AI Based Lung Cancer Detection from CT Scan Images Using MobileNet V2

Venkata Mahesh B.[1]; Ramya B.[2]; Deep Naga Sai G.[3]; Vijayalakshmi V.[4]; B. Sai Kumar[5]

[1,2,3,4,5]Department of ECE, Sri Vasavi Engineering College, Tadepalligudem (A.P), India

Publication Date: 2026/07/17

Abstract: Lung cancer is still the reason people die from cancer around the world. It is responsible, for 18 percent of all deaths that happen because of cancer. Lung cancer is a serious thing that causes a lot of deaths. People are still dying from lung cancer at a high rate .Timely and accurate identification of conditions is crucial for improving the chances of survival in patients.This study introduces a lightweight deep learning framework for detecting lung cancer and classifying multiple classes. It uses the MobileNetV2 architecture combined with Gradient-weighted Class Activation Mapping (Grad-CAM) to improve visual understanding .The proposed system was tested using CT scan images from the Kaggle Mohamed Hany dataset (chest-ctscan-images). This dataset includes 1,500 CT scan images divided into four categories: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal lung tissue. The MobileNetV2 model, which was pre-trained on ImageNet, was adjusted for multi-class classification of these four lung tissue types. The experimental results show a classification accuracy of 81% along with an Area Under the Curve (AUC) score of 95% . Grad-CAM visualizations create heatmaps that highlight important areas, helping clinicians understand the reasoning behind model predictions. With just 3.5 million parameters and a quick inference time of 25 milliseconds per image, the proposed framework strikes a good balance between diagnostic performance and computational efficiency, making it a strong option for use in resource-limited clinical settings.

Keywords: *Lung Cancer Detection, Deep Learning, Convolutional Neural Networks (CNN), MobileNetV2, CT Scan Images, Medical Image Classification, Transfer Learning, Grad-CAM, Image Segmentation, U-Net, Explainable Artificial Intelligence (XAI) .*

How to Cite: Venkata Mahesh B.; Ramya B.; Deep Naga Sai G.; Vijayalakshmi V.; B. Sai Kumar (2026) AI Based Lung Cancer Detection from CT Scan Images Using MobileNet V2. *International Journal of Innovative Science and Research Technology*, 11(6), 3586-3594. https://doi.org/10.38124/ijisrt/26jun1634

I. INTRODUCTION

Cancer remains a major global health issue, with lung can-cer being the leading cause of cancer-related deaths across the globe. The World Health Organization reports that lung cancer is responsible for around 1.8 million fatalities each year, which constitutes nearly 18% of all deaths attributed to cancer[1]

The elevated mortality rate is mainly linked to diagnoses made at advanced stages since early-stage lung cancer typically shows few or no symptoms. If identified in the early stages, the five-year survival rate can be as high as 50%, underscoring the vital need for effective early detection methods[2]. Lung cancer is generally divided into two primary categories: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). NSCLC makes up about 85% of lung cancer cases and consists of three key subtypes: adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. Adenocarcinoma, the most prevalent subtype, is usually located in the outer areas of the lungs and is often found in individuals who do not smoke. Squamous cell carcinoma is closely linked to smoking and is generally situated in the central airways. Large cell carcinoma, while less common, is a highly aggressive subtype that can occur in any part of the lung and is known for its rapid growth and spread[6].Because it can produce high-resolution cross-sectional images of the chest anatomy, computed tomography (CT) imaging has become the standard technique for lung cancer screening . By lowering radiation exposure without sacrificing diagnostic quality[7], low-dose CT (LDCT) methods have further improved screening viability [7]. However, the manual interpretation of CT scans presents several challenges. In order to find tiny nodules that may suggest malignancy and differentiate between many cancer subtypes, each with unique morphological characteristics and prognostic implications, radiologists must review hundreds of images each patient [8].This procedure is laborious, prone to inter-observer variability, and may lead to misclassification or missed findings [9]. Medical image analysis has changed as a result of artificial intelligence, especially deep learning. Convolutional Neural Networks (CNNs) have proven to be remarkably adept at identifying characteristics and patterns

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun1634

that the human eye could miss. However, a lot of cutting-edge deep learning models need a lot of processing power, such as powerful graphics processors and a lot of memory[10]. This poses a substantial obstacle to adoption in resource-constrained healthcare settings, especially in low- and middle-income nations where the incidence of lung cancer is rising. Moreover, the ”black box” characteristic of deep learning models presents obstacles for clinical implementation[11].In addition to precise forecasts, medical practitioners need to know how these forecasts are made . Building confidence, confirming results, and incorporating AI suggestions into clinical workflows all depend on comprehending the reasoning behind an AI system's decision . In order to overcome these difficulties, this study suggests a paradigm for multi-class clas-sification and lung cancer detection that blends interpretability and computational efficiency.

