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LUNG NODULE DETECTION FOR CT-GUIDED BIOPSY IMAGES USING DEEP LEARNING

B. Prashanthi[1], S.P. Angelin Claret[2*]
Department of Computer Science, Faculty of Science and Humanities, SRM Institute of Science and Technology, Kattankulathur, Chennai - 603203, Tamil Nadu, India[1]
Department of Computational Intelligence, School of Computing, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai - 603203, Tamil Nadu, India[2*]
prashanthi.bhaskaran@gmail.com[1], angelins@srmist.edu.in[2*]

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**Corresponding Author*

ABSTRACT
The recent advancements in artificial intelligence enhance the detection and classification of lung nodules via computed tomography scans, addressing the critical need for early diagnosis of lung cancer. The lung cancer when identified at the earlier stages, the chance of survival is higher. The methodology encompasses a modern deep-learning approach applied to a private dataset obtained from the Barnard Institute of Radiology at Madras Medical College, Chennai, which has been granted ethical approval. The results from applying the proposed Convolutional Neural Network model are promising, with an accuracy of 99.3% in malignancy detection, signifying a notable advancement in the precise diagnosis of lung cancer through non-invasive imaging techniques. Beyond academia, the findings of this study have significant implications for real-world healthcare settings. By providing a reliable and automated solution for lung nodule detection, this research contributes to early diagnosis and personalized treatment strategies for lung cancer patients. The value of the present work lies in its potential to reduce morbidity through the early detection of lung cancer, thus contributing to both clinical practice and the ongoing development of AI applications in healthcare. Our research may serve as a model for further studies in digital health care at Madras Medical College, aiming to improve patient outcomes through technology-driven diagnostics.
Keywords: *Convolutional Neural Network, Deep Learning Technique, Lung Tumor Stages, Benign and Malignancy Lesions Specification, Lung Cancer Prediction*.

1. Introduction

Recently biomedical image processing and the classification of diseases have emerged in research widely (Yuan et al., 2018). The automation of lung nodule detection has great significance for treating lung cancer at the earliest and increasing patients' survival. Nowadays lung cancer is also developing more in women. The image screening with different modalities like chest x-ray, the Computer Tomography (CT) image scans and the CT guided lung biopsy image is suggested to locate lung cancer (Alakwaa et al., 2017). The disease that could be identified by scanned images is cardiomegaly most effective and well-advanced image-sensing modality is a CT scan (Gedam & Rumale, 2024). The CT scan outcome is sensitive thus it produces around 75 to 130 slices of scanned image of the patients. So, the CT scans grab the attention of identifying the lung nodule point exactly thus the treatment has more potential (Singh et al., 2020). Lung cancer categorization, lung nodule segmentation, and lung cancer detection with CNN are all major subjects in medical studies. An abundance of research has been devoted to enhancing the precision and effectiveness of these methodologies. Computer-aided detection (CAD) systems, deep learning models, and advanced learning techniques are some of the methods that researchers are investigating. Preprocessing techniques like as image smoothing, edge sharpening, and noise reduction are employed to improve the quality of lung images. The histogram-based thresholding, linked component analysis, and lung extraction techniques are utilized in the process of lung segmentation implementation. Several different machine learning methods, including random forest, support vector machine (SVM), naive Bayes, K-nearest neighbor (KNN), and convolutional neural network (CNN), have been utilized to detect and classify lung cancer. These technologies have demonstrated excellent results in the early detection and correct diagnosis of lung cancer, which can be of tremendous importance to healthcare systems as well as medical research (Saya Sudhakar Babu et al., 2023), (Sivasankaran & Dhanaraj, 2024), (Kanagaraj & Priya, 2021).

The article addresses the recent developments and potential challenges. In this work, researchers looked at two different models for identifying and segmenting pulmonary nodules from whole-body CT scans: Mask-RCNN and 3D Faster-RCNN. Using CT images to differentiate between benign and cancerous lung nodules was the main emphasis. According to the results, these algorithms make it easier and more accurate to diagnose pulmonary nodules, which can lead to the diagnosis of lung cancer (Kumar et al., 2022). A shortcoming of the Mask-RCNN technique was its inability to completely capture border information due to issues such as small jitter at the boundary. Despite these challenges, the research shows that computational methods have great potential for enhancing patient care in the detection and treatment of lung cancer and for increasing the accuracy of diagnoses for pulmonary nodules (Muñoz-Aseguinolaza et al., 2023).

2. Overview of Computational Method

The AI algorithm mimics the human brain's cognitive function and intelligence to recognize the trained objects. Machine learning (ML) algorithms are capable of extracting knowledge from trained databases to predict the region of interest (Tama et al., 2022). The Deep learning models eventually ensure the building model, decision-making, and performance evaluation of results (Hatuwal & Thapa, 2020). Artificial Intelligence (AI) approaches have been used in virtually all aspects of cancer during the last few years, from fundamental research to medication development and clinical treatment (Tomassini et al., 2023). Over the last decade, AI has made significant contributions to a range of health challenges, including cancer detection. Deep learning technique, a subset of AI that is very versatile and performs automatic feature extraction, is rapidly being used in cancer research, both fundamental and clinical (Neal Joshua et al., 2021) (Saleh et al., 2021). ML is one of the most well-known disciplines that aim to excerpt usable information from datasets to create prediction models that will eventually guide decision-making (Wu et al., 2023) (Grd et al., 2024). The predictive models are to identify the problem for prediction, produce or curate relevant datasets, and build and evaluate the model shown in Figure 1. Supervised learning and unsupervised learning are the two main types of machine learning methodologies. A collection of labeled data (classes) specified by a set of features is used as training in supervised learning to construct a model that maps features to classes. Unsupervised learning, on the other hand, requires no labeling and relies on characteristics to uncover data classes (Shen et al., 2021).

