EfficientNet Deep Learning Model for Lung Cancer Early Diagnosis from Computed Tomography Scan Images with Transfer Learning

Noor Ayesha [1], Ibrahim Hayatu Hassan [2], Abeer Rashad Mirdad [3], and Amjad R. Khan [3,*]

[1] Center of Excellence in Cyber Security (CYBEX), Prince Sultan University, Riyadh 11586, Saudi Arabia
[2] Department of Computer Science, Ahmadu Bello University, Zaria 810106, Nigeria
[3] AIDA Lab, College of Computer and Information Science (CCIS), Prince Sultan University, Riyadh, Saudi Arabia
Email: drnayesha@gmail.com (N.A.); ihhassan@abu.edu.ng (I.H.H.); amirdad@psu.edu.sa (A.R.M.); arkhan2030@gmail.com (A.R.K.)
*Corresponding author

Abstract—**Lung cancer is a lethal ailment which has a significant fatality rate among individuals affected by the disease. Timely detection and accurate staging of lung cancer can significantly improve patient survival rate. Computed Tomography (CT) scans are usually employed for diagnosing lung cancer, but manual examination can be slow and error-prone. To address this issue, deep learning techniques are being utilized to speed up and improve the accuracy of detecting cancerous and non-cancerous CT scans. Therefore, this study introduced an innovative transfer learning method aimed at improving the precision of lung cancer classification. The proposed method was built based on the EfficientNet model, modified with additional custom Convolutional Neural Network (CNN) layers and an attention mechanism for accurate lung cancer classification. Experimental analysis was conducted, utilizing eight variants of the modified EfficientNet (B0–B7) using three lung cancer CT scan datasets, comprising IQ-OTH/NCCD, Chest-CT scan, and LIDC-IDRI, grouped into 3, 4, and 2 classes respectively. Various data augmentation techniques were utilized to address the problem of class imbalance and mitigate any biases present. The model achieved accuracies of 99.5%, 98.0%, and 90.3% on the IQ-OTH/NCCD, Chest-CT scan, and LIDC-IDRI datasets, respectively. The results depict that the modified EfficientNetB1 performed better than other presented approaches with respect to both accuracy, sensitivity, F1-Score, and precision. The outcome also indicates that the presented method is more appropriate for multi-class classification of lung cancer.**

Keywords—**transfer learning, EfficientNet, Computed Tomography (CT), lungs cancer, classification, health risks**

I. INTRODUCTION

Lung cancer remains a leading cause of mortality worldwide, accounting for approximately 1.8 million deaths in 2021 [1–4]. Early and accurate diagnosis significantly improves survival rates, making automated classification of lung cancer using Computed Tomography (CT) scans an essential research area. Traditional diagnostic methods rely on manual interpretation, which can be time-consuming and subjective. To address these challenges, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have been increasingly adopted for medical image analysis [5, 6].

EfficientNet, a family of CNN architectures optimized using compound scaling, has demonstrated superior performance in various image classification tasks. EfficientNet models (B0–B7) balance depth, width, and resolution, making them efficient and scalable for deep learning applications in medical imaging. Despite their success, existing EfficientNet-based approaches for lung cancer classification have limitations, such as insufficient feature extraction and a lack of adaptability to multi-class classification tasks [7].

This study enhances EfficientNet's capability for lung cancer classification by introducing additional CNN layers and attention mechanisms. Attention mechanisms enable the model to focus on the most relevant regions of CT scan images, improving feature representation and classification accuracy [7]. Unlike prior works that use generic transfer learning without task-specific enhancements, our method combines domain-relevant CNN modules with adaptive attention layers tuned for lesion detection and shape irregularity. This results in substantial performance gains as shown in our comparative experiments.

The rest of the article is structured as follows: Section II encompasses the existing work, which includes several works on lung cancer categorization or detection. Section III elaborates on the methodology of the proposed framework. Sections IV and V present the results and discussion, respectively. Section VI closes the article with discourses possible future work.

II. LITERATURE REVIEW

This section provides an overview of recent studies focusing on lung cancer categorization using various deep learning architectures. Shalini *et al.* [8], introduced a novel

Manuscript received February 6, 2025; revised March 10, 2025; accepted April 24, 2025; published July 15, 2025.

hybrid deep learning approach for precise identification of lung cancer. The proposed approach incorporated a 3D-CNN to enhance detection accuracy. The outcomes of their efforts were assessed according to accuracy, sensitivity, precision, and F1-Score. A comparative analysis indicates the superiority of this method compared to CNN, SVM, DNN, RNN, NB, and RF achieving an accuracy of 95%.

Recent research conducted in [9] introduced a deep neural network that aids in the Computer-Aided Diagnosis (CAD) of lung cancer. The main focus of the paper was to overcome the issue of limited data availability in medical image examination by integrating Domain Adaptation (DA) method into the classification model. The performance of three models, namely VGG19, Xception, and VGG16 are examined, in correctly categorizing lung images. The results demonstrated the remarkable classification capabilities of these models. These findings underscore the effectiveness of transfer learning, preprocessing approaches, and CNN in facilitating the detection and diagnosis of lung cancer.