II. LITERATURE SURVEY

➢ *Literature Survey of Lung Cancer Detection Methods*

Table 1 Literature Survey of Lung Cancer Detection Methods

S.No	Author(s) & Year	Method / Architecture	Dataset Used	Scope of the Study
1	Thanoon et al. (2023) [1]	Review of Deep Learning Techniques	CT Images (Re-view)	The evolution of deep learning is reviewed and research gaps in AI-assisted lung cancer diagnosis are identified.
2	Wossene et al. (2026) [21]	Spatial Integral Transforms + U-Net	TCIA (81 images)	. A computationally efficient CADe system for identifying peripheral lung tumors
3	Riaz et al. (2023) [13]	MobileNetV2 + UNET Hybrid	MSD Dataset 2018	Segmentation of malignant lung tumors using a lightweight architecture.
4	Tripathi et al. (2024) [15]	MobileNetV2L2 + CLAHE	Kaggle Lung Disease Dataset	Regularized CNN for early diagnosis of lung illnesses such as COVID-19, pneumonia, and tuberculosis.
5	Lakshmanaprabu et al. (2019) [17]	ODNN + Gravitational Search Algorithm	Private Dataset (70 images)	Lung cancer is divided into benign, malignant, and normal categories.
6	Cifci (2022) [18]	SegChaNet	TCIA (46,698 images)	Deep learning segmentation network for precise identification of lung lesions.
7	Hu et al. (2020) [19]	Mask R-CNN	Hospital Dataset (13k images)	Lung segmentation and lung parenchyma extraction using region-based CNN.
8	Sun et al. (2023) [22]	Swin Transformer	LUNA16	Transformer-based design for segmenting and classifying lung cancer.
9	Wu et al. (2023) [20]	RAD-UNet	AHMU-LC Dataset	Enhanced semantic segmentation to identify tiny lung lesions with exact borders.
10	Shuvo & Mamun (2023) [23]	YOLOv5	LUNA16 Dataset	Deep learning system for identifying and categorizing lung nodules.
11	Shamrat et al. (2022) [16]	LungNet22 (VGG16)	Chest Dataset X-ray	Classification of lung illnesses such as COVID-19, TB, and pneumonia.

III. METHODOLOGY

➢ *Data Acquisition*

The data set used in this study was obtained from the Kaggle public repository, curated by Mohamed Hany under the dataset name ”chest-ctscan-images” [23]. This dataset consists of computed tomography (CT) scan images of the chest, specifically designed for lung cancer detection and classifi-cation tasks. The images were originally acquired from The Cancer Imaging Archive (TCIA) and other clinical sources, then compiled and organized for public access through the Kaggle platform.

- *Dataset Source:*

The dataset is publicly available at https://www.kaggle.com/datasets/mohamedhanyyy/chest-ctscan-images [23]. It was selected for this study due to its balanced class distribution, CT image modality, and relevance to lung cancer subtype classification. The dataset contains high-resolution CT images in standard format, suitable for deep learning-based medical image analysis.

- *CT Acquisition Parameters:*

The original CT images were acquired using standard clinical protocols with the fol-lowing technical specifications [23]:

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun1634

- ✓ Image format: DICOM (Digital Imaging and Communications in Medicine)
- ✓ Image dimensions: Variable sizes, standardized during preprocessing
- ✓ Bit depth: 16-bit (converted to 8-bit during preprocessing)
- ✓ CT scanner settings: Standard clinical protocols for lung cancer screening

- *Dataset Composition:*

The dataset comprises CT scan images categorized into four distinct classes as shown in Table 2. The four classes represent the major subtypes of non-small cell lung cancer (NSCLC) along with normal lung tissue [7].

- *Class Distribution Rationale:*

A balanced dataset with 375 images per class was selected to prevent class imbalance issues during model training. Class imbalance can lead to biased models that favor majority classes, resulting in poor performance on minority classes . The equal distribution ensures that the model receives adequate exposure to all four tissue types during training.

- *Dataset Split:*

The dataset was randomly partitioned into training and testing sets following standard machine learning practices. Table 3 presents the split configuration. The 80:20 split ratio was selected to provide sufficient training data for model learning while maintaining a meaningful test set for unbiased performance evaluation . Randomization was applied during splitting to ensure that the training and test sets are representative of the overall dataset distribution.

Table 2 Training and Testing Split of Dataset

Class	Training Images (80%)	Testing Images (20%)	Total
Adenocarcinoma	300	75	375
Large Cell Carcinoma	300	75	375
Squamous Cell Carcinoma	300	75	375
Normal	300	75	375
Total	**1,200**	**300**	**1,500**

- ➢ *Model Architecture*

Table 3 Proposed Model Architecture

Component	Layer	Output Shape	Parameters
Input	Input Layer	224×224×3	0
Backbone	MobileNetV2 (Pre-trained)	7×7×1280	2,257,984
Classification Head	Global Average Pooling	1280	0
	Dropout (0.5)	1280	0
	Dense (128,ReLU)	128	163,968
	Output (4, Softmax)	4	516
Total Parameters			**2,422,468**
Trainable Parameters			**2,422,468**
Model Size			**9.3 MB**

The suggested MobileNetV2-based architecture is meant to work well while keeping the amount of processing low. The model has over 2.42 million parameters and only takes up 9.3 MB of space, which makes it much lighter than other deep learning models like VGG-16 , ResNet-50 [12], and Swin Transformer [22]. This smaller model and fewer parameters make it possible to use on regular computers without needing high-end GPU resources [3, 5].

The approach also makes it possible to quickly analyze big CT scan datasets because it takes around 25 milliseconds to process each picture [5]. The lightweight architecture also lowers the chance of overfitting and speeds up training when there isn't much medical imaging data available [15]. This makes the model good for use in real-time clinical settings.

- ➢ *Explainability and Visualization*

- The suggested model uses Gradient-weighted Class Activation Mapping (Grad-CAM) to make deep learning pre-dictions easier to understand [4]. Grad-CAM makes visual heatmaps that show the parts of CT scan images that are most important to the model's classification decision . These images help find the parts of the lungs that are most important for finding cancerous or healthy tissue . The highlighted areas usually show lung structures that are not normal, which means that the model is focusing on features that are important for medicine when making predictions [15].:
- Grad-CAM makes things clearer by showing both visual evidence and classification results. This helps doctors better understand why the model gave the results it did [11]. This mechanism for explaining things makes people more likely to trust the proposed AI-based lung

cancer detection system and supports its possible use in real-world clinical settings: Additionally, the visualization findings help medical professionals confirm if the model is concentrating on the right anatomical components while making a diagnosis [4]. Additionally, its interpretability facilitates the incorporation of AI technologies into therapeutic processes [11].