DL is rapidly being employed in biomedical research, with applications in images and videos in particular to simulate how neurons function and it links neurons into multi-layered neural networks has transformed image analysis, with training on millions of digital photos allowing machines to spot objects in images better than people (Tagnamas et al., 2024) (Kuncan et al., 2024). The significant progress in the disciplines of image categorization, object identification, and image retrieval. Deep neural networks excel at solving a variety of medical imaging challenges (Gao et al., 2020). Transfer learning is a Pre-trained CNN model that has prior knowledge of prediction. The learned features from the pre-trained models are then transferred to the various models as such VGG16, DenseNet201, and ResNet50 are three deep-learning models that were used in most of the research (Shaziya & Kattula, 2022). Because it is extensively used for generic image classification problems. Among all, ResNet has increased the number of layers, which was built to perform image recognition tasks more accurately. ResNet comes in a variety of layer-based topologies, including ResNet50, ResNet101, and ResNet50V2(Sadıkoğlu et al., 2024) (S. Wang et al., 2020a) (Alemayehu et al., 2024) (Gupta et al., 2023) (Vasavi & Sruthi, 2023)

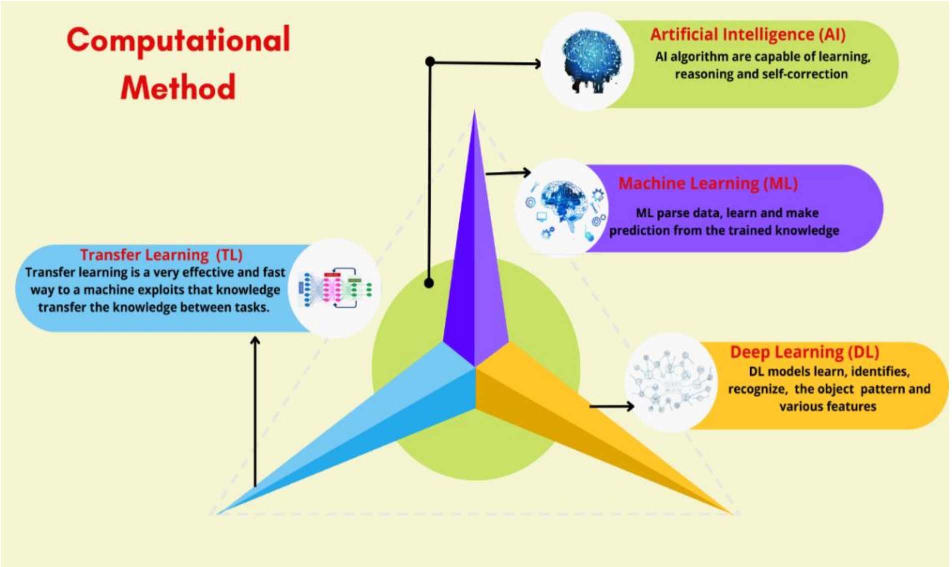


Fig. 1. The representation of computational methods such as AI, ML, DL, and TL.

