# LUNG CANCER CLASSIFICATION USING MODIFIED U-NET BASED LOBE SEGMENTATION AND NODULE DETECTION


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***ABSTRACT:*** *Due to the advancements in technology, people can now get CT scans done in no time. Recognized as one of the leading causes of cancer, it is estimated that lung cancer will claim the life of out of every 10 people in their lifetime, making early detection ever more crucial. Deep learning techniques and the newly introduced tools in machine learning are assisting in the fight against cancer by aiding in quick detection. Currently, working towards fully automating the identification of lung cancer through CT scans using artificial intelligence neuro-fuzzy systems, the basis supported by the use of intelligent systems. With Cancer Imaging Archive, we built a hybrid system that improves the accuracy in lung cancer detection, utilizes CAD systems, and enhances scan algorithms.*



*Keywords: Lung cancer detection, artificial intelligence, CAD, accuracy.*


## 1. INTRODUCTION

Lung cancer has a high phenomenon and death between all other cancer. About 1,958,310 total new cancer cases and 609,820 deaths from cancer are expected to occur in the United States in 2023, including 350 deaths per day from lung cancer. A diagnosis of an early lung cancer can reduce mortality and increase the survival rate of about 54% up to 5 years. Image processing methods have been used to examine medical images for many years. Computer aided diagnosis (CAD) system can provide rapid, accurate and efficient diagnosis of the disease, which can help in the treatment of patients. Early detection of diseases, such as breast cancer, kidney stones, brain cancer, blood cancer, stomach cancer and lung cancer, become a major cause of death rate. In this regard, various research efforts have been made to help and improve the diagnosis process of diseases from medical imagination. Researchers have developed various divisions or models to detect lung cancer tumors to provide assistance to radiologist. Lung cancer division methods are divided into two types: the first type includes traditional techniques while the second type contains deep learning (DL) technique. Traditional techniques are mostly focused on intensity-based methods such as areas growing, adaptive limits, morphological method, active-size models and size analysis. However, these methods are not strong in terms of tumor size variation and also not suitable for lung segment tumors. Image segmentation divides an image into different image objects and boundaries. Medical image segmentation plays a decisive role in the detection of several diseases through deep learning methods. Automated segmentation methods based on CT and MRI has increased in demand. Deep learning networks mostly used encoder-decoder architectures and deep generative models for medical image segmentation. U-Net and modified U-Net structures have become popular architectures in deep learning for the detection of lung cancer. One of the major advantages these deep networks have is their hierarchical feature extraction, which allows precise segmentation of the lung lobes and localization of potentially suspicious nodules.

The U-Net-based model crops the feature maps from the encoding component, copy them to the decoding component, and for segmentation map generation. Pulmonary cancer nodules are detected by various researchers using different segmentation methods. Deep learning-based CAD solutions can decrease the burden of medical experts to detect various diseases particularly segmentation, detection, and classification of lung cancer nodules.

This research presents an automatic deep learning-based model that segments, detects, and classifies lung nodules increases the accuracy rate, and reduces false positives while detecting lung nodules.The goal of this project is to develop a robust framework for automated lung cancer classification using medical imaging.The framework involves two primary components:

1. Segmenting lung lobes using a modified U-Net architecture.

2. Detecting and classifying lung nodules to determinemalignancy.

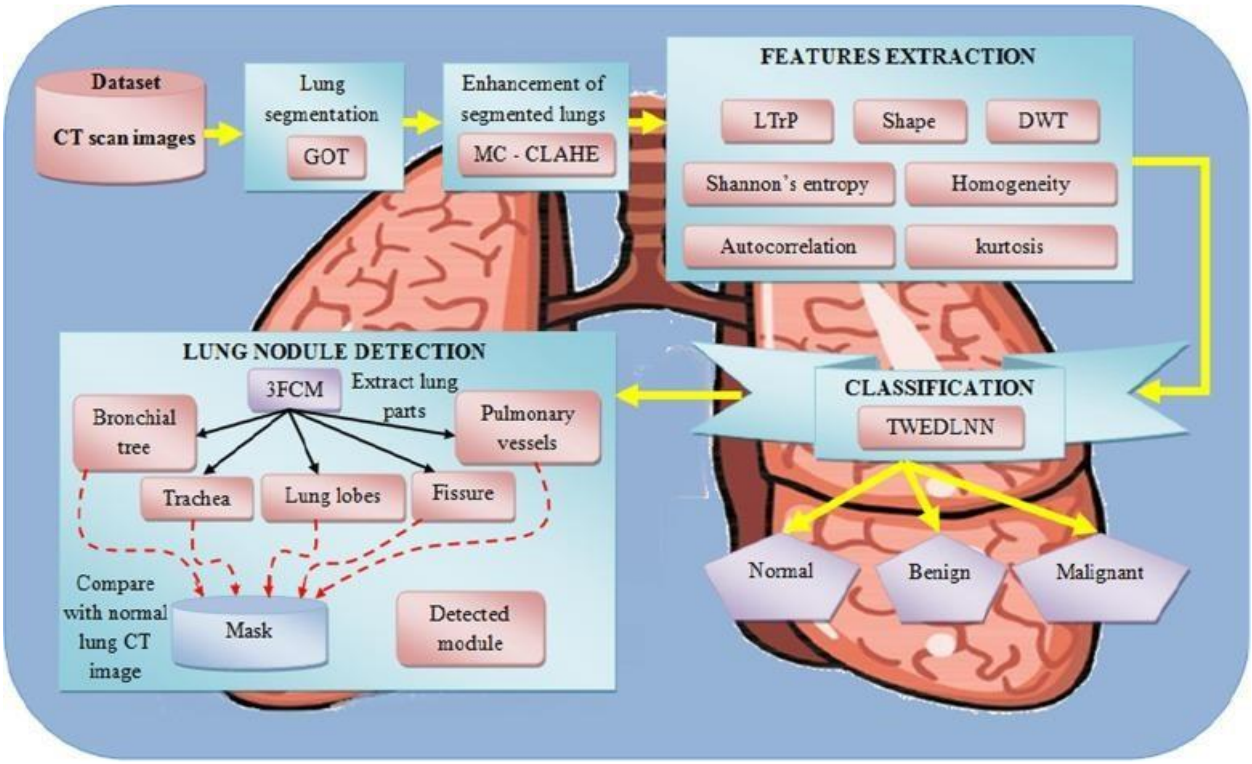


**Fig 1.1 Detection of lung nodule and cancer**

## 2. RELATED WORK

- Lung Lobe Segmentation:

The U-Net model is today the de facto standard for the task of medical image segmentation, and its use for lung lobe segmentation is established. An example of what such work in the field generally entails is given below:

* Typical U-Net Applications: The majority of the research simply uses the regular 2D or 3D U-Net architecture as is to segment a single lung lobe from a CT scan. The research usually explores other loss functions (e.g., Focal loss, Dice loss), the labeling results depend on the classification accuracy of the benchmark classifier trained with data augmentation, and network depths for enhancing the quality of segmentation.

* Extended U-Net Architectures: A number of various extensions of the base U-Net Boundary Refinement: Modified U-Nets often leverage attention or boundary-sensitive features to enhance identification of the fissures that delineate lobe borders, which is a challenging task. 3D Contextualization: Many methods even extend to 3D U-Net-like methods in order to ensure volumetric information about lung CT scans are preserved across slices and make spatially consistent decisions.

* Multi-Scale Feature Fusion: improving the feature aggregation process in the decoder using higher-level techniques of feature aggregation between various scales.

* Deep Supervision: Including mid-level supervision in a few levels of the decoder to allow learning and enhance fine detail segmentation.

* Multi-Atlas Segmentation: Although not U-Net based per se, the same holds that multi-atlas segmentation is an older method where several pre-segmented atlases are registered to a new image and a consensus segmentation is calculated. Some works can compare the performance of U-Nets with such methods.

Evaluation Metrics: Segmentation performance in this research is measured with stringent metrics such as Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Hausdorff distance, and Average Symmetric Surface Distance (ASSD).

II. Lung Nodule Detection:

The most critical work in lung cancer diagnosis is the identification of nodules. Under this topic, research investigates:

* Conventional Computer Vision Methods: The prior work employed more conventional image processing methods such as blob detection, thresholding, and shape measurement, usually complemented by machine learning from classifiers (i.e., Support Vector Machines, AdaBoost) to detect possible nodules.

* Convolutional Neural Networks (CNNs): With advancements in deep learning, CNNs continue to be the most popular means of detection of nodules. Techniques such as Faster R-CNN, YOLO, and RetinaNet are utilized extensively for the same.

* 3D CNNs: Since CT scans are three-dimensional, 3D CNNs are especially suited to nodule detection since they can handle three-dimensional spatial context.

* Minimization of False Positives: The hardest aspect of nodule detection is that there is too high a rate of false positives (structures which are not nodules but are detected as nodules).