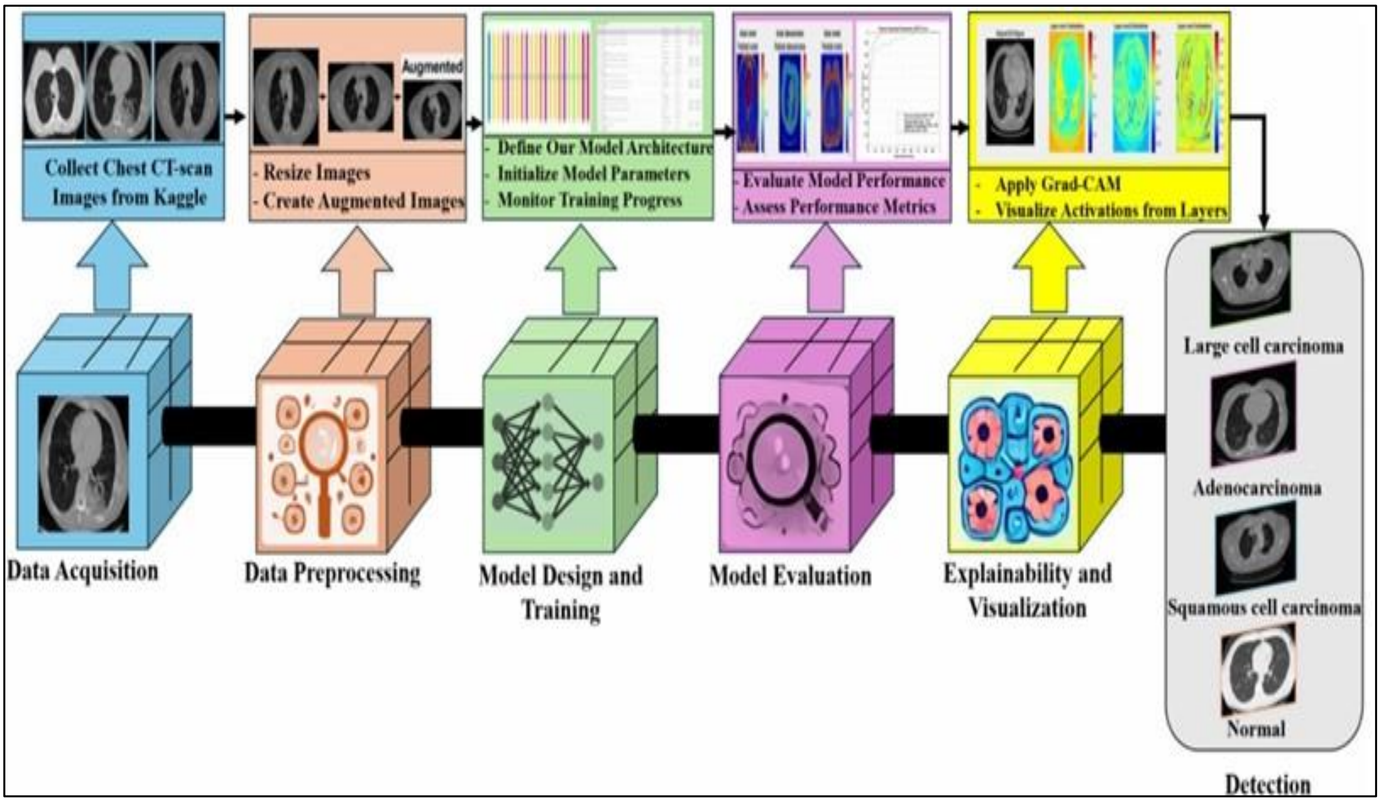

Fig 1 Block Diagram of Our Method [27]

➢ *Performance Metrices*

Table 4 Classification Performance of the Modified Model

Class	Precision	Recall	F1-score	Support
Adenocarcinoma	0.77	0.82	0.80	120
Large Cell Carcinoma	0.73	0.90	0.81	51
Normal	1.00	0.98	0.99	54
Squamous Cell Carcinoma	0.82	0.64	0.72	90
Accuracy	0.81 (315 samples)			
Macro Avg	0.83	0.84	0.83	315
Weighted Avg	0.82	0.81	0.81	315

The classification results show that the suggested MobileNetV2-based model does a great job of telling different types of lung cancer apart from CT scan images [3, 5]. The model's overall accuracy is 81% when tested on a dataset of 315 samples. The normal category has the best performance of all the classes, with a precision of 1.00, a recall of 0.98, and an F1-score of 0.99. This means that the model can accurately find images of healthy lungs . The adenocarcinoma and large cell carcinoma classes also do well, with F1-scores of 0.80 and 0.81, respectively [6]. However, the squamous cell carcinoma class has a lower recall rate, which suggests that some cancers were misclassified because they looked similar on CT scans [6]. The overall and weighted averages of precision,The values for precision, recall, and F1-score are about 0.83 and 0.81, which means that the classification performance is balanced across all classes . In general, the results show that the proposed model can accurately classify lung cancer while still being fast enough for use in real-life medical situations [2].