3. Literature of Lung Nodules and Lung Lesions

Patients with some lung infections are suggested for a CT scan to detect the abnormality or nodule which may either be a malignant tumor or a benign tumor. The nodule is categorized based on its clinical contexts like size, shape, and location. The tumor nodule size might be large or smaller, and the shapes are a ball-like structure or irregular, location such as juxta-pleural, juxta-vascular, or well-circumscribed. The lung biopsy gives detailed information on detected nodules. The size, shape, and density of the tumor can be examined accurately. In some cases, the task of identifying the nodule becomes meticulous because misinterpretation leads to wrong treatment. The classification of tumors with the Computer Aided Diagnosis system using a deep learning model can reduce the false positive ratio when applied (Zhang et al., 2021). The lung is a vital organ that immediately affects vulnerable airborne infections and injuries. Respiratory diseases are the leading causes of lung cancer that lead to death. The major lung diseases are chronic obstructive pulmonary disease (COPD), pneumonia, tuberculosis (TB), asthma, occupational lung diseases, and lung cancer. Thus, the statistic report made by WHO brings out that the COPD, about 65 million people suffer from this disease on the other hand 3 million die due to this disease every year, and pneumonia is the most dangerous disease found commonly in children. Tuberculosis affects over 10 million people out of which 1.4 million die every year (WHO, 2020) (Sekar et al., 2023a). The research explores the application of a region-based convolutional neural network (R-CNN) to segment lung nodules CT images. This technique improves the identification of lung cancer. The convolutional neural network effectively segmented lung areas. The study employed a region-based convolutional neural network (R-CNN) to perform semantic segmentation, specifically separating the lung nodule region from the rest of the lung. This approach improves the detection of lung cancer and enhances the extraction of potential nodules. The R-CNN network comprised 4 convolution layers and 2 max-pooling layers, with a precision of 98.28% (Chu et al., 2019). The study applied advanced machine learning techniques, including Inception V3, Random Forest, and CNN, to automatically identify lung cancer cells. The dataset for this project consisted of 220,025 lung cancer tissue photos in RGB format, sourced from Kaggle. The dataset was divided into two regions, with 130,908 images allocated for training and 89,117 images for testing. To address the dataset's imbalance, down sampling was employed to reduce instances in the noncancerous class. VGG16 and Inception V3 were used to process the photos and extract features, which served as input data for the neural networks and random forest techniques. The method tackled a multi-classification problem involving cancer and non-cancer categories. The Adam optimizer was utilized to determine the optimal learning rate for the model. The proposed method exhibited favorable outcomes in terms of accuracy, precision, recall, F-score, and specificity measures in identifying lung cancer. The accuracy values were 97.09%, precision was 96.89%, recall was 97.31%, F-score measure was 97.09%, and specificity measure was 96.88%. The trained deep convolutional neural network effectively extracted critical information from histopathological lung cancer tissue images, enhancing efficiency and accuracy in identifying and diagnosing lung cancer cells (Abd Al-Ameer et al., 2022). The paper introduces a fully automated approach for lung cancer detection, employing DL techniques and CNN, specifically ResNet50 and Vgg16 architectures. Employing the LUNA16 dataset, comprising 5000 CT scan images divided into training and testing sets, the study focuses on feature extraction and classification. Convolutional layers within the CNN are operated to extract features from input CT scan images, while fully connected layers facilitate neuron connections across different layers. The research reports an accuracy of 0.9850 with ResNet50 and 0.90175 with Vgg16, achieved through multiple epochs and steps per epoch during the training process. The findings highlight the effectiveness of the proposed method in accurately classifying CT scan images, with ResNet50 demonstrating superior performance over Vgg16 (Susritha et al., 2023). The paper introduces a method employing CNNs to distinguish between malignant and non-malignant lung nodules, leveraging digital images as input data. This CNN technique is renowned for its high yield and accuracy in classification tasks. To address potential degradation during image acquisition, the proposed approach incorporates a median filter during the pre-processing stage. Once the lung CT images are segmented, they are fed into the CNN architecture, specifically trained to detect malignant nodules. The SoftMax layer then determines the outcome with ±95% confidence interval, providing a measure of uncertainty around the accuracy estimate. Compared to X-ray images, CT scans offer superior precision in analyzing lung nodules, achieving an accuracy level of approximately ±90%. The research presents a method for detecting lung cancer in real time using a Convolutional Neural Network (CNN). The CNN model underwent training using an extensive dataset of chest CT scans and showed commendable accuracy of 91.18% and 0.25% sensitivity in the identification of lung cancer. The technology can rapidly analyze CT scans, providing substantial advantages in clinical environments. A CNN-based approach reliably detects lung cancer by analyzing CT images. CT scans can be processed quickly by a real-time system (Dhanagopal et al., 2024).

Lung Nodules and Stages of Lung Cancer

The Lung (Pulmonary) nodule is a form of abnormal growth in the lung with one or several nodules. The nodules may grow in any region of the lung, most of them are benign (Not cancerous) shown in Table 1, and the few and far between them may be a sign of lung cancer and develop into malignancy nodules (Cancerous) shown in Table 2. When lung tissue is inflamed by an infection or sickness, a tiny clump of cells called a granuloma can develop. A granuloma in the lung can calcify or harden over time, resulting in a noncancerous lung nodule. Autoimmune diseases such as inflammatory disease and sarcoidosis. Infections caused by fungi, such as histoplasmosis. Air irritants or contaminants while breathing are other causes of noncancerous lung nodules. Infections of the respiratory system, such as tuberculosis (TB) and Tissue scarring all are closer to benign. Lung nodules are located using CT scans. The CT image predicts the nodule location, Attenuation, size, margin, and shape of the nodules detected in the CT image. Stage 1: Small and localized tumors that appear in the lung are considered to be the initial stage of cancer development. Stages 2 and 3: The highly advanced malignancies that may have migrated to the lungs and other organs. Stage 4 or Metastatic cancer: The advanced stage of cancer that spreads throughout the body and has reached the final stage of cancer. This is considered to be the high-risk state of lung cancer.