Mamun *et al.* [10] introduced a MobileNetV2 and CNN model that shows potential in enhancing the accuracy and timeliness of healthcare screening processes. The main objective of this model is to utilize AI techniques for discovery of lung cancer by analyzing CT scans. In order to evaluate the effectiveness of their study, the researchers contrasted their work with other works. The model presented demonstrated higher efficacy in comparison to the others. This model achieved an impressive accuracy rate of 92%.

In another investigation, Ibrahim *et al.* [11] utilized the EfficientNetB3 model for lung cancer categorization. The algorithm was designed to classify four distinct forms, namely normal, squamous carcinoma, large carcinoma, and adenocarcinoma, by leveraging CT scan images that were appropriately labeled. The findings demonstrated that the proposed model exhibited a 2.13% enhancement in comparison to the best-trained classifier, achieving an accuracy of 96% using the CT-scan images dataset. This work holds the ability to enhance lung cancer detection on a broader scale.

Nigudgi and Bhyri [12] presented a lung cancer CT image classification combining VGG16, AlexNet, and GoogLeNet, using SVM as a classification algorithm. This work combines three pre-trained models for feature extraction and applied SVM for the classification process. They evaluated their work using IQ-OTH/NCCD dataset which is a multi-classification dataset and compared with other approaches using accuracy. This work achieved 97% accuracy, which is higher than the compared techniques.

Narin and Onur [13] presented a lung cancer classification model using deep learning models, utilizing AlexNet and Resnet50. Efficacy of these models was evaluated on IQ-OTH/NCCD dataset with AlexNet achieving the overall best accuracy of 98.6%.

In Ref. [14], a transfer learning technique was implemented for lung cancer detection utilizing GoogLeNet. The presented work utilizes IQ-OTH/NCCD lung cancer dataset to ascertain the model effectiveness. Experimental findings demonstrate that this model achieved 94.4% overall accuracy, beating other methods earlier presented using the same dataset.

Al-Yasriy *et al.* [15] introduced a lung cancer classification model, employing the CNN method combined with AlexNet pre-trained model. The model proposed by the researchers attained an impressive overall accuracy of 93.5%, demonstrating exceptional performance on the IQ-OTH/NCCD dataset. This section basically supports the background section by providing evidence for the proposed hypothesis. This section should be more comprehensive and thoroughly describe all the studies that you have mentioned in the background section. It should also elaborate on all studies that form evidence for the present study and discuss the current trends.

Hammad *et al.* [16] presented a lung cancer prediction model combining CNN layers with Long Short-Term Memory (LSTM) optimized with genetic algorithm. Their model achieved and accuracy of 95.47% on X-ray dataset, 98.70% on CT images and 98.93% overall performance on combine models. Jain *et al.* [17] presented an enhanced model for lung cancer classification employing Logistic Regression, MLP Classifier, Gaussian NB Classifier, and Intelligent Feature Selection using K-Means and Fuzzy Logic. Additionally, ensemble learning is incorporated through a voting classifier. The model achieved the highest accuracy of 98.50%. Alkhonoini *et al.* [18] introduce a lung cancer classification model ASPP-Unet with whale Optimization algorithm. The model achieved an accuracy of 98.68% on CT scan images

III. Materials and Methods

Dataset used and the methods applied to train and validate the suggested model for classifying lung cancer from CT scans are outlined in this segment. Fig. 1 illustrates the process flow of the suggested approach. Initially, CT scan images from the dataset are imported and various pre-processing techniques are implemented to enhance image quality. Due to the challenge of obtaining a sufficiently large annotated dataset for model training in medical imaging tasks, data augmentation techniques are used to artificially increase the amount of training samples. The core procedure of this work is built on transfer learning, where diverse versions of EfficientNet models are tuned for binary and multi-class lung cancer categorization across two, three, and four categories. The subsequent sections provide detailed information on the preprocessing procedures, data enhancement methods, architecture of the presented model, and the evaluation metrics used for model assessment. The pseudocode for the proposed model is provided in Algorithm 1.

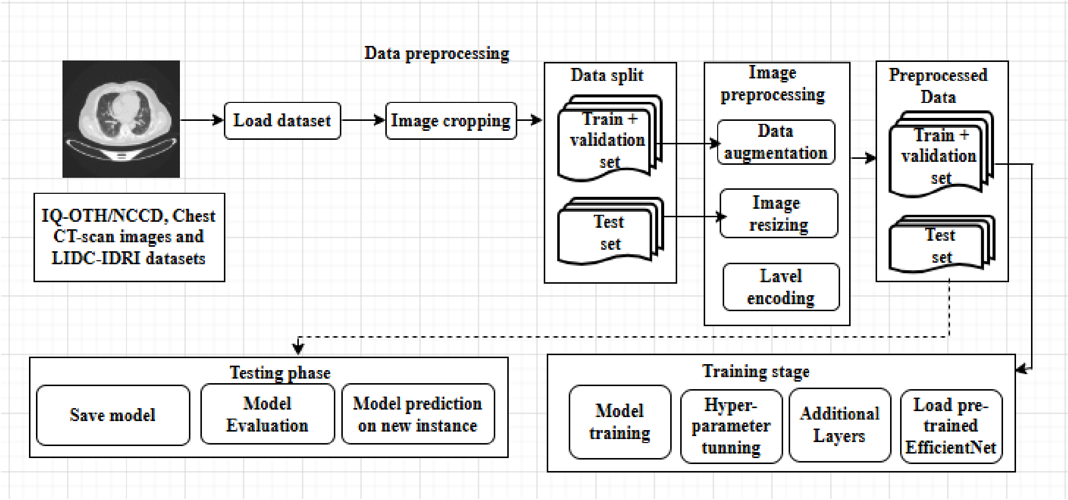


Fig. 1. Proposed model workflow.