## 3. BACKGROUND OF THE WORK

Lung cancer is still one of the major causes of cancer death globally, mainly because of its late diagnosis and virulence. Early detection and proper classification of lung cancer are essential to enhance the survival rate of patients. Medical imaging, particularly computed tomography (CT) scans, is an important tool in the detection and evaluation of lung nodules — small lumps of tissue in the lungs that are either benign or cancerous.Conventional analysis of CT scans is, to a significant degree, dependent on visual interpretation by radiologists and encompasses tedious steps, susceptibility to human mistakes, and possibilities of generating non-uniform test results. Shortcomings of the conventional analysis were overcome ten years ago when deep-learning-based automatic methods gained prominence. The use of convolutional neural networks (CNNs), in specific, has proven highly effective in a wide range of medical image-related tasks considering the fact that they learn hierarchical features automatically from data.Out of various CNN architectures, U-Net is one of the robust models in the case of biomedical image segmentation because it possesses an encoder-decoder framework that can learn low-level and high-level features. However, standard U-Net architectures may lack the ability to be employed for complex tasks like lung lobe segmentation and nodule detection, where anatomical variability and subtle imaging variability may complicate segmentation. To tackle such challenges, the current paper introduces a **Modified U-Net** model specifically tailored for **lung lobe segmentation and nodule detection**. Incorporating additional features such as attention mechanisms, deeper convolutional operations, or improved skip connections into the U-Net model enables the system to perform better in executing accurate localization and segmentation of lung structures.

## 4. PROPOSED WORK

In proposed to develop automated methods to accurately identify and classify lung cancer in CT scans by using computational intelligence techniques. The process typically involves lobe segmentation, extracting candidate nodules, and classifying nodules as either cancer or non-cancer. The proposed lung cancer classification uses modified U-Net based lobe segmentation and nodule detection model consisting of three phases. The first phase segments lobe using CT slice and predicted mask using modified U-Net architecture and the second phase extracts candidate nodule using predicted mask and label employing modified U-Net architecture. Finally, the third phase is based on modified AlexNet and a support vector machine is applied to classify candidate nodules into cancer and non-cancer. Eventually, lung cancer detection at an early stage will reduce the mortality rate. Finally, the early detection of lung cancer will reduce the mortality rate by giving chances for earlier diagnosis and treatment, prior to the disease reaching advanced, less curable forms. Early treatment significantly enhances the prognosis of patients, allowing for less invasive treatment and increasing the likelihood of full recovery. Moreover, the detection of cancerous nodules in their early stages can minimize lung tissue damage and cancer metastasis to other organs, which is the major cause of cancer-induced mortality. The use of an automated, effective, and accurate lung cancer classification system also reduces the workload of radiologists, giving a second opinion that facilitates faster and surer clinical decision-making.

In addition, intelligent systems can analyze large volumes of CT scan data, thereby facilitating wider and more evenly distributed screening programs. Finally, this technology has the potential to transform the healthcare system, saving many lives and optimizing the use of medical resources through early and accurate lung cancer detection.

We suggest applying computational intelligence techniques to create automated methods for correctly detecting and categorizing lung cancer in CT scans. Lobe segmentation, nodule extraction, and nodule classification as either cancerous or non-cancerous are commonly included in the procedure. The three-phase modified U-Net lobe segmentation and nodule detection model is used in the proposed lung cancer classification. The first stage uses a CT slice and a modified U-Net architecture to segment the lobe, and the second stage uses a modified U-Net architecture to extract a candidate nodule using a predicted mask and label.