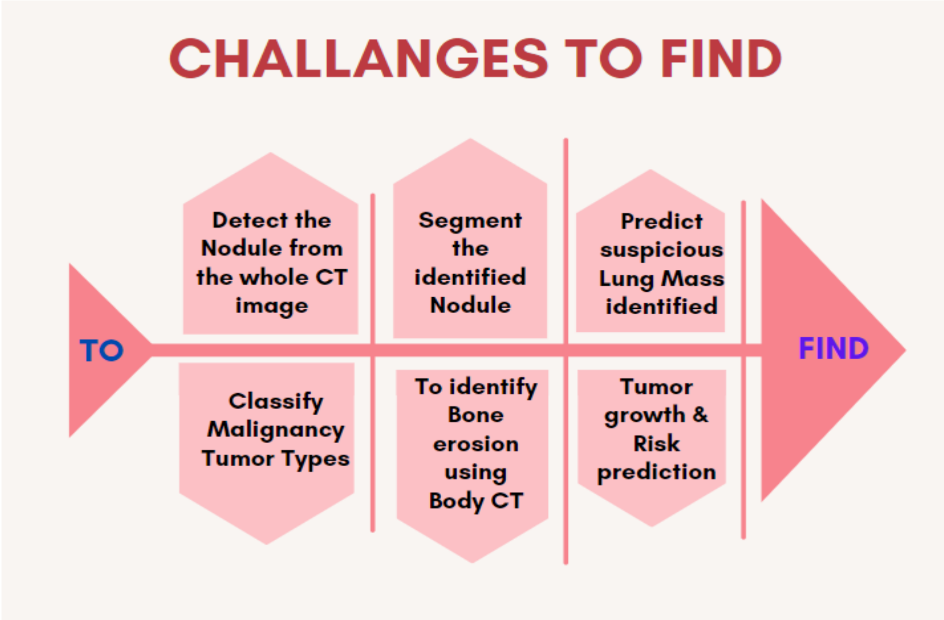


Fig 2. The Fishbone Diagram Of Identified Research Gaps In The Literature Review

Table 1 - Benign Lung Lesion Description

Benign Lung Nodule Description – Non-Cancerous			
Location Side:	Right	Left	Both
Site:	Upper Lobe Middle Lobe Lower Lobe	Upper Lobe Middle Lobe Lower Lobe	Bilateral
Benign Cases	- Infectious - Pleura Effusion - COPD - Fibrotic stands - Pneumonia	- Neuro Plastic Consolidation - Aspergilloma - Fungal Ball - Emphysematous - TB Infection	- Iatrogenic - Bronchiectasis - GGO - Cardiogenic - Metastasis
Specification	-No bone Erosion - Cavity Interior	- Well-defined - Mideastern Shift	- Bulla - Collapsed

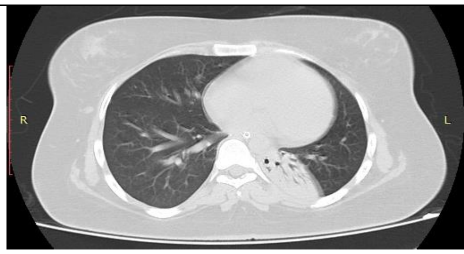
Table 2 - Malignant Lung Lesion Description

Malignant Lung Lesion Description – Tumor			
Location side:	Right	Left	Both
Site:	Upper Lobe Middle Lobe Lower Lobe	Upper Lobe Middle Lobe Lower Lobe	Bilateral
Abutting	Pleura	Mediastinum	Nil
Size	< 1cm	1 – 3 cm	> 3cm
Margin	Smooth	Lobulated	Spiculated
Shape	Round	Irregular / Linear	Ovoid
Texture	Non-Solid / GGO	Part Solid Mixed	Solid
Tumor – Lung Interface	Coarse	Unclear	Smooth

4. Proposed Methodology

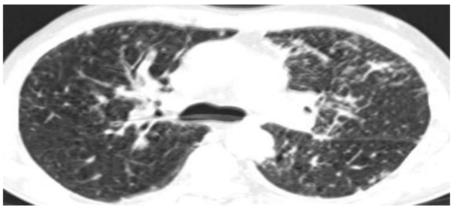
4.1. Identified challenges in the literature on lung automation: The prediction of the primary tumor or secondary tumor plays a major role in the diagnosis of the cancer and treatment of the further spread of cancer. The primary type of tumor is the one that develops in the lungs. The secondary type of tumor has spread due to the cancer from other parts of the body. Lung cancer needs to be identified as the spread of tumor cells to other parts of the body. Thus, the CT Body slices ensure bone erosion and the breakthrough of tumor cells that penetrate the body. The Lesions detected need to be predicted exactly either malignant or benign tumors to save the patient at the earliest. The various categories of benign tumors need to be detected. The histopathology cannot suspect the tumor cells at the earlier stage of appearance of tumor cells such cases can be identified using the deep learning model. The research challenges are shown in Figure 2.

a. NORMAL
Category: Normal
Lung without any infections.

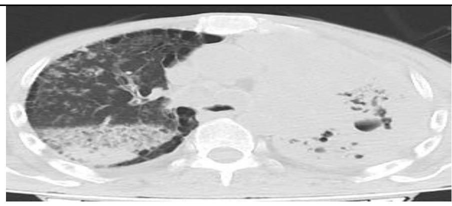


b. BENIGN (Pneumonia)
Category: Benign
The Pneumonia is noticed at the superior segment of the left lower lobe.

Fig. 3. The CT Scan Image of patients with a. Normal and b. Pneumonia.

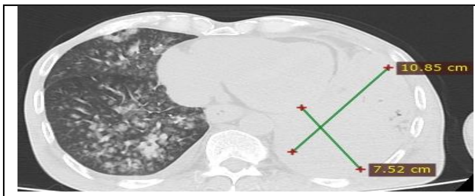


a. **MALIGNANT TUMOUR**
Category: MALIGNANT
Cancer Type: Non-Small Cell Carcinoma The Appearance of thick and multiple fragments of fibrocollagenous tissues confirms the malignancy.

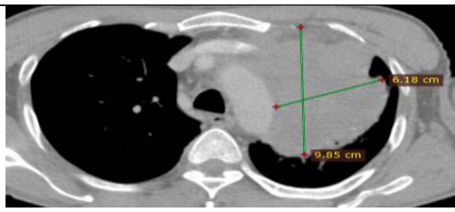


b. MALIGNANT TUMOUR
Category: MALIGNANT
Cancer Type: Carcinoma
Left centenary **lobular NODULE** noted in left lung field with bone erosion, Mediastinal and plural contact consolidation of the right lower lobe.