Algorithm 1. Pseudocode of the proposed model

Input: IQ-OTH/NCCD,Chest-CT scan,and LIDC-IDRI Lung cancer dasets
Output:Deep learning Lung cancer model
Data loading and preprocesing
1.Loading lung cancer dataset
2.Preprocesing
- Cropping
- Resizing
- Spitting the data into training,testing and validation sets

Data augumentation (training data)
Model Building
Load EfficientNet (B0) as based model
Freez some of the efficientNet layers
Add attention layer to the based model
Block 1
Block 2
Add dense (Unit=256), batch normalization, Activation and droupout layer (0.2)
Block 2
Fully connected layer + LeakyReIU + Dropout + Regulirazation
Output for binary and multi-classification
Use Reduce LROnPlateu for learning rate scheduling
Model Training
Train and monitor the model using the training validation sets using 40 epocs using the learning rate schedular
Model Evaluation
Evaluate the model using test set based on accuracy, precision, recall, and F1-Score
Visualize the model performance using confusion matrix
Save the trained model

A. Datasets

This research utilized three datasets including IQ-OTH/NCCD [19], Chest CT Images [20], and LIDC-IDRI [21] for lung cancer identification using CT-scan images. The datasets were divided into training, testing, and validation sets, with 3, 4, and 2 classes, respectively. Table I shows the distribution of the three datasets utilized provided, the cases, total cases and class wise cases of each dataset.

TABLE I. DATASETS DISTRIBUTION (BEFORE DATA AUGMENTATION)

Datasets	Cases	Instances	Patients
Chest CT-scan dataset	Adenocarcinoma	338	
	Large cell carcinoma	260	
	Squamous cell carcinoma	215	
	Normal	187	
	Total	1000	
LIDC-IDRI dataset	Benign	1015	
	Malignant	1051	
	Total	2066	
IQ-OTH/NCCD dataset	Benign	120	15
	Malignant	561	40
	Normal	416	55
	Total	1097	110

B. Pre-processing

This section outlines the preprocessing steps for preparing the dataset. Initially, images are shuffled within classes to reduce bias, followed by an 80:20 train-test split. To improve efficiency, unnecessary background and noise are removed by cropping the largest lung contour. The cropped images are then augmented and resized to 240×240×3 to match the EfficientNet input requirements, standardizing dimensions and reducing resource load. Finally, labels are numerically encoded: IQ-OTH/NCCD uses 0 (normal), 1 (benign), 2 (malignant); Chest CT-scan uses 0 (adenocarcinoma), 1 (large cell carcinoma), 2 (squamous cell carcinoma), 3 (normal); LIDC-IDRI uses 0 (benign) and 1 (malignant). These steps ensure optimal model training and evaluation.

C. Data Augmentation

The IQ-OTH/NCCD and Chest CT-scan datasets, containing 1097 and 1000 CT scan images respectively, are augmented to address the limitation of training a deep CNN framework with insufficient data. Data augmentation techniques, including rotation, translation, mirroring, shearing, cropping, and flipping, are applied to expand the datasets and improve model resilience and generalization, reducing overfitting [22, 23]. In the IQ-OTH/NCCD dataset, augmentation factors of 16, 4, and 5 are used for benign, malignant, and normal images, respectively, with the benign class (having the fewest images) receiving the most augmentation. For the Chest CT-scan dataset, augmentation factors of 3, 3, 2, and 3 are applied to normal, squamous cell carcinoma, adenocarcinoma, and large cell carcinoma images, respectively. These techniques are applied only to the training samples, as shown in Table II.

TABLE II. METHODOLOGICAL ENHANCEMENTS FOR AUGMENTATION

Method	Tunning
Rotation	20
height_shift	0.3
width_shift	0.3
zoom	0.3
Shear	0.3
Brightness	[0.2, 0.1]
Horizontal_flip	True
Featurewise_center	True
Featurewise_std_normalization	True

D. *Proposed Framework*

This portion details the transfer learning technique utilized in the suggested model, emphasizing the specific architectural modifications recommended for different variants of the EfficientNet family (B0–B7).

The incorporation of additional CNN layers into the baseline EfficientN*et al*lows for enhanced extraction of fine-grained spatial features often indicative of lung cancer anomalies. These custom layers are designed to deepen the model's representational capacity, enabling it to detect subtle lesion patterns that may not be captured by the standard EfficientNet blocks. Furthermore, the attention mechanism enables the network to focus selectively on informative regions of CT scans, filtering out irrelevant background noise and enhancing interpretability. This synergy significantly augments the diagnostic capability of the base EfficientNet, as demonstrated by our comparative analysis.

1) *Transfer learning*

CNNs automate feature extraction (via convolutional/pooling layers) for classification, surpassing classical methods [24, 25]. However, their reliance on large datasets poses challenges in medical imaging due to limited annotated data. Transfer learning addresses this by adapting pre-trained models (e.g., ImageNet) to target domains like lung cancer CT scans. Fine-tuning adjusts model weights to bridge domain gaps (e.g., ImageNet vs. CT scans), either by freezing layers or integrating classifiers. This study fine-tunes eight EfficientNet variants (B0–B7) on lung CT images, extracting feature maps for classification via fully connected layers.

