to segregate between juxta-pleural nodules. [32] Zhao et al. enhanced shape-based segmentation with nodule gradient and sphere residence measures

After separating the lung from the original image using a genetic algorithm, Jaafar et al. used morphology and the Susan thinning approach to identify the lung's borders in [33]. Several methods for segmenting volumetric lung nodules are described in the literature. As illustrated in Figure 4, they can be divided into five groups: dynamic programming, deformable models, region growth, and mathematical morphology. Both Zhao et al. [33] and Yankelevitz et al. [33] used the thresholding technique, in which the K-Mean clustering or the average incline magnitudes algorithm can be used to get the proper threshold values. Table 1 presents a thorough evaluation of the techniques used to identify and classify lung cancer.

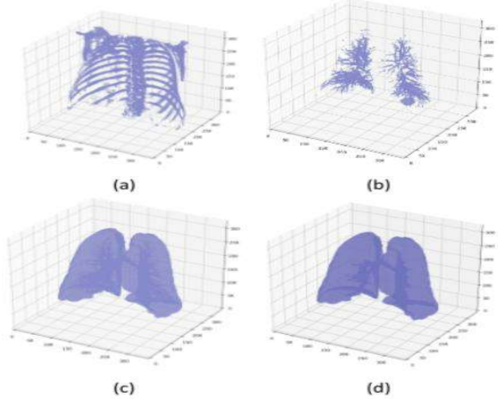

Figure 3. 3D Based Approach for Predicting Lung Cancer

Table 1. Review of Different Lung Classification Method

S.No	Authors	Methodology type	Image Type	Feature Description	Accuracy
1	Thakur, S. et al.	3D CNN	CT Images	3d pulmonary nodules detection	92
2	Pandian, R.	3D CNN	CT Images	Cyto pathological identification	83
3	Raunak Dey et al.	3d CNN, 3d multi - output network,3d Dense Net	3D CT Images	Low-dose CT images	86.84
4	Nicolas Coudray, Paolo Santiago Ocampo	Inspection V3 convolutional neural network , SVM, Naive Bayes	CT images	Training, validation and testing	96.1%

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5	Sneha Balannolla, A Kousar Nikhath	U-NET model, VGG-Net	CT images	Largest, average, smallest nodules detection ect	97.1
6	Shimpy Goyal, Rajiv Singh	FRNN-LSTM,SVM,K-NN	X-ray images, MRI images	Quality enhance filtering	95
7	Lei Cong, Wanbing Feng, Zhigang Yao	Least absolute shrinkage and selection operator, cross validation	CT images	Low -dose image, radiology features	84.8
8	Mohamed Shakeel, Mohd Aboobaider	CNN, deep belief network, FCN	2D,3D CT images	Images features (CAD)	97.3
9	Sean Blandin Knight	Enhanced bountiful clustering method (IPCT) ,deep learning promptly skilled neural network	CT images	Images preprocessing, images features	96.42
10	Siddharth Bhatia, Yash Sinha, Lavika Goel	Images acquisition, filtering segmentation	2D,3D , CT images	Images features algorithm, preprocessing techniques	95.68%
11	Suren Makaju et al.	Deep Residential Net, XGBoost Regresser, Random faster	CT images	Preprocessing, segmentation, normalization ect	84
12	Meraj Begum Shaikh Ismail	Gabor filter, watershed segmentation, ect	CT images	Classification of benign or malignant, images features	92%
13	Shah	CNN	CT images	Shape and texture	92.3%
14	Markaras	CNN	CT images	MTANN classifier	89%
15	Turkey and Swensen	CNN	CT images	Subjective feature	85.4%

RESULT AND DISCUSSION:

- **CNN and variants (56%)**: This includes a wide range of convolutional neural network methods like 3D CNN, CNN, VGG-Net, Dense Net, and other deep CNN architectures. These are most popular due to their strong performance in image processing tasks like nodule detection and classification.

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- **SVM (10%)**: Support Vector Machines are often used as classifiers, either standalone or in combination with CNN-based feature extraction.
- **Clustering and Filtering (13%)**: Techniques like IPCT, Gabor filters, and watershed segmentation focus on feature enhancement and segmentation before applying classification algorithms.
- **Other Techniques (13%)**: This includes less commonly used or supporting methods like LASSO, cross-validation, and ensemble methods.