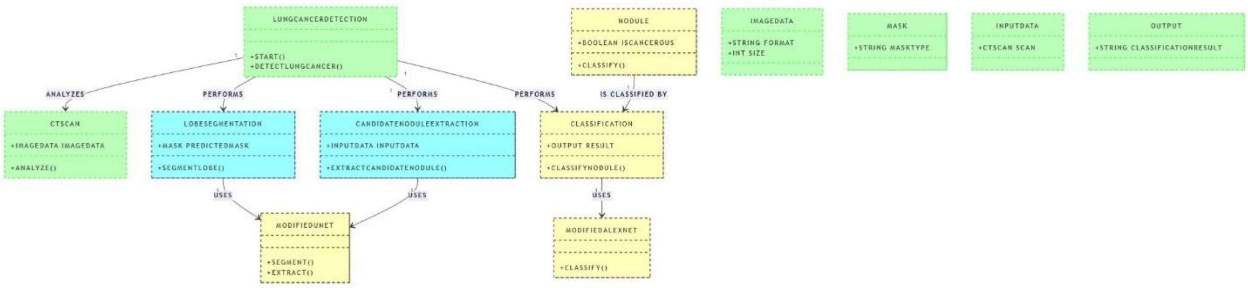


Fig 2: Proposed work

The dataset is preprocessed by resizing, normalization, augmentation, and dividing it into training, validation, and test sets. A suitable YOLO version, i.e., YOLOv3 or YOLOv4, is selected, and transfer learning is employed to pretrain the model on a massive dataset such as COCO and then fine-tune on the crack detection dataset zBuilding a crack detection system using YOLO involves several key steps. Initially, a diverse dataset of images featuring buildings with cracks is collected, varying in lighting conditions, weather, crack types, and building materials. These images are then manually annotated to label the crack locations. Next, the dataset undergoes preprocessing, including resizing, normalization, augmentation, and splitting into training, validation, and testing sets. A suitable YOLO variant, such as YOLOv3 or YOLOv4, is selected, and transfer learning is employed to pretrain the model on a large dataset like COCO before fine-tuning it on the crack detection dataset. Training involves adjusting the model's weights to minimize the disparity between predicted bounding boxes and ground truth annotations. Following training, the model's performance is evaluated using metrics like precision, recall, and F1-score on a separate validation set, with adjustments made as necessary. Post-processing techniques like non- maximum suppression are then applied to refine the detected bounding boxes and filter out false positives.

**YOLO ALGORITHM**

The You Only Look Once (YOLO) algorithm is a single pass real-time object detection framework based on neural networks. The YOLO algorithm steps are as follows:

The YOLO algorithm divides the input image into a grid of cells and predicts the probability of the object's presence in each cell and the coordinates of the object's bounding box. It also predicts the class of the object.
• Input image is passed through a CNN to extract features of the image.
• Features are then passed through a sequence of fully connected layers, which make class probability and bounding box coordinate predictions.
•\tImage is divided into a grid of cells, and each cell predicts a set of bounding boxes and class probabilities.
•\tThe output of the network is a set of bounding boxes and class probabilities for each cell.
•\tFiltering of bounding boxes is then achieved by a post-processing algorithm known as non-max suppression to remove redundant boxes and choose the box with the highest probability.
•\tFinal output is the predicted bounding boxes and class label for every object in the picture. • Network output is a set of bounding boxes and class probabilities per cell.
• Bounding box filtering is then done by a post-processing technique called non-max suppression to eliminate duplicate boxes and select the box with the most probability.
• Final output is predicted bounding boxes and class label for each object in the image.

YOLOv1 was the first to initiate single-stage object detection and presented the grid-based method. It had 24 convolutional layers followed by 2 fully connected layers. Although groundbreaking in terms of speed (45 FPS), YOLOv1 had difficulties detecting small objects and grouped objects because of spatial limitations by the grid system. The initial implementation utilized a 7×7 grid, where each cell predicted 2 bounding boxes and 20 class probabilities (for PASCAL VOC dataset).

YOLOv2 brought a number of enhancements:
- Batch normalization applied to all convolutional layers
- Increased resolution input images (from 448×448 to 416×416)
- Anchor boxes (fixed shapes) to enhance bounding box prediction
- Dimension clusters via k-means to decide best anchor box dimensions
- Direct location prediction to make training more stable
- Multi-scale training for improved generalization
- Darknet-19 backbone (19 convolutional layers + 11 residual layers)
- WordTree concept for hierarchical classification (YOLO9000 variant)

YOLOv3 introduced major architectural advancements:
- Darknet-53 backbone with residual links (53 convolutional blocks)
- Multi-scale predictions with feature pyramid networks (FPN)
- Three detection scales (13×13, 26×26, 52×52 grids)
- Binary cross-entropy loss for class prediction
- Prediction in 9 anchor boxes (3 per scale)
- Logistic regression to predict objectness score
- Each box predicts 4 coordinates (tx, ty, tw, th)

YOLOv4 added many state-of-the-art methods:
- CSPDarknet53 backbone (Cross-Stage Partial Networks)
- Spatial Pyramid Pooling (SPP) and Path Aggregation Network (PAN)
- Data augmentation: Mosaic, CutMix, and self-adversarial training
- Bag of Freebies (BoF): CutMix and Mosaic data augmentation, DropBlock regularization
- Bag of Specials (BoS): Mish activation, Cross-stage partial connections
- CIoU loss for bounding box regression
- Reached 43.5% AP on MS COCO dataset at 65 FPS