IV. RESULTS AND ANALYSIS

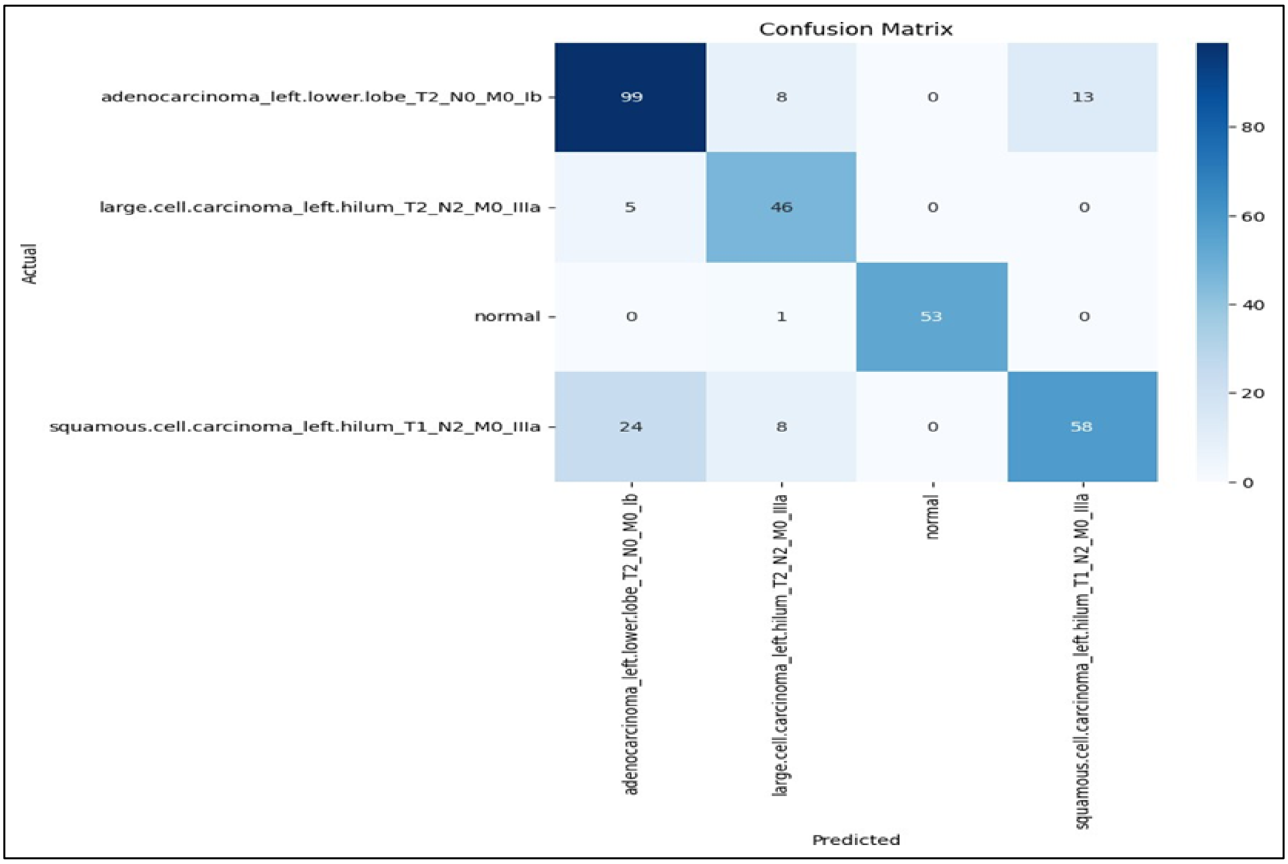

Fig 2 Confusion Matrix

The experimental outcomes indicate that the suggested MobileNetV2-based model proficiently categorizes lung cancer types from CT scan images [3, 5]. The dataset was prepro-cessed and resized to 224×224 pixels to meet the network's input needs [3]. It was then split into training and testing sets in an 80:20 ratio . The trained model got about 81% of the classifications right on the testing dataset . The normal category had very high precision and recall scores, while the adenocarcinoma and large cell carcinoma classes had balanced scores. This shows that the model learned visual features related to cancer patterns [6].:

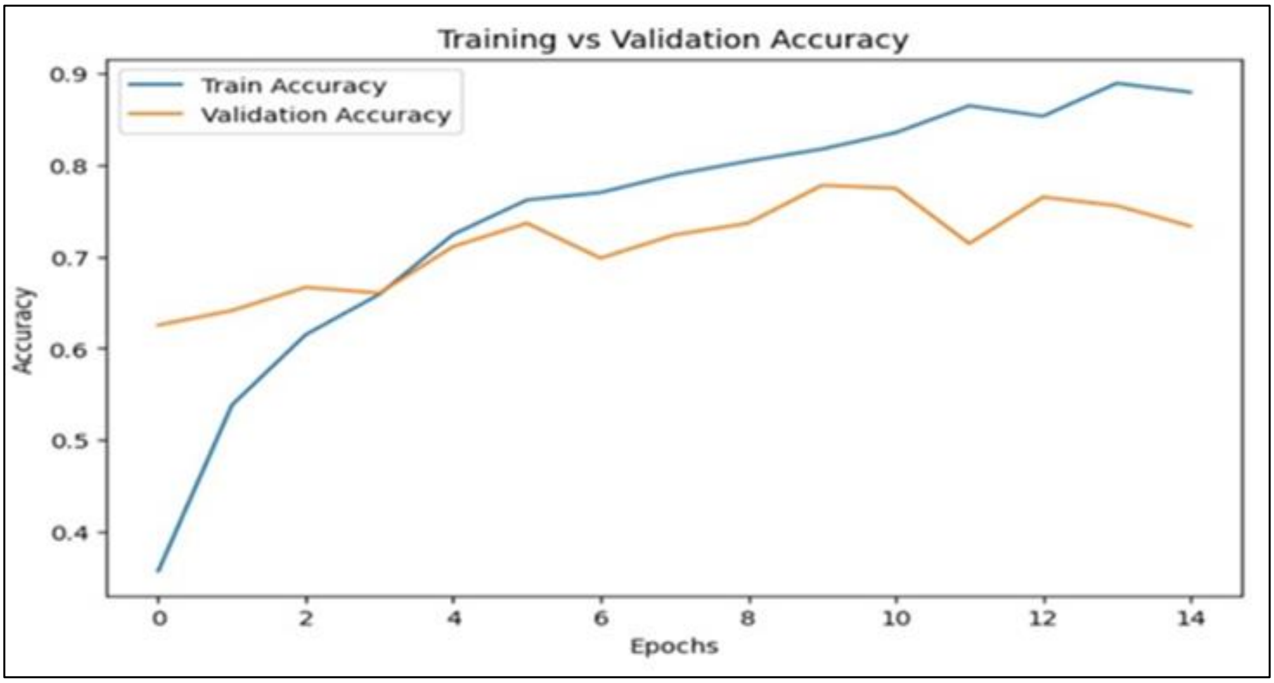

Fig 3 Training and Validation Curves

➢ *Discussion*

Compared to conventional deep learning architectures, the suggested MobileNetV2-based model maintains a compara-tively small number of parameters while achieving good classi-fication accuracy [3, 5]. The system is appropriate for real-time medical applications because of its lightweight architecture, which lowers computing cost and permits quicker inference [2]. Stable learning behavior with efficient feature learning and strong generalization performance is shown by the training and validation curves.