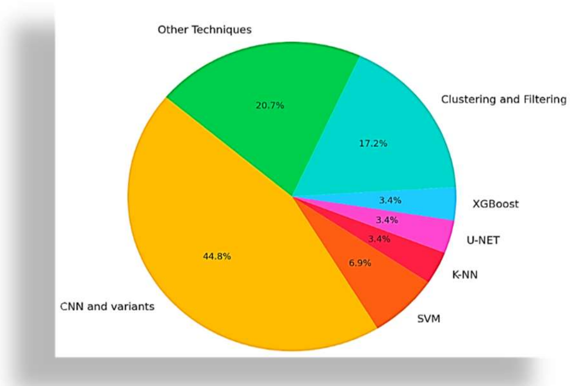

Figure 4 : Standard Methodological Frameworks

- **U-NET, K-NN, XGBoost (each ~3%)**: These are specialized methods with individual strengths, used less frequently but often in combination with CNNs or other networks.

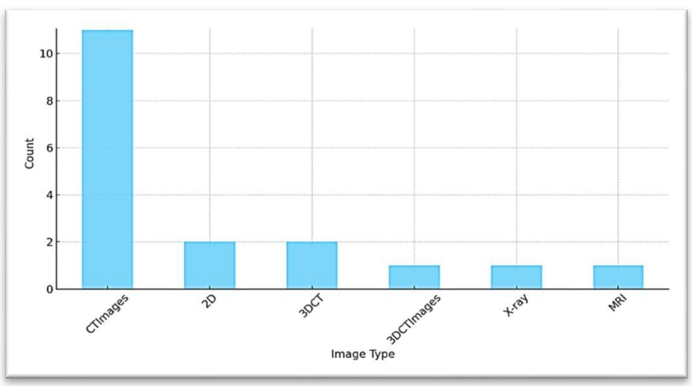

Figure 5 : Prevalence of Various Medical Image Types

Figure 5 visualizes the distribution of different medical image types used in a collection of 15 research studies focusing on deep learning and image processing techniques.

- **CT Images** are the most commonly used, appearing in **12 studies**, underscoring their importance in medical imaging and computer-aided diagnosis.
- **2D and 3D CT Images** were explicitly mentioned in **2 studies**, highlighting the evolution toward multi-dimensional data processing.
- **X-ray and MRI Images** appeared once, showing their niche application in combination with other imaging modalities.

This distribution reflects the dominance of CT imaging in the field, likely due to its detailed anatomical resolution and wide availability in clinical practice. It also highlights a trend toward using 3D imaging data for more robust model performance. Numerous studies have explored different methodologies for lung cancer detection and classification, primarily using convolutional neural networks (CNN). The accuracy of these methods varies depending on the dataset, image type, and features extracted. A

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comparison of existing techniques reveals that CNN-based methods achieve high accuracy, emphasizing the importance of feature extraction and preprocessing in improving classification outcomes.

CONCLUSION:

Lung cancer remains a leading cause of mortality, with increasing prevalence. CAD systems play a crucial role in improving early detection through preprocessing, segmentation, and classification techniques. Current research highlights the effectiveness of various algorithms, but further advancements are needed to enhance sensitivity, reduce false positives, and improve automation levels. The integration of CAD systems with electronic health records can further optimize diagnostic processes. Future advancements in technology and automation will facilitate the early detection of lung cancer, aiding in timely intervention and improved patient outcomes.

REFERENCE :

1. Thakur, S. K., Singh, D. P., & Choudhary, J. (2020). Lung cancer identification: a review on detection and classification. Cancer and Metastasis Reviews, 39, 989-998.
2. Pandian, R., Vedanarayanan, V., Kumar, D. R., & Rajakumar, R. (2022). Detection and classification of lung cancer using CNN and Google net. Measurement: Sensors, 24, 100588
3. Homma, N. (2011). CT Image based computer-aided lung cancer diagnosis. Theory and applications of CT imaging and analysis, 3-14.
4. Analysis, Prof. Noriyasu Homma (Ed.), ISBN: 978-953-307-2340,InTech,Availablefrom
5. Mahersia, H., Zaroug, M., & Gabralla, L. (2015). Lung cancer detection on CT scan images: a review on the analysis techniques. Lung Cancer, 4(4).
6. .Bong, C. W., Yoong Lam, H., & Kamarulzaman, H. (2012). A novel image segmentation technique for lung computed tomography images. In Knowledge Technology: Third Knowledge Technology Week, KTW 2011, Kajang, Malaysia, July 18-22, 2011. Revised Selected Papers (pp. 103-112). Springer Berlin Heidelberg.
7. Caselles, V., Kimmel, R., Sapiro, G., & Sbert, C. (1997). Minimal surfaces based object segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 19(4), 394-398.
8. Chiou, Y. S., Lure, Y. F., Freedman, M. T., & Fritz, S. (1993, June). Application of neural network based hybrid system for lung nodule detection. In [1993] Computer-Based Medical Systems-Proceedings of the Sixth Annual IEEE Symposium (pp. 211-216). IEEE.
9. Choi, W. J., Majid, A., & Choi, T. S. (2009). Computerized Detection of Pulmonary Nodule Based on Two-Dimensional PCA. In Computational Science and Its Applications–ICCSA 2009: International Conference, Seoul, Korea, June 29-July 2, 2009, Proceedings, Part II 9 (pp. 693-702). Springer Berlin Heidelberg.
10. Ceylan, M., ÖZBAY, Y., UÇAN, O. N., & Yildirim, E. (2010). A novel method for lung segmentation on chest CT images: complex-valued artificial neural network with complex wavelet transform. Turkish Journal of Electrical Engineering and Computer Sciences, 18(4), 613-624.
11. El-Bazl, A., Farag, A. A., Falk, R., & La Rocca, R. (2003, April). Automatic identification of lung abnormalities in chest spiral CT scans. In 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03). (Vol. 2, pp. II-261). IEEE.
12. El-Baz, A., Gimel'farb, G., Falk, R., & El-Ghar, M. A. (2011). 3D MGRF-based appearance modeling for robust segmentation of pulmonary nodules in 3D LDCT chest images. Lung imaging and computer aided diagnosis, 3, 51-63.

