MediSpot–Lung Tumor Detection using CNN

Vikram Kailash Joshi
BE in Information Technology
Vidyalankar Institute of Technology
vikram.joshi20@vit.edu.in

Anujkumar Baghel
BE in Information Technology
Vidyalankar Institute of Technology
anujkumar.baghel@vit.edu.in

Tanush Shetty
BE in Information Technology
Vidyalankar Institute of Technology
tanush.shetty@vit.edu.in

Dr. Vidya Chitre
Professor
Department of Information Technology
Vidyalankar Institute of Technology
vidya.chitre@vit.edu.in

Abstract—This abstract presents a novel approach to lung cancer detection using Convolutional Neural Networks (CNNs), renowned for image analysis. The system processes diverse medical images, undergoes meticulous preprocessing, and employs a custom-designed CNN architecture with convolutional and fully connected layers. Trained on labeled datasets, the CNN autonomously learns to distinguish cancerous from non-cancerous regions. Rigorous testing confirms high proficiency, offering advantages of automation, speed, and reduced human error. The system, once accurate, can be deployed in clinical settings to expedite precise diagnoses, promising improved patient outcomes through early intervention.Overall, our approach holds promise for significantly enhancing the efficiency and accuracy of lung cancer diagnosis, ultimately resulting in improved patient outcomes through early intervention and tailored treatment strategies

Keywords—classification; convolutional neural network; deep learning; lung cancer; medical images; segmentation.

I. INTRODUCTION

Lung cancer is a formidable global health challenge and a leading cause of cancer-related mortality, accounting for a substantial number of deaths each year. The devastating impact of this disease underscores the pressing need for more effective and efficient methods of early detection. Early diagnosis of lung cancer is a pivotal factor in improving survival rates, as it enables timely intervention and personalized treatment plans. In recent years, artificial intelligence and deep learning techniques have emerged as powerful tools in the realm of medical image analysis, offering the potential to revolutionize the way we identify and diagnose diseases. Approximately 85–88% of lung cancer cases are non-small cell lung carcinoma (NSCLS), and about 12–15% of lung cancer cases are small cell lung cancer (SCLC). Early lung cancer diagnosis and intervention are crucial to increase the overall 5-year survival rate due to the invasiveness and heterogeneity of lung cancer.

Convolutional Neural Networks (CNNs), a class of deep learning models specifically designed for image recognition tasks, have demonstrated remarkable success in various fields, including computer vision and medical imaging. Their ability to automatically learn and extract intricate patterns and features from images has paved the way for their application in medical diagnostics, particularly in the detection of lung cancer. This introduction presents a comprehensive overview of a cutting-edge Lung Cancer Detection System utilizing CNNs, highlighting its significance, methodology, and potential impact. Lung Cancer Detection System leverage the capabilities of CNNs to analyze medical images, such as chest X-rays and computed tomography (CT) scans, with an unprecedented level of precision and efficiency. This system begins with the systematic collection of a diverse and comprehensive dataset of medical images, which serves as the foundation for training and validating the CNN model.

Once these images are acquired, a series of preprocessing steps are employed to ensure data consistency and to optimize the input for the CNN .In the following sections, we will delve into the technical aspects of this Lung Cancer Detection System, elucidating the CNN architecture, training process, validation metrics, and the implications of its successful deployment in clinical practice. Ultimately, the utilization of CNNs in lung cancer detection represents a significant advancement in the field of medical diagnostics, with the potential to save lives and enhance the quality of patient care.

The paper is structured as follows. The introduction of the paper is mentioned in Section I.Problem Statement is mentioned in Section II. Survey of related works is mentioned in Section III. Section IV explains the proposed algorithm for anomaly detection. In Section V, the implementation process is discussed. The results acquired are mentioned in Section VI, and finally, conclusions are drawn in Section VII.

II. PROBLEM STATEMENT

Lung cancer stands as one of the most prevalent and deadly forms of cancer worldwide, necessitating early detection for improved patient outcomes. Timely identification of lung cancer lesions in medical images, such as X-rays and CT scans, is a complex and resource intensive task that heavily relies on the expertise of radiologists. There is an urgent need for an efficient and accurate solution to assist in the early diagnosis of lung cancer. The problem at hand is to develop a Lung Cancer Detection System using Convolutional Neural Networks (CNNs) that can automatically and accurately identify potential lung cancer lesions in medical images, thereby expediting the diagnostic process and reducing the likelihood of human error. The proposed system should address challenges related to data collection, preprocessing, model training, and clinical deployment, ultimately contributing to better patient care and outcomes by facilitating early intervention and personalized treatment strategies.