Fig. 4. a. Malignancy tumor and b. with detected Lung Lesion of the patients.



a. UNPREDICTED LUNG MASS
The left lung Biopsy Image is marked with a huge Lung mass. The Lesion of 7.5X10.8cm on the right infection has developed and spread all over the lung.**Category: Suspicious**
Either: Malignant or Benign?
The Lung Mass is Suspicious reported by the histopathology report and by the radiologist.



b. **UNPREDICTED LUNG MASS**
An anterior Mediastinal Mass of 6x9.8cm on the left lung is noted. The detected lung mass is huge with calcium deposits.
Category: Suspicious
Either: Malignant or Benign?
The Lung Mass is Suspicious reported by the histopathology report and by the radiologist.

Fig. 5. The Lung CT Scan Image of a and b are Suspicious and thus cannot predict the Tumor category by the pathologist by histopathology report and the radiologist.

4.2 Lung Cancer Datasets Resources

The lung cancer datasets available from existing literature are listed in Table 3. The NSCLC has the highest classification of lung dataset with 10,835 patients' CT images. Lung cancer literature has few public and private lung datasets. The CT lung image datasets are described in Table 3 the number of cases associated with the dataset is listed in the table. The available datasets are classified into normal, benign, and malignancy classes. The discussed article uses various online datasets Lung Image Database Consortium (LIDC), Lung Image Database Consortium and Image Database Resource Initiative (LIDC–IDRI), Early Lung Cancer Action Program (ELCAP), Lung Nodule Analysis 2016 (LUNA16), Database of Japanese Society of Radiological Technology (JSRT) are the famous public dataset. The proposed dataset samples are shown in figure 3,4,5 noramal, benign, malignant and suspictious respectively.

Table 3 - Lung Cancer Dataset Description

Lung Dataset and Its Description

S.No	Dataset	Samples	Image Type
1	LIDC- IDRI	1018 patients	CT
2	Lung Nodule Analysis 2016 (LUNA 16)	880 patients	CT
3	Kaggle Data Science Bowl	1397 patients	CT
4	Lung Image Database Consortium (LIDC)	1024 patients	CT
5	National Lung Screening Trial (NLST)	2100 patients	CT
6	MedGift (Interstitial Lung Diseases) ILD Dataset	480 patients	CT
7	Non-Small Cell Lung Carcinoma (NSCLC)	221 patients	CT
8	Indian Lung CT Image Database (ILCID)	400 patients	CT
9	LNDb Challenge Dataset	294 patients	CT
10	LOLA 11	55 cases	CT
11	LONI Image Data Archive	99 cases	CT
12	Rider Dataset	322 patients	CT
13	Proposed Private Dataset BIRL Dataset	287 Cases	CT

4.3 BIRL Dataset Description

This research article uses a private dataset that is received from Madras Medical College, Barnard Institute of Radiology, Lung CT Image Dataset. The dataset description is shown in Figure 6. The images are categorized as normal cases 100, benign cases 100, and malignant cases 87 in total. The dataset is preprocessed, augmented, applied image enhancements, and labeled into classes with confirmation of HPE reports of each patient.

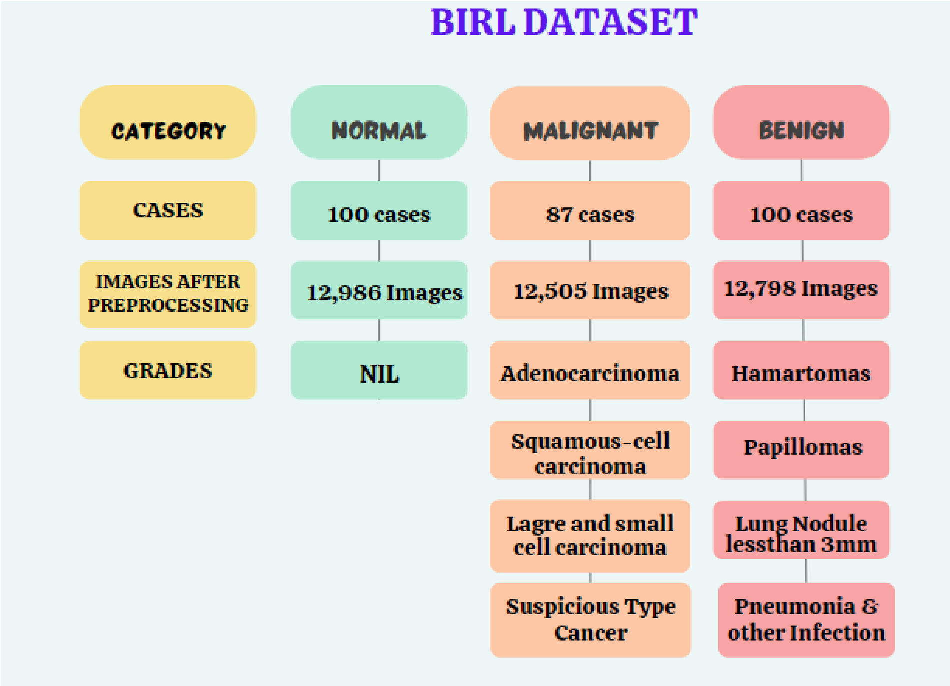


Fig. 6. Dataset Description.