YOLOv5 targeted optimization and deployment:
- PyTorch implementation (earlier versions used Darknet)
- Four model sizes: Small (S), Medium (M), Large (L), and Xlarge (X)
- Focus layer for effective feature extraction
- CSP bottleneck blocks
- Hyperparameter optimization in abundance
- Auto-learning of anchor boxes
- Robust export capabilities for multiple deployment targets

YOLOv6 brought in:
- EfficientRep backbone and Rep-PAN neck
- Anchor-free detection head
- Hybrid loss functions
- Tailored for industrial use cases
- Multiple model sizes for varying computational constraints
- Quantization-aware training for edge deployment

YOLOv7 improved performance by:
- E-ELAN (Extended Efficient Layer Aggregation Network) backbone
- Model-scaling techniques for parameter-efficient usage

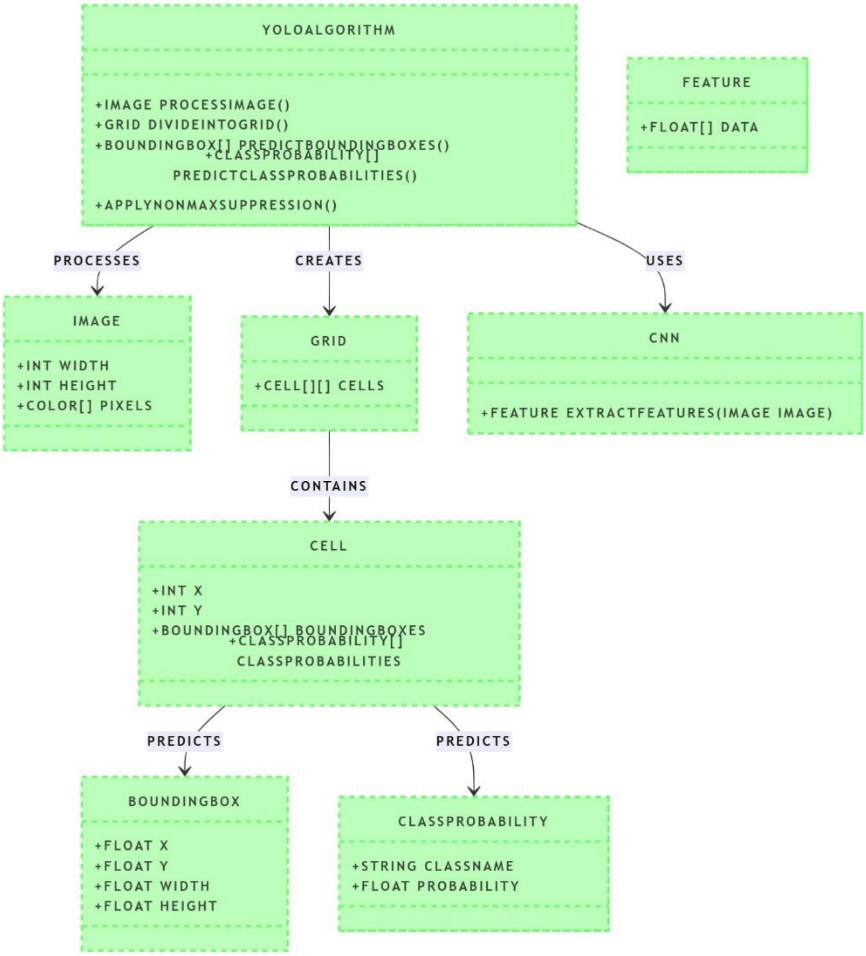


Fig 3: YOLO architecture

## 5. EXPERIMENTAL RESULTS

The data sets are gathered from roboflow website with two classes like cracks and normal. The simulation can be performed in python and model file can be created using YOLO algorithm using Tensorflow library. Then can evaluate the performance using accuracy metrics. The accuracy metric is evaluated as

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} * 100$$

Where as,

TP – True positive rate, TN- True negative rate, FP – False positive rate, FN- False negative rate.