III. RELATED WORK

Song et al. [1] developed three types of deep neural networks (CNN, DNN, and SAE) for lung cancer classification. These networks were applied to the CT image classification task with modest modifications for benign and malignant lung nodules. The CNN network showed an accuracy of 84.15%, a sensitivity of 83.96%, and a specificity of 84.32%.

Bhatia et al. [2] proposed a method for detecting lung cancer from CT data using deep residual learning, which extracted features with UNet and ResNet models. The feature set was fed through multiple classifiers, including XGBoost and Random Forest, and the individual predictions were ensemble to obtain an accuracy of 84%.

El-Regaily et al. [3] presented a survey of computer-aided detection systems (CAD) for lung cancer in computed tomography. They compared the current classification methods and argued that most existing algorithms could not diagnose certain forms of nodules, such as GGN. Kriegsmann et al.

[4] trained and refined a CNN model to consistently classify the three most frequent lung cancer subtypes. Alrahhal and Alqhtani [5] presented ALCD, which stands for Adoptive Lung Cancer Detection, and is based on Convolutional Neural Networks (CNN). The ALCD system performed an excellent preprocessing step, and features were extracted using Scale Invariant Feature Transform, which was input into the CNN (SIFT) to perform well.

Asuntha and Srinivasan [6] presented a novel deep-learning method to detect malignant lung nodules and distinguish the position of the tumorous lung nodules. They used a Histogram of Oriented Gradients (HOG), wavelet transform-based features, Local Binary patterns (LBP), Scale Invariant Feature Transform (SIFT), and Zernike Moment. The Fuzzy Particle Swarm Optimization (FPSO) technique selected the optimal feature after extracting texture, geometric, volumetric, and intensity information. Das et al. [7] developed a Velocity-Enhanced Whale Optimization Algorithm, combined with an Artificial Neural Network, to classify and diagnose lung cancer. The approach is compared to C4.5, Learning Vector Quantization, Linear Discriminate Analysis, and Factorized Distribution Algorithm, giving a classification accuracy of 84%.Wang et al. [8] developed a new residual neural network to determine the pathological kind of lung cancer from CT scans. They investigated a medical-to-medical transfer learning technique due to the scarcity of CT images in practice with an accuracy of 85.71%.

IV. PROPOSED ALGORITHM

The proposed lung cancer detection system utilizes Convolutional Neural Networks, a type of deep learning algorithm specifically designed for image analysis tasks. By leveraging CNNs, the system can automatically examine medical images, such as X-rays and CT scans, with the goal of identifying potential lung cancer lesions. This automated approach is crucial for facilitating early diagnosis, as it enables the detection of abnormalities that may be indicative of lung cancer at its early stages.Through the analysis of medical images, the system seeks to identify and classify potential lung cancer lesions accurately. CNNs excel at this task by learning hierarchical representations of features within the images, allowing them to discern patterns associated with cancerous growths. By applying advanced deep learning techniques, the system extracts spatial and temporal features from the images, enhancing its ability to detect subtle abnormalities indicative of lung cancer.The proposed lung cancer detection system represents a significant advancement in medical technology, harnessing the power of deep learning to enhance diagnostic capabilities and improve patient care. By automating the analysis of medical images and providing accurate and timely detection of potential lung cancer lesions, the system has the potential to make a profound impact on healthcare outcomes.