EfficientNet addresses CNN overparameterization by employing compound scaling, which uniformly scales depth (α), width (β), and resolution (γ) using fixed coefficients. Instead of arbitrary scaling, EfficientNet applies these coefficients in a structured manner to optimize computational efficiency while maintaining high performance. In this study, we adopted the standard EfficientNet scaling coefficients proposed in EfficientNet's original implementation (α = 1.2, β = 1.1 and γ = 1.15). These values ensure a balanced increase in model capacity across EfficientNet variants (B0–B7), optimizing feature extraction for lung cancer classification Fig. 2 provides an overview of the transfer learning concept.

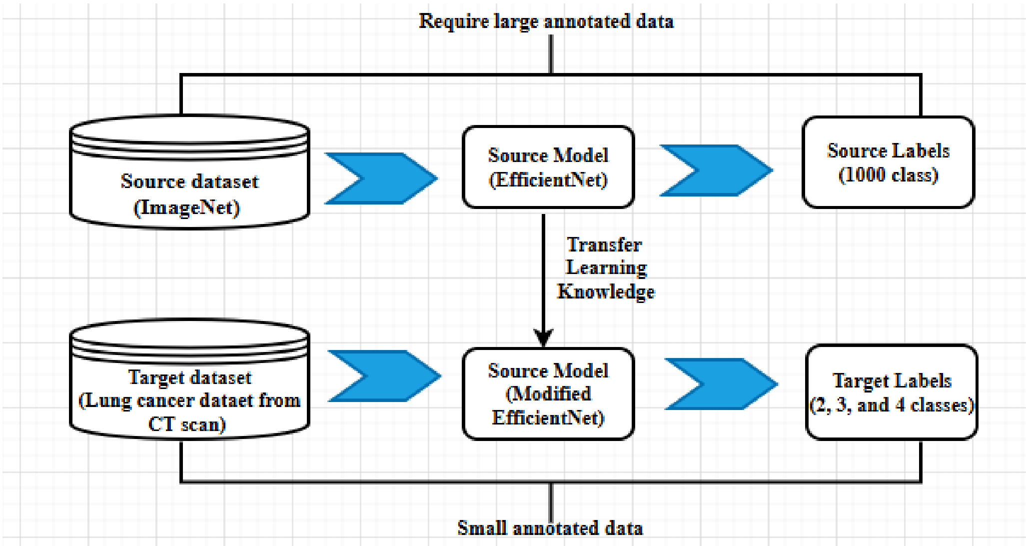


Fig. 2. The overall notion of transfer learning.

2) *Classification using modified EfficientNet*

EfficientNet addresses CNN overparameterization (excessive depth/layers) via systematic compound scaling, balancing depth, width, and resolution with fixed coefficients (α, β, γ) to optimize efficiency. Unlike random scaling, this method proportionally adjusts dimensions, limiting computational load (flops) to ~2^∅, where ∅ is user-defined. The EfficientNet series (B0–B7) uses MBConv layers (from MobileNetV2) for efficiency, with B0 having 5.3 M parameters and B7 scaling to 66M. Pre-trained on ImageNet, these models are fine-tuned for lung cancer CT-scan classification. Fig. 3 depict the building block of EfficientNets. A well-scripted methods sections lays the foundation for your research by outlining the different methods you used to derive your results. The methods used to achieve the objectives must be described precisely and in sufficient detail, so as to allow a competent reader to repeat the work done by the author.

In this study, pre-trained EfficientNet architectures (B0–B7) are modified: the final layer is replaced with Global Average Pooling (dimensionality reduction), BatchNormalization, Dense layers, LeakyReLU activation, dropout (0.5 probability), and attention mechanisms to enhance feature extraction. The output layer is adapted to 2, 3, and 4 units (Softmax) for dataset-specific labels (benign/malignant, carcinoma subtypes). Layers are partially frozen during fine-tuning to align ImageNet-derived features with CT-scan nuances, improving classification accuracy while mitigating overfitting.

3) Performance evaluation metrics

Performance metrics serve as numerical indicators utilized to assess the efficiency of deep learning models. These metrics are essential for comparing different models or systems in terms of their effectiveness in solving a particular problem, evaluating the efficacy of a model in addressing a specific task, and finding areas for enhancement. In this research, five common performance measures including sensitivity (recall), F1-Score, precision, accuracy, and confusion matrix were employed, as detailed in [26, 27]. These measures are outlined in Table III.