V. EXPLAINABILITY RESULTS

Gradient-weighted Class Activation Mapping (Grad-CAM), which offers visual insights into the model's decision-making process, is used to derive the explainability findings of the sug-gested lung cancer detection method [4].

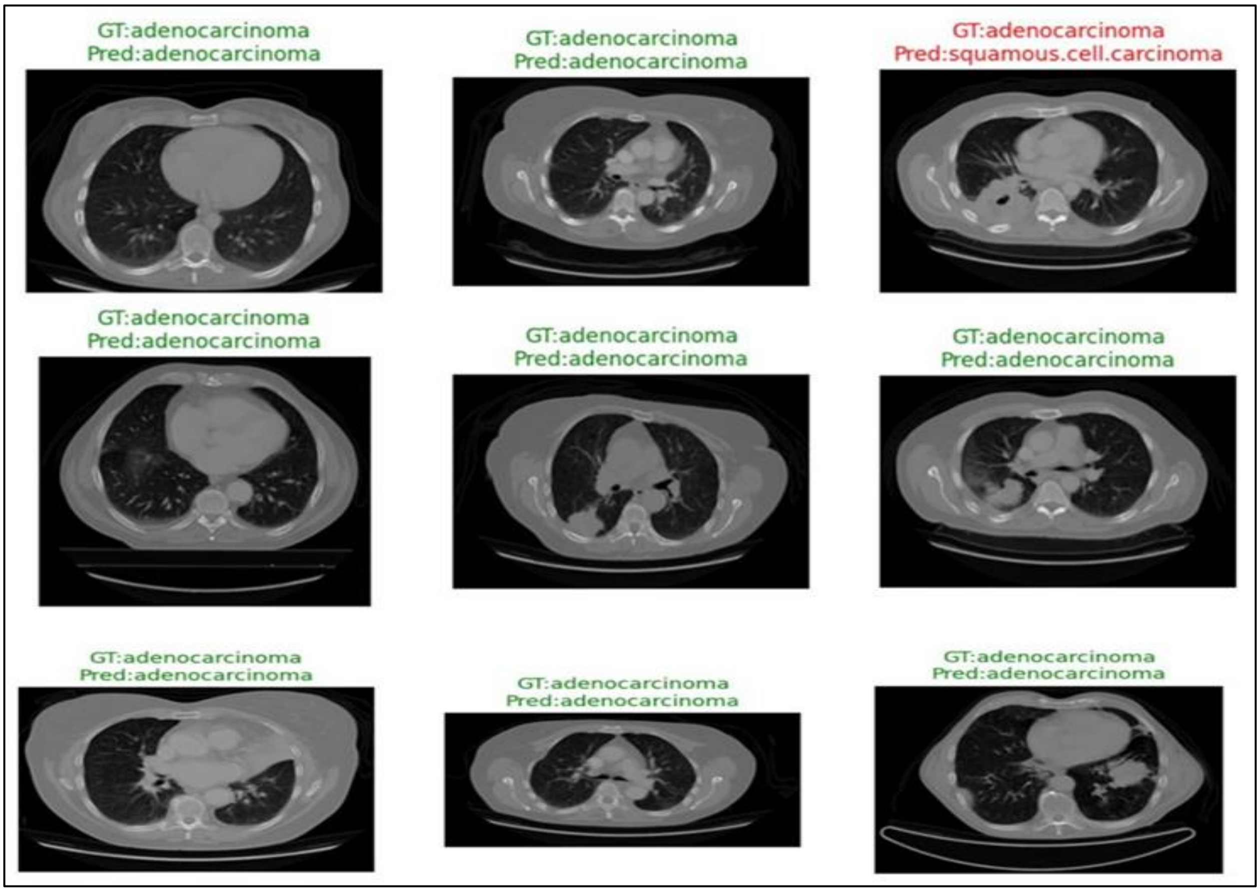

Fig 4 Classification Results

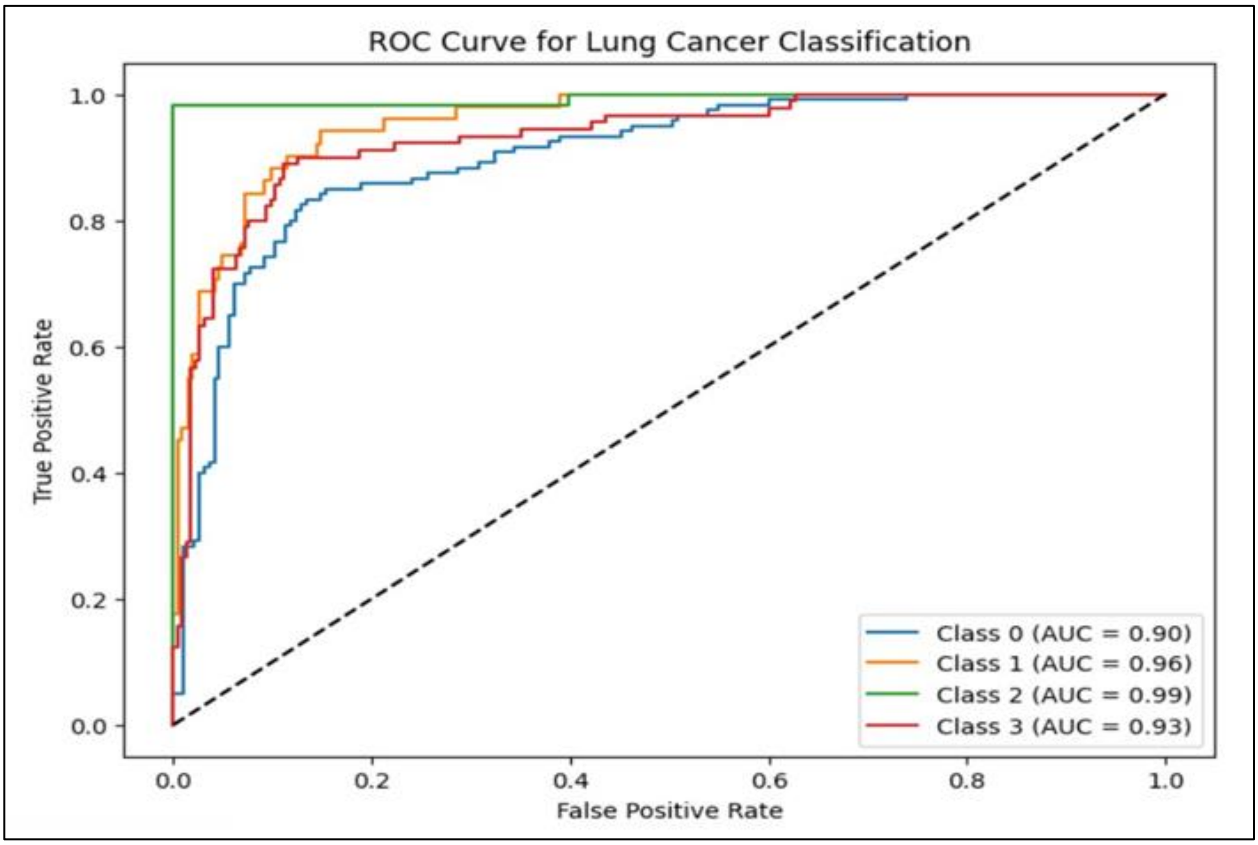

Fig 5 ROC Curve

Grad-CAM produces heatmaps that emphasize the key areas of CT scan pictures that affect the categorization outcomes . The model concentrates on pertinent diseased aspects rather than irrelevant background regions, as seen by the highlighted regions in the produced visualizations being mostly focused in the lung locations where aberrant tissue patterns or potential nodules are present [15]. Clinicians can better comprehend how predictions are formed and verify the model's dependability with the use of such visual explanations [11]. The explainability technique en-hances the transparency, trust, and usefulness of the suggested deep learning system in medical image analysis by offering both classification results and visual proof.