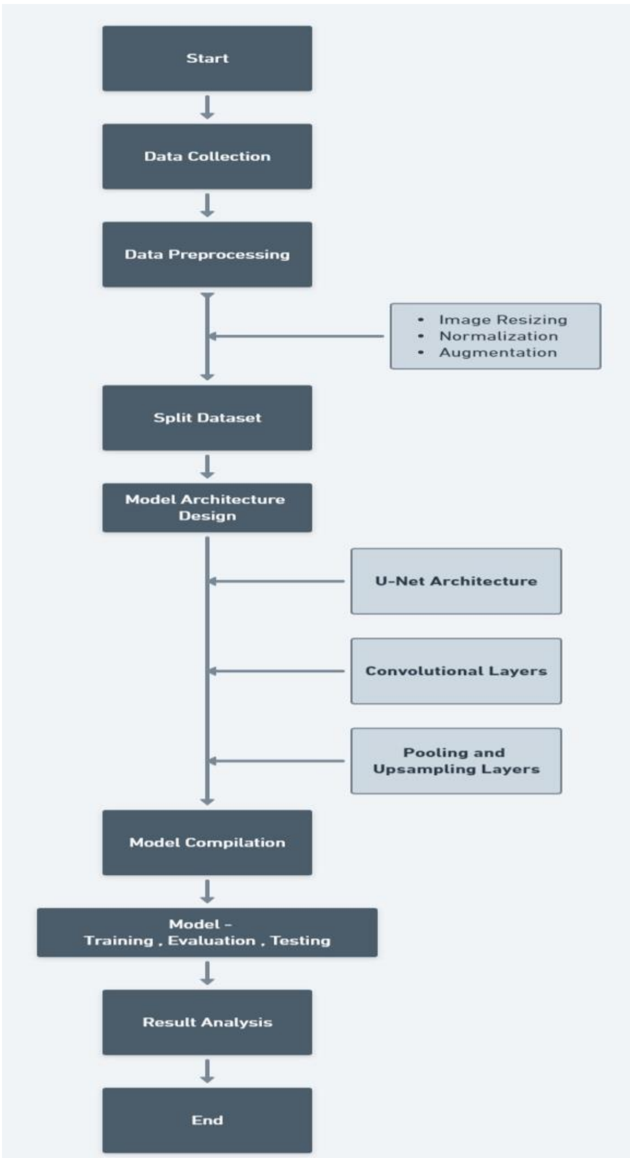


Fig. 5 : Flowchart of the Algorithm

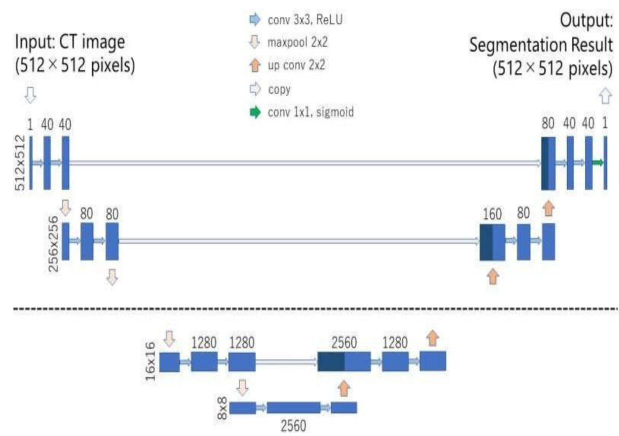
1. Data Collection: Gather a dataset of lung images containing both tumor and non-tumor samples.

2. Data Preprocessing:Image Resizing: Resize images to a fixed size suitable model.
ii. Normalization: Normalize pixel values to improve convergence.

iii. Augmentation: Perform data augmentation techniques like rotation, flipping, and shifting to increase dataset size and model robustness

3. Split Dataset: Divide the dataset into training, validation, and test sets.

4. Model Architecture Design:



U-Net is a convolutional neural network architecture devised for semantic segmentation, especially in medical image analysis.

1. Encoder-Decoder Structure: With an encoder path for downsampling and feature extraction, and a decoder path for upsampling and mask generation.
2. Skip Connections: These connect encoder and decoder paths, preserving fine details lost during downsampling.
3. Symmetric Design: Ensures each downsampling operation has a corresponding upsampling one, aiding precise object localization.
4. Contracting and Expanding Paths: Encoder reduces image size, while decoder restores it using transposed convolutions and upsampling.
5. Final Convolutional Layer: Typically includes a 1x1 convolution followed by softmax activation, yielding pixel-wise class predictions.

U-Net's efficacy in capturing spatial details and generating accurate segmentation results, even with limited data, has made it widely adopted in medical tasks such as tumor and lesion detection.