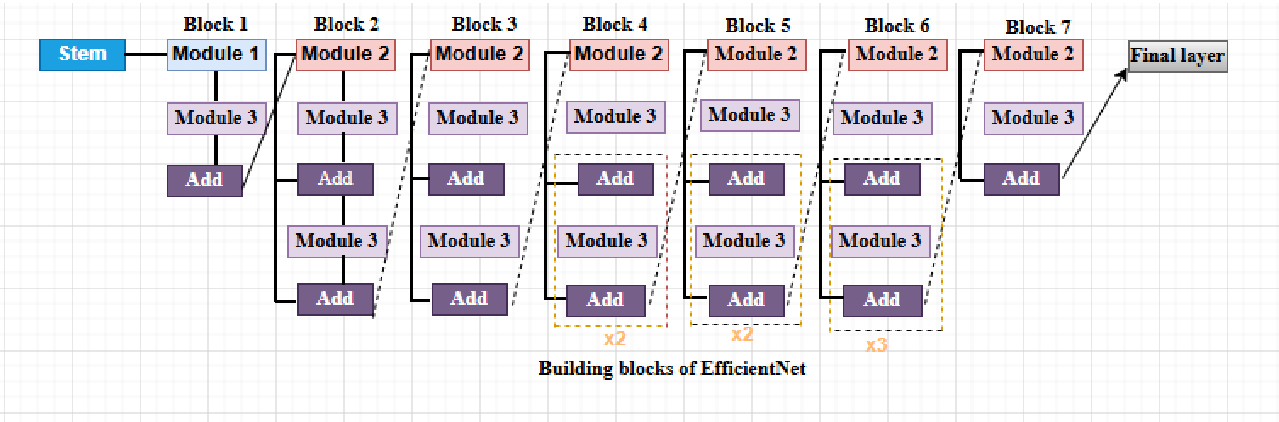


Fig. 3. Structural blocks of EfficientNets architecture.

TABLE III. PERFORMANCE METRICS AND THEIR DESCRIPTION

Metrics	Description	Formula
Accuracy	Assesses the overall efficacy of a model and calculated as the fraction of exact positive and negative predictions to the entire number of predictions made.	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
Sensitivity (Recall)	Define the fraction of exact positive cases recognized properly	$Recall = \frac{TP}{TP+FN}$
Precision	Defined as the correct positive outcome	$Precision = \frac{TP}{TP+FP}$
F1-Score	Computed as the harmonic mean of recall and precision	$F_1 = \frac{2 \times precision \times recall}{precision + recall}$

IV. RESULT AND DISCUSSION

This article introduces a transfer learning method for classifying lung cancer into binary and multi-classes by utilizing customized pre-trained models called (ModifiedEfficienNetB0–B7) on CT scan images. The effectiveness of these models was verified using CT scan images from IQ-OTH/NCCD, Chest CT-scan, and LIDC-IDRI datasets. The outcomes of this study are detailed in the subsequent section.

A. Performance Analysis of the Proposed Models on IQ-OTH/NCCD Dataset

This segment evaluates eight modified EfficientNet models (B0–B7) for classifying CT scan images from IQ-OTH/NCCD into normal, benign, and malignant categories. As shown in Table IV, all models performed strongly across four evaluation metrics. ModifiedEfficienNetB1 and ModifiedEfficienNetB4 achieved the highest accuracy of 99.5%, while ModifiedEfficienNetB5 had the lowest at 95.5%. The other models (B0, B2, B3, B6, B7) demonstrated accuracies between 96.8% and 98.6%. Figs. 4–6 shows the accuracy comparison of these models.

The sensitivity/recall metrics, shown in Table IV, reveal an average sensitivity of 99.6% for detecting malignant cases, with ModifiedEfficientNetB4 achieving 100% recall and ModifiedEfficientNetB5 showing the lowest sensitivity at 96%. For normal cases, performance was strong, while benign case detection ranged from 79.0% to 97.0%. Precision metrics (Table IV) indicate proficiency in reducing false positives, with values from 92.0% to 100%. F1-Scores (Table IV) balance precision and recall, ranging from 85.0% to 99.0%. Overall, the models exhibit robust performance across all metrics.

TABLE IV. PERFORMANCE OF MODIFIED EFFICIENTNET (B0–B7) FOR LUNG CANCER CLASSIFICATION USING IQ-OTH/NCCD DATASET

Model	Precision (%)			Sensitivity/Recall (%)			F1-Score (%)			Accuracy (%)
	Benign	Malignant	Normal	Benign	Malignant	Normal	Benign	Malignant	Normal	
ModifiedEfficienNetB0	96.0	100	96.0	90.0	100	99.0	93.0	100	98.0	98.2
ModifiedEfficienNetB1	97.0	100	99.0	97.0	100	99.0	97.0	100	99.0	**99.5**
ModifiedEfficienNetB2	96.0	100	93.0	83.0	99.0	99.0	89.0	100	96.0	96.8
ModifiedEfficienNetB3	96.0	100	95.0	86.0	100	99.0	91.0	100	97.0	97.7
ModifiedEfficienNetB4	100	100	98.0	93.0	100	100	96.0	100	99.0	**99.1**
ModifiedEfficienNetB5	92.0	99.0	92.0	79.0	99.0	96.0	85.0	99.0	94.0	95.5
ModifiedEfficienNetB6	96.0	100	94.0	83.0	100	99.0	89.0	100	96.0	97.3
ModifiedEfficienNetB7	97.0	100	98.0	97.0	99.0	99.0	97.0	100	98.0	98.6