5. Proposed Methodology

Multiple convolutional and pooling layers are stacked consecutively in a conventional CNN architecture. High-level features are captured by deeper layers, and low-level features are captured by shallower levels. Labeled data is used to train these networks, and backpropagation is used to determine the filter weights. In a variety of computer vision applications, such as object identification, image segmentation, and image classification, CNNs have demonstrated remarkable effectiveness. They have also been used in other fields, such as speech recognition and natural language processing, where grid-like data structures can be converted into a CNN-processable format. In a variety of computer vision applications, such as object identification, image segmentation, and image classification shown in table 4. They have also been used in other fields, such as speech recognition and natural language processing, where grid-like data structures can be converted into a CNN-processable format. The system's convolutional layers are organized into three distinct layers. The first layer utilizes 32 filters with a kernel size of (3, 3) and the ReLU activation function to extract low-level features such as textures and edges. The second layer, also using the ReLU activation function, employs 64 filters with a kernel size of (3, 3) to extract higher-level features. To get the feature maps ready for the fully linked layers, the third convolutional layer simplifies them and removes more complicated features. Before being fed into the fully connected layers, the output of the convolutional layers is transformed into a one-dimensional array. A total of 128 neurons activated by the ReLU function make up the first dense layer; this layer aids in the combining and abstraction of features, and the output layer generates a probability score that indicates the input image's cancer likelihood. The CNN model is shown in Figure 7.

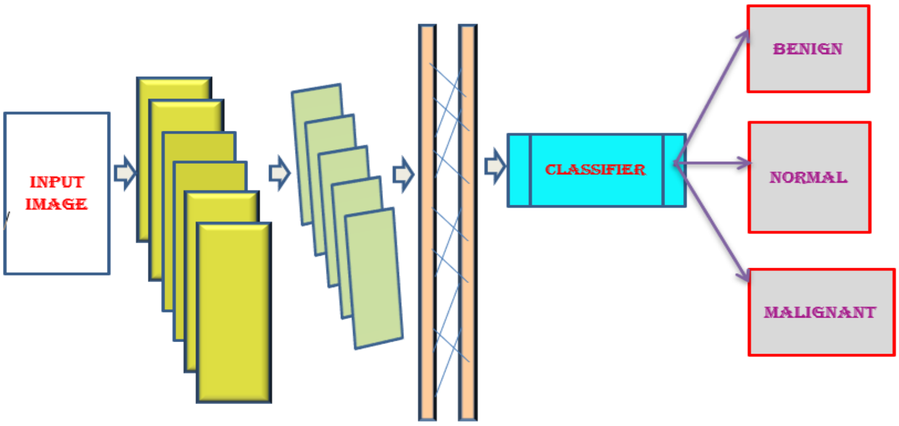


Fig. 7. The Proposed Convolutional Neural Network detects lung tumors either benign, Benign, Malignant, or Normal.

The basic processes of lung cancer detection and classification are image acquisition, pre-processing, and training data for the machine to learn. *Image acquisition:* Image acquisition is one most important phases to automate lung cancer detection and disease classification. Image acquisition is the first phase of the implementation process. To train the machine the images are the basic objects to make the computer understand better. The various images obtained from radiologists are Chest X-ray, CT scan, sputum smear microscopy, CT-guided biopsy, and Histopathology Images. The images focused are Chest X-rays, CT scans, and CT-guided biopsy images. Pre-processing: Pre-processing has a major contribution to automating the detection of lung cancer and the disease. This is the second phase in the implementation process. This phase is used to enhance the input image, modify the image, locate the region of interest (ROI), edge detection, and so on. The categorical data may help the computer system model to understand better. Pre-processing is a process concerning nodules and non-nodules. Training phase: The third phase is the training phase. The selection of an algorithm is a major task of the training phase. The classification of lung disease, detection of lung nodule points, and the prediction of benign and malignant tumors concerning deep learning, transfer learning, and convolution neural network models to outproduce the most accurate results. Deep learning is the best technique for the automation of lung cancer shown in figure 8.

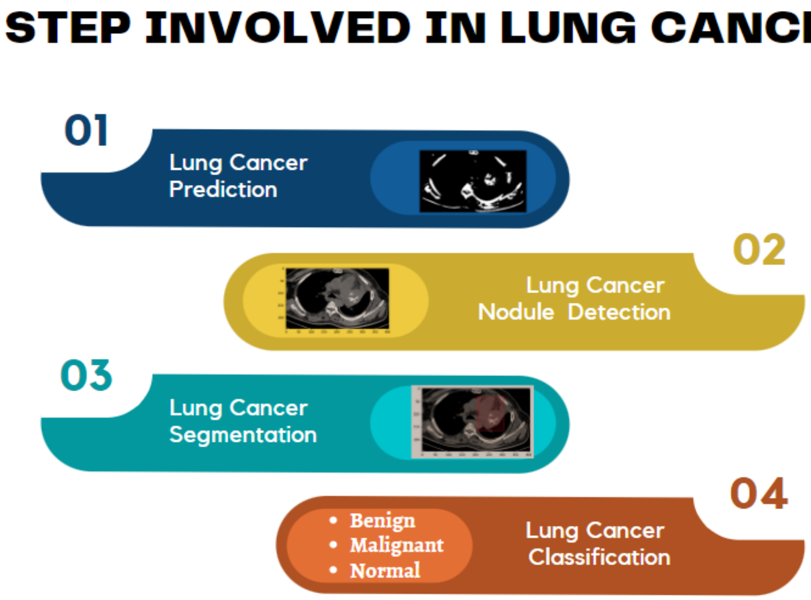


Fig. 8. The Lung Cancer Automation Process With Lung Tumor Detection Is Shown With Output.