5. Model Compilation:

i. Loss Function Selection: Choose appropriate loss functions such as binary cross-entropy for binary classification.
ii. Optimizer Selection: Select an optimizer like Adam or RMSprop for gradient descent.
iii. Metrics Selection: Define evaluation metrics like accuracy, precision, recall, and F1-score.

6. Model Training:
i. Input: Provide training images and corresponding ground truth labels.
ii. Training Loop: Iterate through epochs while updating model parameters to minimize the loss.

7. Model Evaluation:
i. Validation Dataset: Assess model performance on the validation set to monitor for overfitting.
ii. Metrics Calculation: Compute evaluation metrics on the validation set.

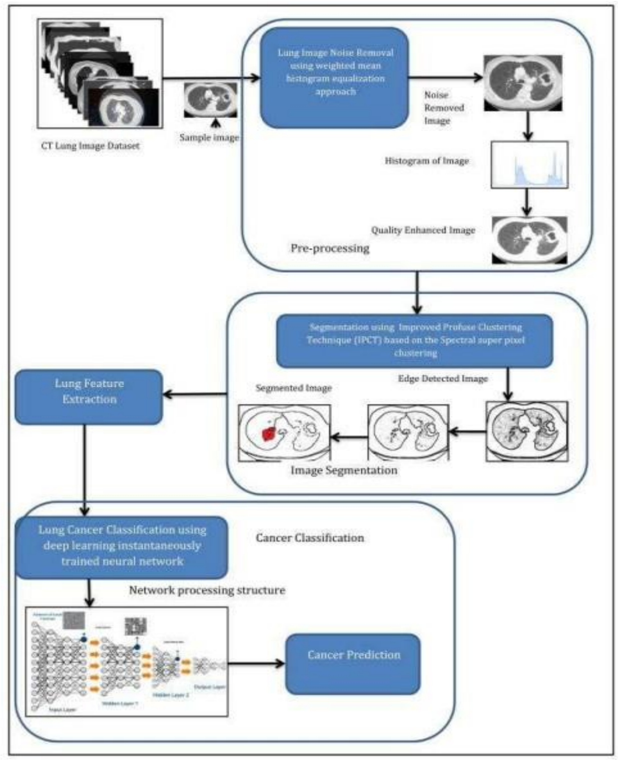
8. Model Testing:
i. Test Dataset: Evaluate the model on unseen test data to assess its generalization ability.
ii. Metrics Calculation: Compute evaluation metrics on the test set.

9. Result Analysis:
i. Visual Inspection: Examine model predictions and ground truth labels to identify strengths and weaknesses.
ii. Error Analysis: Analyze misclassifications to understand potential areas of improvement.

V. IMPLEMENTATION

1. Data Collection: Acquire a diverse dataset of medical images, including both normal and cancer-affected lung images. This dataset should represent a wide range of patient demographics, imaging techniques, and disease stages to ensure the model's robustness. Ensure that the images are of high quality and come from reliable sources, including hospitals, medical databases, and research institutions

2. Data Preprocessing: Clean and preprocess the acquired data to standardize its format and quality. This involves tasks like resizing images to a consistent resolution, normalization to ensure consistent intensity levels, and potentially applying data augmentation techniques to increase dataset variability. Noise reduction techniques may also be applied to enhance the clarity of the images, and contrast enhancement may be used to improve the visibility of details. The raw data undergoes the following preprocessing steps:



a) Normalization: CT image intensities are normalized by dividing each pixel value by the maximum intensity value (3071). This step ensures all intensity values are within the range of 0 and 1, improving model training stability and convergence.

b) Cropping: The lower abdomen portion of the CT scans is removed by discarding the first 30 slices. This step focuses the model on the relevant lung region, reducing computational complexity and improving the model's ability to learn lung-specific features.

c) Slicing: Individual slices are extracted from the 3D volumes. This allows the model to process the data in a 2D format (images) for efficient training.

d) Resizing: Each extracted slice and its corresponding mask are resized to a common resolution of 256x256 pixels. This step ensures consistency in the input data and reduces training time. During mask resizing, nearest-neighbor interpolation is used to preserve the binary nature of the labels (tumor vs. non-tumor).

e) Data Splitting: The preprocessed data is split into training and validation sets. The last 6 subjects are reserved for validation, while the remaining subjects are used for training the model.