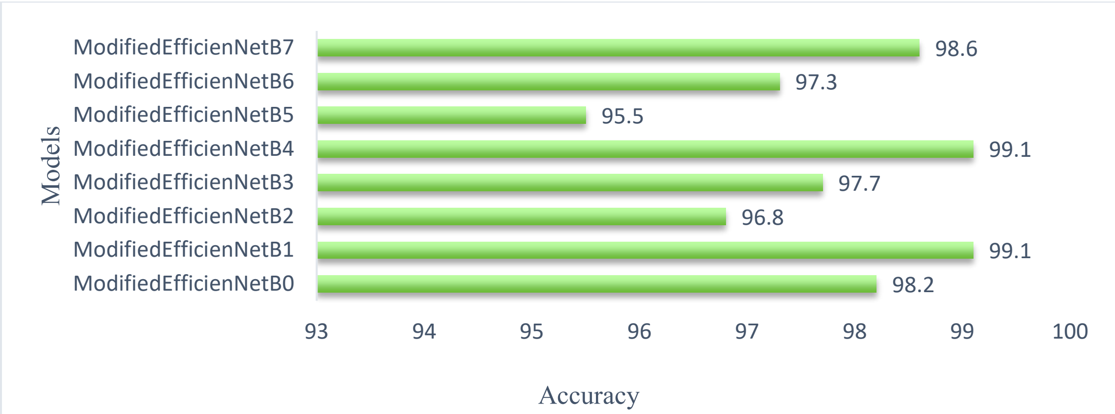


Fig. 4. Accuracy comparison of the eight modified EfficientNet (B0–B7) on IQ-OTH/NCCD dataset

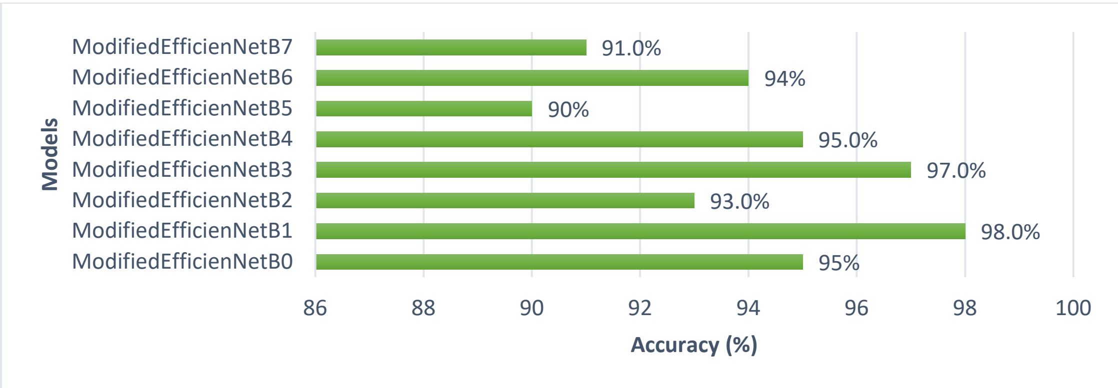


Fig. 5. Accuracy comparison of the eight modified EfficientNet (B0–B7) on Chest CT-scan images.

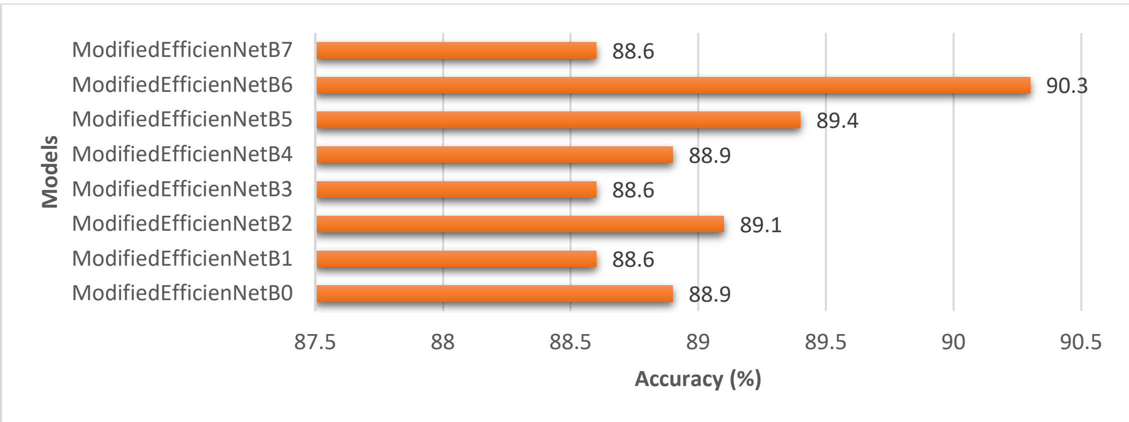


Fig. 6. Performance of the eight modified EfficientNet (B0–B7) on LIDC-IDRI dataset using Accuracy.

A well-presented results section coupled with a convincing discussion will definitely prove the novelty and importance of your study. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

B. Performance Analysis of the Proposed Models on Chest CT-Scan Image Dataset

This section evaluates eight modified EfficientNet models (B0–B7) on a Chest CT-scan dataset containing four classes: normal, adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. As shown in Table V and Fig. 5, ModifiedEfficientNetB1 achieved the highest accuracy, while ModifiedEfficientNetB5 had the lowest at 93.5%. Other models (B0, B2, B3, B6, B7) performed well, with accuracies ranging from 94.0% to 97.0%. ModifiedEfficientNetB1 showed high precision and F1-Score across all classes except squamous cell carcinoma. ModifiedEfficientNetB4 and B5 demonstrated strong performance in precision, sensitivity, and F1-Score, while B2 had slightly lower metrics. B3 exhibited balanced performance across all metrics.