Implementation phases: The lung nodule detection and classification of tumors is the major phase in automatic nodule point detection. The 3D region growing technology brings a massive difference in segmenting and detecting the lung nodule point. The nodule points identified are classified as benign or malignant tumors. The hybrid sphere sampling method is based on the feature selection method. To break the input images into slices the CNN features and build slice algorithms are performed to detect lung cancer. The principal component analysis is implemented for the fusion of multiple kernels learning to detect the nodule point. Thus, the method gives better accuracy at 99.3%.

Table 4 - Comparison of Lung Nodule Technique With The Proposed Method

Citation	Method	Outcome	Accuracy
(Gupta et al., 2023)	Masks generation to separate the nodule and pleura Automatic seed points selection Fuzzy connectedness with Adaptive threshold estimation MRFC	Nodules connected to the pleura or vessels	95%
(Makaju et al., 2018)	Pre-processing involves a Median filter & and Gaussian filter for the segmentation watershed Algorithm, and SVM Classifier	Lung Cancer Detection	92%
(Gu et al., 2018)	Otsu's threshold to locate ROI 3D region growing technology voxel seed selection & 3D region growing	Lung segmentation & Lung nodule detection.	92.9%
(Q. Wang et al., 2019)	Raw candidate patches detected ResNet to classify	Lung Nodule Detection	92.8%
(S. Wang et al., 2020b)	Residual neural network SIGMOD activation function for pre-training, Sigmoid activation Transfer Learning	Pathological type of lung cancer	85.71%
(Chen et al., 2021)	MV-SIR model, VH, and SH features extraction	Lung Nodule Segmentation	92.6%
(Stephen et al., 2021)	Grad-CAM, ReLu Network, 3D CNN, AlexNet	Lung nodule classification	97%
(Dutande et al., 2021)	MIP for nodule segmentation, Binary classification, SquExUNet	Lung nodule segmentation and classification	80%
(Chen et al., 2021)	Spatial information and clustering, Gaussian Distribution of seed point, Gaussian mixture model	Pathological lung segmentation	98.5%
(Agarwala et al., 2020)	Transfer learning, P-Net, Natural color image processing	Interstitial lung disease detection	85.5%
(Prashanthi & Angelin Claret, 2023)	Nodule segmentation with ResNodNet and Classification using CNN	Lung Tumour Segmentation	98.6%
PROPOSED METHOD	**Lung Nodule Detection for CT-Guided Biopsy Images Using Deep Learning**	**Lung tumor Classification**	**99.3%**

6. Results and Discussion

Our investigation employed a deep neural network architecture constructed using the Sequential model from the Keras toolkit. Tailored for image processing tasks, the network was specifically designed for binary classification tasks. It operates on RGB images of size 128x128 pixels, employing a sequence of convolutional and pooling layers followed by fully connected layers. Shown in Figure 9.

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_6 (Conv2D)           (None, 126, 126, 32)      896       
                                                                 
 max_pooling2d_6 (MaxPoolin  (None, 63, 63, 32)        0         
 g2D)                                                            
                                                                 
 conv2d_7 (Conv2D)           (None, 61, 61, 64)        18496     
                                                                 
 max_pooling2d_7 (MaxPoolin  (None, 30, 30, 64)        0         
 g2D)                                                            
                                                                 
 conv2d_8 (Conv2D)           (None, 28, 28, 128)       73856     
                                                                 
 max_pooling2d_8 (MaxPoolin  (None, 14, 14, 128)       0         
 g2D)                                                            
                                                                 
 flatten_2 (Flatten)         (None, 25088)             0         
                                                                 
 dense_4 (Dense)             (None, 128)               3211392   
                                                                 
 dense_5 (Dense)             (None, 1)                 129       
                                                                 
=================================================================
Total params: 3304769 (12.61 MB)
Trainable params: 3304769 (12.61 MB)
Non-trainable params: 0 (0.00 Byte)
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Fig. 9. The Model Summary of Proposed CNN.

The initial layer consists of a 2D convolutional layer with 32 filters, each employing a 3x3 kernel size and the rectified linear unit (ReLU) activation function. This layer extracts features from input images by applying the filters across the image. Subsequently, a 2D max-pooling layer with a 2x2 window down samples the representation obtained from the convolutional layer by selecting the maximum value within each window, thereby reducing spatial dimensions. The network then incorporates 64-filter and 128-filter 2D convolutional layers, each with a 3x3 kernel size and ReLU activation. This pattern of convolutional layers followed by max-pooling layers is repeated twice, allowing the network to detect increasingly complex patterns and features. A flattened layer follows the convolutional and pooling layers, converting the multidimensional feature maps into a one-dimensional array for further processing. Next, a fully connected Dense layer with 128 nodes and ReLU activation performs high-level reasoning using the learned features. The final component is a Dense output layer with a single node using sigmoid activation, representing the binary classification task. This layer outputs the likelihood of the input belonging to one of two classes in this case, the presence or absence of cancer. For optimization, the model utilizes the Adam optimization technique, an improvement over stochastic gradient descent. The binary cross-entropy loss function is employed, as it is well-suited for binary classification tasks.

Model performance is evaluated using the accuracy metric, which measures the proportion of correctly predicted instances.