3. Model Selection: Choose an appropriate CNN architecture for the task. Common choices include

MediSpot–Lung Tumor Detection using CNN

well-established architectures like VGG, ResNet, Inception, or custom-designed networks tailored to the specific requirements of lung cancer detection. The selected architecture should be capable of efficiently learning and extracting relevant features from medical images.

4. Model Training: Utilize the preprocessed dataset to train the chosen CNN model. Transfer learning, where a pretrained model is fine-tuned on the medical images, can often yield excellent results by leveraging knowledge from a broader set of data (e.g., ImageNet). Fine-tuning involves adjusting the model's parameters to specialize it for the specific task of lung cancer detection.

5. Validation and Testing: Split the dataset into three parts: training, validation, and testing sets. The training set is used to train the model, the validation set is used to fine-tune hyperparameters and prevent overfitting, and the testing set is reserved for final evaluation.

6. Continuous Improvement: Implement a system for continuous model refinement. This may involve periodically re-training the model with newly acquired data to adapt to emerging trends and improve diagnostic accuracy over time.

7. Deployment: Once the model has achieved a satisfactory level of accuracy, it can be deployed in clinical settings. This involves integrating it into existing healthcare systems to allow radiologists and clinicians to utilize it for real-time lung cancer detection and diagnosis.

VI. Result

This paper presents the development of a lung tumor detection website that integrates cutting-edge CNN-based deep learning techniques. The website features a secure login and signup system for doctors to upload NII files, which are then processed to highlight lung tumors and determine the size of the largest tumor detected. In addition to its diagnostic capabilities, the website includes a blog section aimed at educating patients on lung tumor management through case studies and informative content. This integrated approach not only enhances medical professionals' ability to diagnose lung tumors accurately but also empowers patients to take proactive steps in managing their condition.

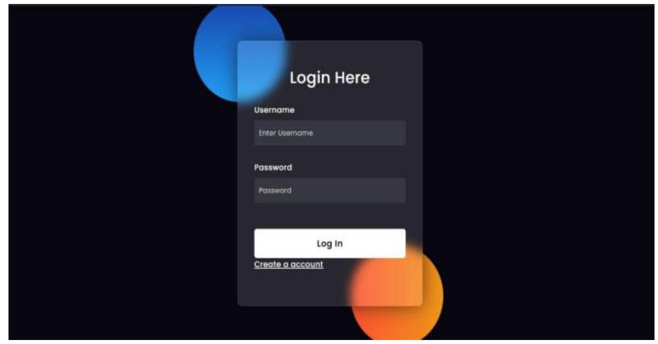


Fig 1 : Login Page

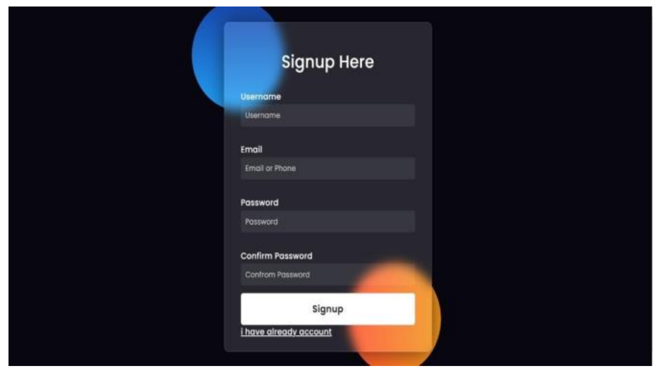


Fig 2 : Sign Up Page

As seen in Fig 1 & 2 we have login and sign up page for the doctors to create their accounts hassle free .