C. Performance Analysis of the Proposed Models on LIDC-IDRI Dataset

The performance of the seven modified EfficientNet architectures on the LIDC-IDRI dataset is highlighted in this section. The dataset consists of two classes, namely Benign and Malignant. Table VI presents the results of this evaluation. The outcomes depict that modified EfficientNetB6 achieved the highest performance achieving an accuracy of 90.3% and also with high precision and recall. Modified EfficientNet B0, B3 and B7 shows similar performance with least accuracy of 88.6%. Furthermore, modified EfficientNet B1, B2, and B5 shows an accuracy of 88.9%, 89.1% and 89.4% accuracy. Generally, the models perform relatively good on this dataset across all the evaluation measures, with accuracies fluctuating from 88.6% to 90.3%. The result also indicates that the models achieved a balanced precision, recall, and F1-Score, signifying constant efficacy in categorizing both benign and malignant cases. Fig. 6 shows the comparative analyses of these models using accuracy

TABLE V. PERFORMANCE OF MODIFIED EFFICIENTNET (B0–B7) FOR LUNG CANCER CLASSIFICATION USING CHEST CT-SCAN IMAGES DATASET

Metrics	Classes	Models							
		B0	B1	B2	B3	B4	B5	B6	B7
Precision (%)	Adenocarcinoma	97.0	100	92.0	100	97.0	92.0	97.0	95.0
	Large. cell. carcinoma	89.0	93.0	89.0	89.0	90.0	95.0	93.0	91.0
	Normal	100	100	100	100	100	98.0	98.0	98.0
	Squamous. cell. carcinoma	100	98.0	100	98.0	93.0	91.0	95.0	93.0
Sensitivity (%)	Adenocarcinoma	94.0	95.0	94.0	94.0	94.0	89.0	91.0	88.0
	Large. cell. carcinoma	97.0	100	97.0	100	93.0	97.0	97.0	97.0
	Normal	98.0	98.0	98.0	98.0	98.0	98.0	98.0	98.0
	Squamous. cell. carcinoma	98.0	100	92.0	98.0	96.0	92.0	98.0	96.0
F1-Score (%)	Adenocarcinoma	95.0	98.0	93.0	97.0	95.0	90.0	94.0	91.0
	Large. cell. carcinoma	93.0	96.0	93.0	94.0	91.0	96.0	95.0	94.0
	Normal	99.0	99.0	99.0	99.0	99.0	98.0	98.0	98.0
	Squamous. cell. carcinoma	99.0	99.0	96.0	98.0	94.0	92.0	96.0	94.0
Accuracy (%)		96.5	**98.0**	95.0	97.0	95.0	93.5	95.5	94.0

TABLE VI. PERFORMANCE OF MODIFIED EFFICIENTNET (B0–B7) FOR LUNG CANCER CLASSIFICATION USING LIDC-IDRI DATASET

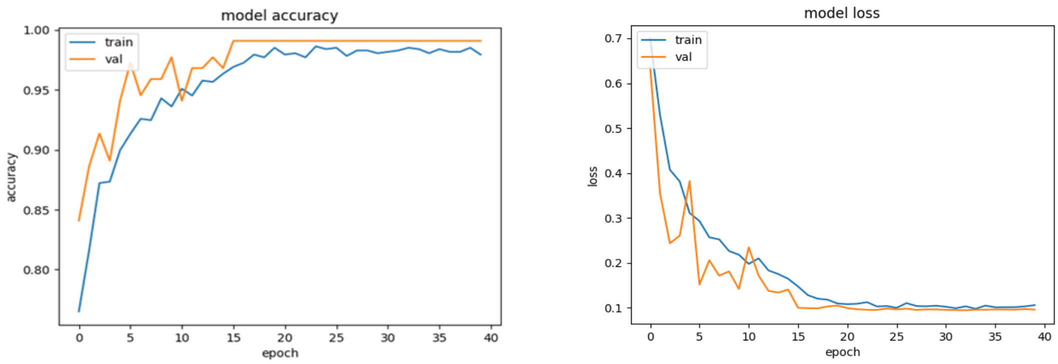
Model	Precision (%)		Recall/Sensitivity (%)		F1-Score (%)		Accuracy (%)
	Benign	Malignant	Benign	Malignant	Benign	Malignant	
ModifiedEfficienNetB0	91.0	87.0	87.0	91.0	89.0	89.0	88.9
ModifiedEfficienNetB1	90.0	87.0	88.0	90.0	89.0	89.0	**88.6**
ModifiedEfficienNetB2	90.0	88.0	88.0	90.0	89.0	89.0	89.1
ModifiedEfficienNetB3	90.0	87.0	87.0	90.0	89.0	89.0	88.6
ModifiedEfficienNetB4	90.0	88.0	89.0	89.0	89.0	89.0	**88.9**
ModifiedEfficienNetB5	90.0	88.0	89.0	90.0	90.0	89.0	89.4
ModifiedEfficienNetB6	92.0	89.0	89.0	92.0	90.0	90.0	**90.3**
ModifiedEfficienNetB7	89.0	88.0	88.0	89.0	89.0	89.0	88.6