Copyright @ 2025 Author

ISSN: 2278-4632
Vol-15, Issue-07, No.01, July: 2025

13. El-Baz, A., Farag, A., Gimel'farb, G., Falk, R., El-Ghar, M. A., & Eldiasty, T. (2006, August). A framework for automatic segmentation of lung nodules from low dose chest CT scans. In 18th International Conference on Pattern Recognition (ICPR'06) (Vol. 3, pp. 611-614). IEEE.
14. Kumar, S. L., Swathy, M., Sathish, S., Sivaraman, J., & Rajasekar, M. (2016). Identification of lung cancer cell using watershed segmentation on CT images. Indian Journal of Science and Technology, 9(1), 1-4.
15. Neto, E. D. A. L., Cordeiro, G. M., & De Carvalho, F. D. A. (2011). Bivariate symbolic regression models for interval-valued variables. Journal of Statistical Computation and Simulation, 81(11), 1727-1744.
16. Ezoe, T., Takizawa, H., Yamamoto, S., Shimizu, A., Matsumoto, T., Tateno, Y., ... & Matsumoto, M. (2002, May). Automatic detection method of lung cancers including ground-glass opacities from chest X-ray CT images. In Medical Imaging 2002: Image Processing (Vol. 4684, pp. 1672-1680). SPIE.
17. Farag, A., Ali, A., Graham, J., Elhabian, S., Farag, A., & Falk, R. (2010). Feature-based lung nodule classification. In Advances in Visual Computing: 6th International Symposium, ISVC 2010, Las Vegas, NV, USA, November 29-December 1, 2010, Proceedings, Part III 6 (pp. 79-88). Springer Berlin Heidelberg.
18. Faizal, K. Z., & Kavitha, V. (2014). An effective segmentation approach for lung CT images using histogram thresholding with EMD refinement. In Proceedings of International Conference on Internet Computing and Information Communications: ICICIC Global 2012 (pp. 483-489). Springer India.
19. Farag, A., Graham, J., Farag, A., & Falk, R. (2009). Lung Nodule Modeling–A Data-Driven Approach. In Advances in Visual Computing: 5th International Symposium, ISVC 2009, Las Vegas, NV, USA, November 30-December 2, 2009, Proceedings, Part I 5 (pp. 347-356). Springer Berlin Heidelberg.
20. Chhabra, T., Dua, G., & Malhotra, T. (2013). Comparative analysis of methods to denoise CT scan images. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 2(7), 3363-3369.
21. AGaikwad, A., Inamdar, A., & Behera, V. (2016). Lung cancer detection using digital Image processing On CT scan Images. International Research Journal of Engineering and Technology (IRJET) in IEEE e-ISSN, 2395-0056.
22. Devaki, K., MuraliBhaskaran, V., & Mohan, M. (2013). Segment Segmentation in Lung CT Images-Preliminary Results. Special Issue of International Journal on Advanced Computer Theory and Engineering (IJACTE), 2(1), 84-89.
23. Frangi, A. F., Niessen, W. J., Vincken, K. L., & Viergever, M. A. (1998). Multiscale vessel enhancement filtering. In Medical Image Computing and Computer-Assisted Intervention—MICCAI'98: First International Conference Cambridge, MA, USA, October 11–13, 1998 Proceedings 1 (pp. 130-137). Springer Berlin Heidelberg.
24. Dabade, S., Chaudhari, S., Jadhav, S., & Nichal, A. (2017, December). A review paper on computer aided system for lung cancer detection. In 2017 International Conference on Big Data, IoT and Data Science (BID) (pp. 97-102). IEEE.
25. Farag, A. A., Abdelmunim, H., Graham, J., Farag, A. A., Elshazly, S., El-Mogy, S., ... & Milam, R. (2011, September). Variational approach for segmentation of lung nodules. In 2011 18th IEEE International Conference on Image Processing (pp. 2157-2160). IEEE.
26. Van Ginneken, B. (2006). Supervised probabilistic segmentation of pulmonary nodules in CT scans. In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2006: 9th International