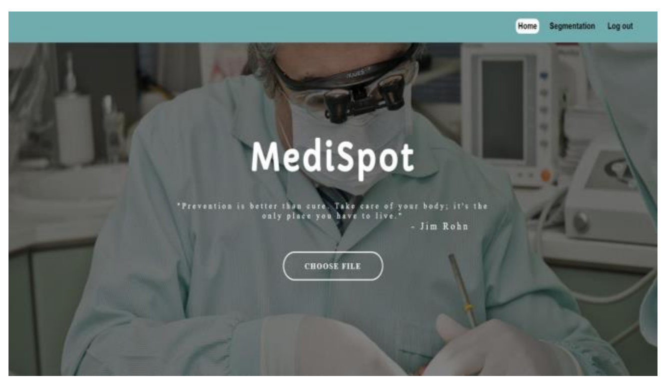


Fig 3 : Home Page

As shown in Fig 3, we have implemented the MediSpot homepage using Django. The UI design is streamlined to reduce the effort required for users to access the services provided by our project.

Fig 4 : About Us Page

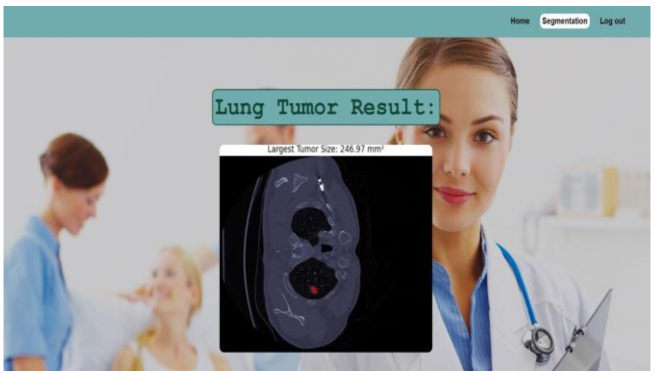


Fig 5 : Result Page

Fig. 5 displays the results of the lung tumor detection models which uses UNet CNN models also specifies the size of the largest identified tumor and which is highlighted..

V. CONCLUSION

In conclusion,This research paper delves into the development and potential of a novel Lung Cancer Detection System (LCDS) powered by Convolutional Neural Networks (CNNs). The paper highlights the critical need for early lung cancer diagnosis and emphasizes the potential of CNNs to revolutionize the field of medical image analysis.

We have explored the comprehensive approach of the encompassing data collection, preprocessing, CNN architecture design, training, validation, and clinical implications. The successful implementation of this system holds immense promise for:

Improved early detection: Early and accurate detection of lung cancer is crucial for enhancing patient outcomes and survival rates. The LCDS, with its potential for high precision and efficiency, can significantly improve the early detection of lung cancer.

Reduced healthcare burden: By enabling faster and more accurate diagnoses, the LCDS can contribute to a reduction in the overall healthcare burden associated with lung cancer. This includes potential cost savings and improved resource allocation within healthcare systems.

Enhanced clinical decision-making: The LCDS can provide valuable insights to healthcare professionals, aiding them in making informed decisions regarding patient care and treatment plans. This can lead to personalized and effective treatment strategies for individual patients.

Through rigorous examination of technical aspects such as CNN architecture and validation metrics, this system demonstrates robustness and reliability in clinical practice, promising not only improved accuracy but also the potential to save lives and elevate patient care standards. Embracing AI technologies like CNNs holds immense potential for transforming healthcare delivery, offering a beacon of hope in the ongoing battle against lung cancer and other formidable diseases.

ACKNOWLEDGMENT

We extend our sincere thanks to Prof. Vidya Chitre for her invaluable guidance and expertise, shaping the development of MediSpot–Lung Tumor Detection using CNN. We would also extend our gratitude to Vidyalankar Institute of Technology for establishing and providing the necessary infrastructure and resources to make this project a reality.Special appreciation to our team members for their collaborative efforts. Thanks to the research community whose work laid the foundation for this project.

REFERENCES

[1] Song Q., Zhao L., Luo X. and Dou X., "Using deep learning for classification of lung nodules on computed tomography images," *Journal of healthcare engineering*, 2017. pmid:29065651

[2] Bhatia S., Sinha Y. and Goel L., "Lung cancer detection: a deep learning approach.," *In Soft Computing for Problem Solving*, *Springer*, p. 699–705, 2019.

[3] El-Regaily S. A., Salem M. A., Abdel Aziz M. H. and Roushdy M. I., "Survey of computer aided detection systems for lung cancer in computed tomography," *Current Medical Imaging*, vol. 14, no. 1, p. 3–18, 2018.