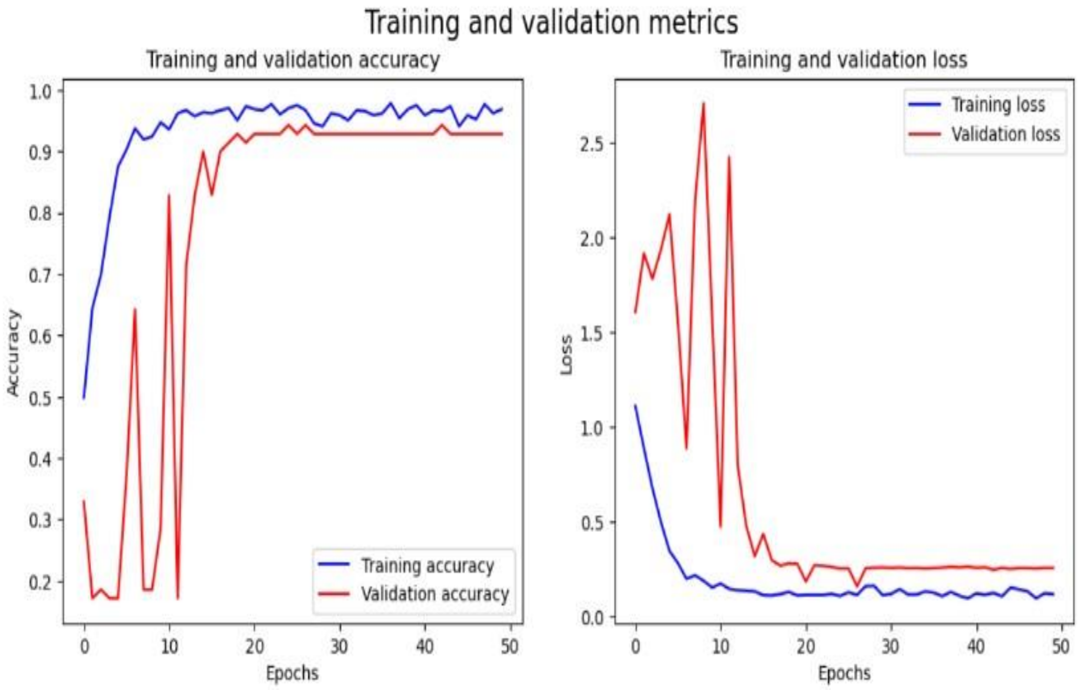

Fig. 10. The Training and validation accuracy, and training and validation loss.

The novelty of our approach lies in the early diagnosis of lung cancer facilitated by our model, which achieved an impressive accuracy of 99.3% during validation at the Madras Medical College. This high accuracy enables timely detection of lung cancer, offering a significant advantage in patient outcomes and treatment planning. By successfully differentiating between malignant and non-cancerous lung nodules, the CNN model trained for lung cancer prediction. This is essential for accurate diagnosis and customized therapy; the plot of Figure 10 shows the training and validation accuracy proof. This model is incredibly good at detecting little abnormalities in CT images that might be signs of lung cancer because it uses sophisticated deep-learning algorithms and an architecture that has been fine-tuned.

7. Conclusion

Finally, with a validation accuracy of 99.3 percent our model is a huge step forward in fighting against lung cancer in its early stages. By allowing for the early identification of lung cancer, this exceptionally high degree of accuracy provides a significant benefit in terms of patient outcomes and treatment planning. As shown by the CNN model trained for lung cancer prediction, our approach improves diagnosis accuracy and allows for personalized therapy by successfully differentiating between carcinogenic and non-cancerous lung nodules. The model's capacity to identify small anomalies in CT images that could be signs of lung cancer is a result of its architecture and advanced deep-learning techniques. Overall, our findings highlight the importance of modern computational tools in improving early identification and treatment results for lung cancer.

Automation in the field of radiology is more prominent nowadays. Most of the patient's case history analysis states that the small lesions detected known to be benign, actually developed to be malignant tumors shortly identified in the case study with the CNN model. Such suspicious types of cancerous lung mass or nodules are made possible to identify by the proposed deep learning model with better validation and accuracy. The challenges of different nodules can be classified with multiclass classification. The suggested methodology outperforms conventional approaches and attains a good accuracy rate in discovering the nodules that develop into cancer at the earlier stage due to pattern matching and knowledge discovery which benefits the patients in the early detection of lung cancer. To identify benign and malignant tumors in the lungs, this is vital. To improve diagnosis accuracy, the model extracts complex characteristics from CT scan images using deep neural networks and sophisticated convolutional neural networks. With its user-friendly design, the technique is perfect for clinical practice and can be quickly and easily implemented. Clinicians can benefit from a user-friendly, efficient diagnostic tool that simplifies the procedure and allows for quick treatment planning. Positive findings from the model's statistical examination point to its potential as a useful diagnostic tool in clinical practice. For future scope, several avenues can be explored to improve the model's performance and applicability: Combining predictions from multiple models or different architectures can enhance the final prediction accuracy and reliability. Employing tools and techniques for model explainability to interpret decisions made by the CNN model can increase trust in its predictions and provide valuable insights for clinical decision-making. In Real-world Testing For practical applications, deploying the trained model in a clinical setting and performing extensive validation with real-world data is crucial for assessing its translational value in diagnosing medical conditions. In sum, the proposed CNN model is a promising step toward automated and accurate medical diagnoses using deep learning. With continual refinement and validation, such models could significantly impact clinical workflows and patient outcomes in the future. Deep learning with 3D technique produces a higher accuracy to find the cancer better. The tendency to detect the tumor and its size using deep learning techniques leads to the solution of automating lung cancer. The contribution of the proposed methodology is to benefit the radiologist by providing an AI prediction model to check the preliminary screening.

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