Table 1: Performance table

| Algorithm | Accuracy (%) |
|---|---|
| Support vector machine | 85 |
| Artificial neural network algorithm | 87 |
| YOLO algorithm | 90 |

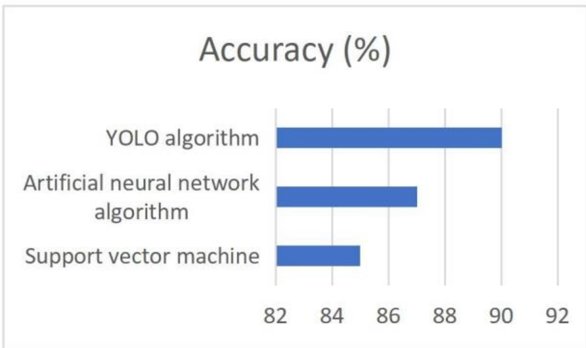


Fig 4: Performance Chart ch t

## 6. CONCLUSION

The project on Lung Cancer Classification Using Modified U-Net Lobe Segmentation and Nodule Detection has demonstrated the potential of combining advanced segmentation and classification techniques to enhance the accuracy and reliability of lung cancer diagnosis. The use of a Modified U-Net architecture for precise lobe segmentation ensures a focused analysis of lung regions, while the integration of deep learning-based nodule detection and classification pipelines provides an effective way to identify and categorize nodules as malignant or benign. This approach leverages cuttingedge advancements in convolutional neural networks (CNNs), attention mechanisms, and multi-scale feature extraction to improve diagnostic efficiency. By automating critical steps in lung cancer detection, the system reduces diagnostic errors, assists radiologists in decision-making, and enables early intervention, which is crucial for improving patient outcomes. Transfer Learning and Domain Adaptation: Training the model on more diverse datasets from different institutions and geographic regions would increase its generalizability. Transfer learning techniques could be used to adapt the model to various types of CT scans, accounting for differences in scanning protocols, equipment, and patient demographics. Explainability and Interpretability: Enhancing the explainability of the model's decision-making process would provide valuable insights for clinicians. Techniques like attention maps or saliency maps could be used to highlight the areas in the CT scan that contribute most to the model's predictions, helping doctors understand the rationale behind the classification results.

## REFERENCES


[1] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in Medical Image Computing and Computer-Assisted Intervention (MICCAI), 2015.

[2] A. A. A. Setio, A. Traverso, T. de Bel, et al., "Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: The LUNA16 challenge," Medical Image Analysis, vol. 42, 2017. Vrochidou, Eleni, et al. "Towards Robotic Marble Resin Application: Crack Detection on Marble Using Deep Learning." Electronics 11.20 (2022): 3289.

[3] G. Litjens, T. Kooi, B. E. Bejnordi, et al., "A survey on deep learning in medical image analysis," Medical Image Analysis, vol. 42, 2017.

[4] O. Oktay, J. Schlemper, L. L. Folgoc, et al., "Attention U-Net: Learning where to look for the pancreas," 2018.

[5] R. J. Gillies, P. E. Kinahan, and H. Hricak, "Radiomics: Images are more than pictures, they are data," Radiology, vol. 278, no. 2, 2016.

[6] S. G. Armato III, G. McLennan, L. Bidaut, et al., "The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): A completed reference database of lung nodules on CT scans," Medical Physics, vol. 38, 2011.

[7] Li Q., Chen L., Li X., Lv X., Xia S., Kang Y. PRF-RW: a progressive random forest-based random walk approach for interactive semi-automated pulmonary lobes segmentation. Int. J. Mach. Learn. Cybern.

[8] Rekha K.V., Itagi A., Bharath K.P., Subramanian B., Kumar R. Handbook of Research on Deep Learning-Based Image Analysis under 28 Constrained and Unconstrained Environments. IGI Global; 2021. Pulomonary nodule classification from CT scan images using machine learning method.

[9] Wang Q., Zhou Y., Ding W., Zhang Z., Muhammad K., Cao Z. Random forest with self-paced bootstrap learning in lung cancer prognosis. ACM Trans. Multimed Comput. Commun. Appl. 2020.

[10] Maleki N., Niaki S.T.A. An intelligent algorithm for lung cancer diagnosis using extracted features from Computerized Tomography images. Healthcare Anal. 2023.

[11] Diciotti S., Lombardo S., Falchini M. et al.: 'Automated segmentation refinement of small lung nodules in CT scans by local shape analysis', IEEE Trans. Biomed. Eng., 2011.

[12] Lin D.T., Yan C.R., Chen W.T.: 'Autonomous detection of pulmonary nodules on CT images with a neural network-based fuzzy system', Comput. Med. Imaging Graph., 2005.

[13] Gasinska A., Kolodziejski L., Niemiec J. et al.: 'Clinical significance of biological differences between cavitated and solid form of squamous cell lung cancer', Lung Cancer, 2005.