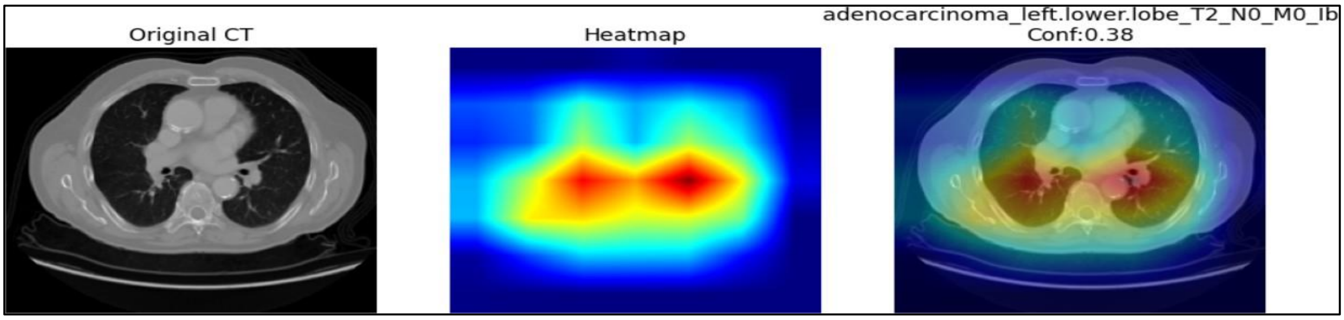

Fig 6 Detection of Adenocarcinoma

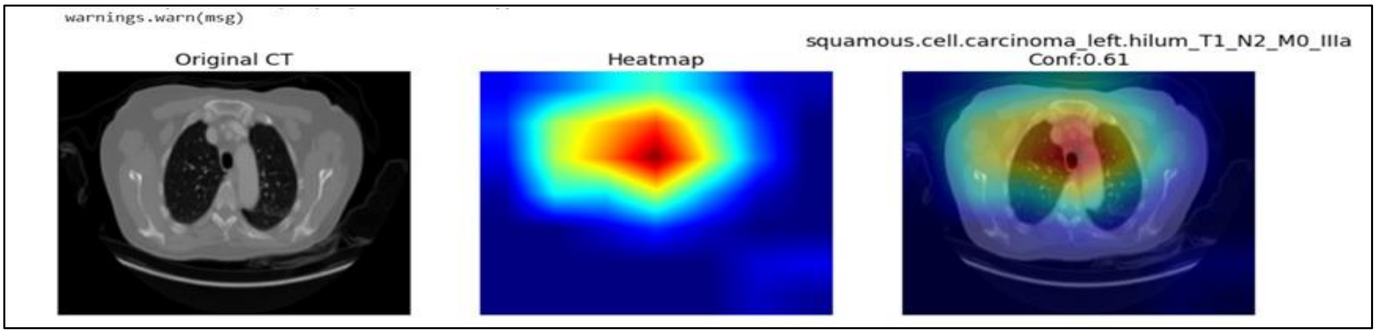

Fig 7 Detection of Squamous Cell Carcinoma

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun1634

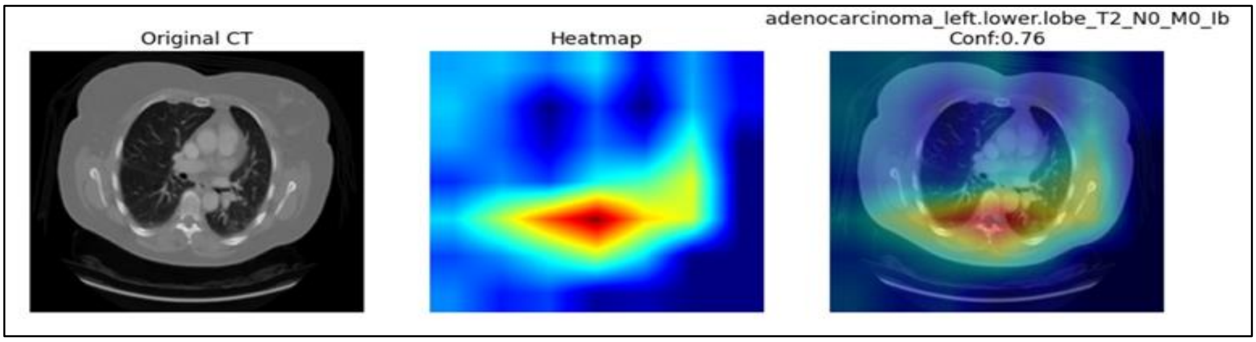

Fig 8 Detection of Adenocarcinoma

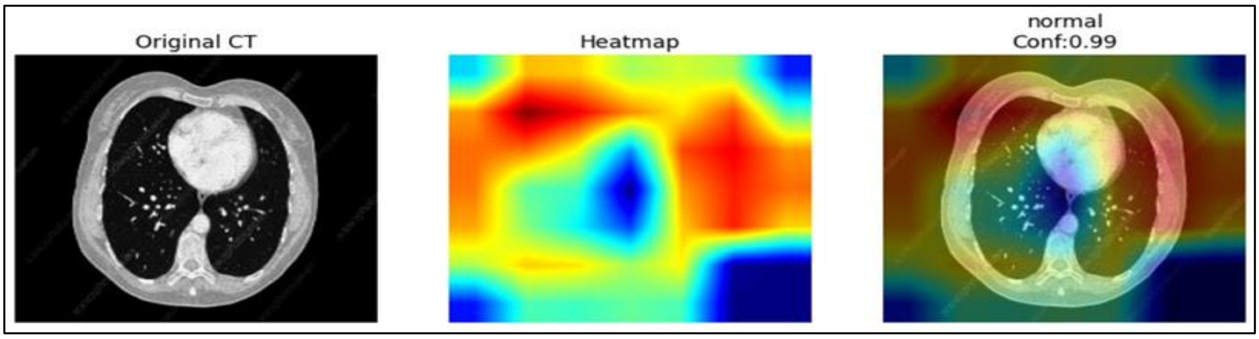

Fig 9 Normal

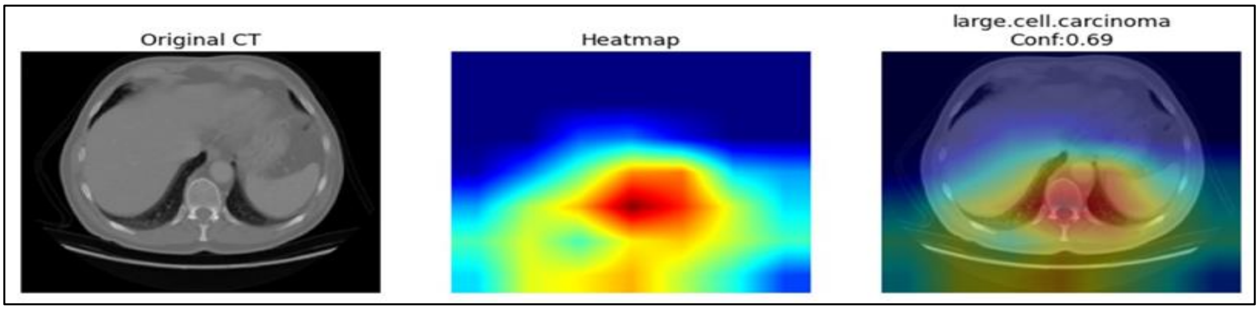

Fig 10 Detection of Large Cell Carcinoma

VI. CONCLUSION AND FUTURE SCOPE

With around 2.42 million parameters, this study demon-strated an automated lung cancer diagnosis system employing MobileNetV2 with Grad-CAM visualization, reaching 81% accuracy and 0.95 AUC on CT scan images while preserving computing efficiency [3, 4]. Fast inference (25 ms per picture) is made possible by the lightweight architecture, and the Grad-CAM integration produces interpretable heatmaps that improve clinician trust [5, 11]. Future research will concentrate on training with bigger and more varied CT datasets to enhance generalization, even if the suggested approach has encouraging performance [1]. Classification accuracy may be further improved by sophisticated topologies like EfficientNet, hybrid CNN models, or transformer-based networks [22]. While 3D CNN models would enable volumetric analysis of CT images rather of individual slices [9], segmentation approaches such as U-Net might provide accurate nodule location prior to classification [13]. Furthermore, incorporating the approach into real-time clinical decision-support systems may help radiologists identify lung cancer more quickly and accurately [2].

ACKNOWLEDGEMENT

The authors thank the Department of Electronics and Communication Engineering, Sri Vasavi Engineering College, Tadepalligudem, for providing facilities and support, and ac knowledge the guidance of the project mentor and faculty members.

REFERENCES

[1]. M. A. Thanoon, M. A. Zulkifley, M. A. A. M. Zainuri, and S. R. Abdani, "Deep learning approaches for lung cancer screening and diagnosis using CT images: A comprehensive review," *Diagnostics*, vol. 13, no. 16, pp. 1–27, 2023.