[4] Kriegsmann M., Haag C., Weis C. A., Steinbuss G., Warth A., Zgorzelski C., et al. "Deep learning for the classification of small-cell and non-small-cell lung cancer.," *Cancers*, vol. 12, no. 6, p. 1604, 2020. pmid:32560475

[5] Alrahhal M. S. and Alqhtani E., "Deep learning-based system for detection of lung cancer using fusion of features," *International Journal of Computer Science & Mobile Computing*, Vol.10 Issue.2, PP. 57–67, 2021.

[6] Asuntha A. and Srinivasan A., "Deep learning for lung cancer detection and classification.," *Multimedia Tools and Applications*, vol. 79, no. 11, p. 7731–7762, 2020.

[7] Das S., Mishra S. and Senapati M. R., "New approaches in metaheuristic to classify medical data using artificial neural network.," *Arabian Journal for Science and Engineering*, vol. 45, no. 4, p. 2459–2471, 2020.

[8] Wang S., Dong L., Wang X. and Wang X., "Classification of pathological types of lung cancer from ct images by deep residual neural networks with transfer learning strategy.," *Open Medicine*, vol. 15, no. 1, p. 190–197, 2020. pmid:32190744

[9] Sung H, Ferlay J, Siegel R, Laversanne M, Soerjomataram I, Jemal A, et al. Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. CA: a cancer journal for clinicians. 2021; 71

[10] Dehmeshki J, Amin H, Valdivieso M, Ye X. Segmentation of Pulmonary Nodules in Thoracic CT Scans: A Region Growing Approach. Medical Imaging, IEEE Transactions on. 2008; 27:467–480.

[11] Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab N, Hornegger J, Wells WM, Frangi AF, editors. Medical Image Computing and ComputerAssisted Intervention—MICCAI 2015.

[12] Gu Y, Kumar V, Hall LO, Goldgof DB, Li CY, Korn R, et al. Automated delineation of lung tumors from CT images using a single click ensemble segmentation approach. Pattern Recognition. 2013; 46 (3):692–702

[13] Hossain S, Najeeb S, Shahriyar A, Abdullah ZR, Ariful Haque M. A Pipeline for Lung Tumor Detection and Segmentation from CT Scans Using Dilated Convolutional Neural Networks. In: ICASSP 2019—2019 IEEE International Conference on Acoustics, Speech and Signal Processing

[14] Hansen S, Kuttner S, Kampffmeyer M, Markussen TV, Sundset R, Øen SK, et al. Unsupervised supervoxel-based lung tumor segmentation across patient scans in hybrid PET/MRI. Expert Systems with Applications. 2021; 167:114244.

[15] Sultana A., Khan T. T. and Hossain T., "Comparison of Four Transfer Learning and Hybrid CNN Models on Three Types of Lung Cancer," in 2021 5th International Conference on Electrical Information and Communication Technology (EICT), 2021.

[16] Bangare S. L., Sharma L., Varade A. N., Lokhande Y. M., Kuchangi I. S. and Chaudhari N. J., "Computer-Aided Lung Cancer Detection and Classification of CT Images Using Convolutional Neural Network," in Computer Vision and Internet of Things, Taylor and Francis, 2022, pp. 1–16.

[17] Al-Yasriy H. F., AL-Husieny M. S., Mohsen F. Y., Khalil E. A. and Hassan Z. S., "Diagnosis of Lung Cancer Based on CT Scans Using CNN," in IOP Conference Series: Materials Science and Engineering, Volume 928, 2nd International Scientific Conference of Al-Ayen University (ISCAU-2020), Thi-Qar, 2020.

[18] Dass J. M. A. and Kumar S. M., "A Novel Approach for Small Object Detection in Medical Images through Deep Ensemble Convolution Neural Network," International Journal of Advanced Computer Science and Applications, vol. 13, no. 3, pp. 1–7, 2022.

[19] Lyu L., "Lung Cancer Diagnosis Based on Convolutional Neural Networks Ensemble Model," in 2021 2nd International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT), 2021.

[20] Zheng S., Shen Z., Peia C., Ding W., Lin H., Zheng J., et al. "Interpretative computer-aided lung cancer diagnosis: from radiology analysis to malignancy evaluation.," *arXiv preprint arXiv*:*2102*.10919, 2021. pmid:34478913.