Copyright @ 2025 Author

ISSN: 2278-4632
Vol-15, Issue-07, No.01, July: 2025

Conference, Copenhagen, Denmark, October 1-6, 2006. Proceedings, Part II 9 (pp. 912-919). Springer Berlin Heidelberg.
27. .Diciotti, S., Picozzi, G., Falchini, M., Mascalchi, M., Villari, N., & Valli, G. (2008). 3-D segmentation algorithm of small lung nodules in spiral CT images. IEEE transactions on Information Technology in Biomedicine, 12(1), 7-19.
28. Gong, J., Gao, T., Bu, R. R., Wang, X. F., & Nie, S. D. (2014). An automatic pulmonary nodules detection method using 3d adaptive template matching. In Life System Modeling and Simulation: International Conference on Life System Modeling and Simulation, LSMS 2014, and International Conference on Intelligent Computing for Sustainable Energy and Environment, ICSEE 2014, Shanghai, China, September 20-23, 2014, Proceedings, Part I (pp. 39-49). Springer Berlin Heidelberg.
29. Itai, Y., Kim, H., Ishikawa, S., Yamamoto, A., & Nakamura, K. (2007). A segmentation method of lung areas by using snakes and automatic detection of abnormal shadow on the areas. International Journal of Innovative Computing Information and Control, 3(2), 277-84.
30. Javed, U., Riaz, M. M., Cheema, T. A., & Zafar, H. M. F. (2013, January). Detection of lung tumor in CE CT images by using weighted support vector machines. In Proceedings of 2013 10th International Bhurban Conference on Applied Sciences & Technology (IBCAST) (pp. 113-116). IEEE.
31. Patil, V. C., & Dhotre, S. R. (2016). Lung cancer detection from images of computer tomography scan. International Journal of Advanced Research in Computer and Communication Engineering ISO 3297: 2007 Certified, 5(7).A
32. Jaffar, M. A., Hussain, A., Jabeen, F., Nazir, M., & Mirza, A. M. (2009). GA-SVM based lungs nodule detection and classification. In Signal Processing, Image Processing and Pattern Recognition: International Conference, SIP 2009, Held as Part of the Future Generation Information Technology Conference, FGIT 2009, Jeju Island, Korea, December 10-12, 2009. Proceedings (pp. 133-140). Springer Berlin Heidelberg.
33. H.aussecker and B. Jahne, A tensor approaches for local structure analysis in multidimensional images in 3-D, Image Anal. Synthesis, pp. 171178, 1996.
34. Kim, H., Nakashima, T., Itai, Y., Maeda, S., kooi Tan, J., & Ishikawa, S. (2007, October). Automatic detection of ground glass opacity from the thoracic MDCT images by using density features. In 2007 International Conference on Control, Automation and Systems (pp. 1274-1277). IEEE.
35. Kockelkorn, T. T., van Rikxoort, E. M., Grutters, J. C., & van Ginneken, B. (2010, April). Interactive lung segmentation in CT scans with severe abnormalities. In 2010 IEEE International Symposium on Biomedical Imaging: From Nano to Macro (pp. 564-567). IEEE.
36. Kostis, W. J., Reeves, A. P., Yankelevitz, D. F., & Henschke, C. I. (2003). Three-dimensional segmentation and growth-rate estimation of small pulmonary nodules in helical CT images. IEEE transactions on medical imaging, 22(10), 1259-1274
37. Giger, M. L., Doi, K., MacMahon, H., Metz, C. E., & Yin, F. F. (1990). Pulmonary nodules: computer-aided detection in digital chest images. Radiographics, 10(1), 41-51.
38. Giger, M. L., Ahn, N., Doi, K., MacMahon, H., & Metz, C. E. (1990). Computerized detection of pulmonary nodules in digital chest images: Use of morphological filters in reducing false-positive detections. Medical Physics, 17(5), 861-865.

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