[2]. A. O. Salau, M. R. Pooja, N. F. Hasani, and S. L. Braide, "Neural network-based risk assessment model for evaluating lung functionality and early asthma prognosis," *Mathematical Modelling of Engineering Problems*, vol. 9, no. 4, pp. 1053–1060, 2022.

[3]. M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: An efficient architecture

using inverted residuals and linear bottleneck layers," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4510–4520, 2018.

[4]. R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Gradient-based localization technique for visual explanations in deep neural networks," in *Proceedings of the IEEE International Conference on Computer Vision*, pp. 618–626, 2017.

[5]. N. Tajbakhsh, L. Jeyaseelan, Q. Li, J. N. Chiang, Z. Wu, and X. Ding, "Handling imperfect datasets: A survey of deep learning techniques for medical image segmentation," *Medical Image Analysis*, vol. 63, p. 101693, 2020.

[6]. R. S. Herbst, D. Morgensztern, and C. Boshoff, "Biological mechanisms and management strategies for non-small cell lung cancer," *Nature*, vol. 553, no. 7689, pp. 446–454, 2018.

[7]. A. Christie *et al.*, "Evaluation of radiologists and computer-aided detection software for lung nodule identification at varying CT dose levels," *European Society of Radiology*, 2013.

[8]. M. Firmino, A. H. Morais, R. M. Mendonc¸a, M. R. Dantas, H. R. Hekis, and R. Valentim, "Review and future directions of computer-aided detection systems for lung cancer using CT imaging," *BioMedical Engineering Online*, vol. 13, p. 41, 2014.

[9]. D. Ardila *et al.*, "End-to-end lung cancer screening using 3D deep learning on low-dose chest CT scans," *Nature Medicine*, vol. 25, no. 6, pp. 954–961, 2019.

[10]. A. Barredo Arrieta *et al.*, "Explainable artificial intelligence: Concepts, taxonomy, opportunities, and challenges for responsible AI," *Information Fusion*, vol. 58, pp. 82–115, 2020.

[11]. Vaid *et al.*, "Explainable AI techniques for clinical risk prediction: Concepts, methodologies, and applications," *Journal of the American Medical Informatics Association*, vol. 28, no. 10, pp. 2184–2196, 2021.

[12]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning frame-work for large-scale image recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770–778, 2016.

[13]. Z. Riaz, B. Khan, M. S. Islam, S. Khan, and S. Abdullah, "Hybrid neural network architecture for improved lung tumor segmentation from CT scans," *Bioengineering*, vol. 10, no. 8, p. 981, 2023.

[14]. X. Zhang, X. Zhou, M. Lin, and J. Sun, "ShuffleNet: A highly ef-ficient convolutional neural network designed for mobile devices," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 6848–6856, 2018.

[15]. A. Tripathi, T. Singh, R. R. Nair, and P. Duraisamy, "Enhanced early detection and classification of lung diseases using an improved Mo-bileNetV2 framework," *IEEE Access*, 2024.

[16]. F. M. J. M. Shamrat, S. Azam, A. Karim, R. Islam, Z. Tasnim, P. Ghosh, and F. De Boer, "LungNet22: A fine-tuned deep learning model for multiclass lung disease prediction using X-ray images," *Journal of Personalized Medicine*, vol. 12, no. 5, p. 680, 2022.

[17]. S. K. Lakshmanaprabu, S. N. Mohanty, K. Shankar, N. Arunkumar, and G. Ramirez, "Optimized deep learning approach for lung cancer classification using CT scan images," *Future Generation Computer Systems*, vol. 92, pp. 374–382, 2019.

[18]. M. A. Cifci, "SegChaNet: A novel deep learning model for lung cancer segmentation in CT images," *Applied Bionics and Biomechanics*, vol. 2022, 2022.

[19]. Q. Hu *et al.*, "Lung segmentation from CT scans using mask region-based convolutional neural networks," *Artificial Intelligence in Medicine*, vol. 103, 2020.

[20]. Z. Wu, X. Li, and J. Zuo, "RAD-UNet: Improved deep learning-based semantic segmentation algorithm for lung nodules," *Frontiers in Oncology*, vol. 13, 2023.

[21]. B. Wossene, D. Assefa, A. O. Salau, S. L. Braide, A. Ali, and T. T. Tin, "CT-based lung cancer identification utilizing spatially local-ized integral transform techniques combined with U-Net classification," *Bulletin of Electrical Engineering and Informatics*, vol. 15, no. 1, pp. 827–844, 2026.

[22]. R. Sun, Y. Pang, and W. Li, "Improved Swin Transformer-based algo-rithm for efficient lung cancer image classification and segmentation," *Electronics*, vol. 12, no. 4, p. 1024, 2023.

[23]. S. B. Shuvo and T. B. Mamun, "An automated deep learning framework for detecting and classifying lung nodules in lung cancer diagnosis," *arXiv preprint arXiv:2305.00046*, 2023.

[24]. T. Dao, A. Gu, A. Ratner, V. Smith, C. De Sa, and C. Re´, "Kernel-based theoretical analysis of modern data augmentation techniques," in *Proceedings of the International Conference on Machine Learning*, pp. 1528–1537, 2023.

[25]. E. D. Cubuk, B. Zoph, D. Mane, V. Vasudevan, and Q. V. Le, "Au-toAugment: Learning optimal data augmentation policies directly from data," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 113–123, 2019.

[26]. F. Zhuang *et al.*, "A comprehensive overview of transfer learning techniques and applications," *Proceedings of the IEEE*, vol. 109, no. 1, pp. 43–76, 2021.

[27]. M. Hammad, M. ElAffendi, A. A. Abd El-Latif, A. A. Ateya, G. Ali, and P. Plawiak, "Explainable artificial intelligence approach for lung cancer detection from CT images using a customized convolutional neural network," *Scientific Reports*, vol. 15, pp. 1–15, 2025.