D. Assessment of the Presented Model (Modified EfficientNetB1) with Existing Literature Using ACCURACY

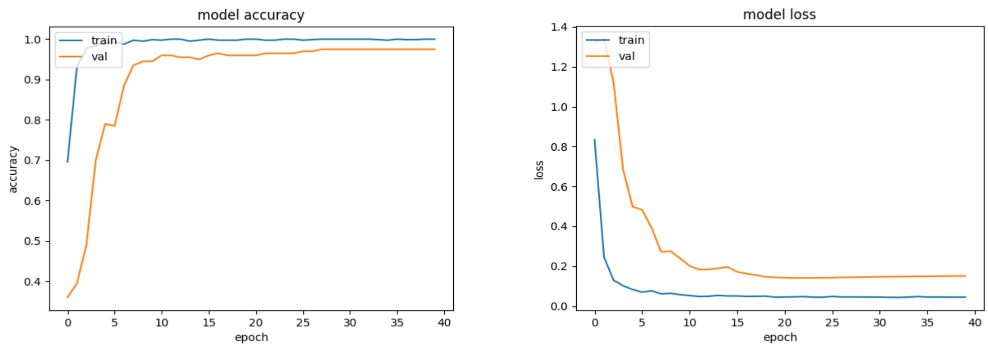
In the literature, a number of research have introduced methods for classification and detection of lung cancer using different datasets. Therefore, to further validate the efficacy of the proposed approach, we compared our best models (ModifiedEfficientNetB1) obtained using the two datasets with some of the recent techniques employing the same type of lung cancer dataset. The comparison was done using accuracy measure, which was the metric used by most of the authors. The outcomes of this assessment were shown in Table VII. The results of the comparison signify that the modified EfficientNetB1 reached the best accuracy in contrast to the other works presented that employed both the chest scan dataset and IQ-OTH/NCCD with an accuracy of 99.5% and 98.0% respectively. However, for LIDC-IDRI dataset, the proposed model achieved a lower accuracy compare to [23] and [25] that uses the same dataset.

TABLE VII. COMPARISON OF THE PRESENTED MODELS WITH SOME OTHER EXISTING WOKS

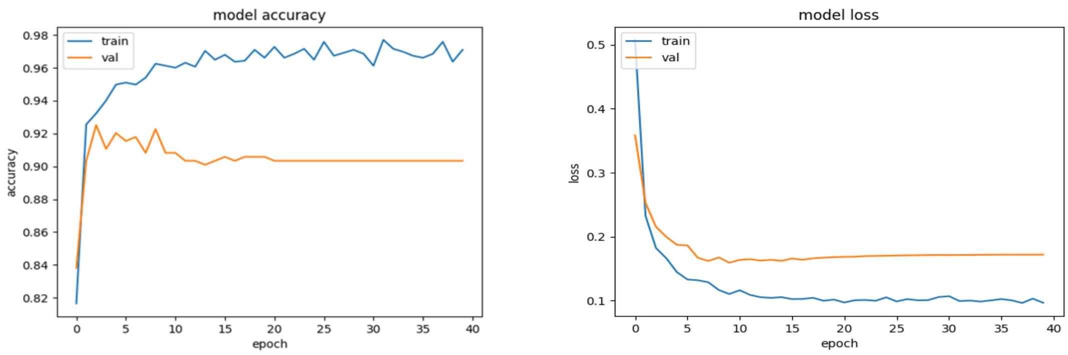
Authors	Method	Dataset	Accuracy
Shalini *et al.* [8]	3D-CNN	CT scan dataset	95%
Ibrahim *et al.* [11]	InceptionNetB3	CT scan dataset	96%
Nigudgi and Bhyri [12]	Hybrid (AlexNet+VGG16+ GoogleNet) + SVM classifier	IQ-OTH/NCCD	97%
Narin and Onur in [13]	AlexNet and Resnet50	IQ-OTH/NCCD	98.6%
AL-Huseiny and Sajit [14]	GoogleNet	IQ-OTH/NCCD	94.4%
Al-Yasriy *et al.* [15]	CNN+AlexNet	IQ-OTH/NCCD	93.5%
Pascal [22]	CNN+Transformer models	IQ-OTH/NCCD	97.6
Bushara *et al.* [23]	CapsNet	LIDC-IDRI	94%
Raza *et al.* [24]	EfficientNet	IQ-OTH/NCCD	99.1%
Liu *et al.* [25]	Mask R-CNN (ResNet101)	LIDC-IDRI	96.6%
Proposed model	EfficientNet + attention layer + CNN layers	IQ-OTH/NCCD, CT scan, and LIDC-IDRI datasets	99.5%, 98.0%, and 90.3



(a)



(b)



(c)

Fig. 7. Model accuracy/loss of (a) modified EfficientNetB1 on IQ-OTH/NCCD (b) modified EfficientNetB1 on chest CT scan (c) modified EfficientNetB1 on LIDC-IDRI dataset.

The lung cancer classification model on the IQ-OTH/NCCD, chest CT scan, and LIDC-IDRI lung cancer datasets was developed by employing a transfer learning approach. This approach utilized eight modified EfficientNet pre-trained (B0–B7) model. Experimental analysis indicates that the trained models have obtained a good result in all the three datasets in terms of the metrics adapted. For the IQ-OTH/NCCD and chest CT scan datasets, the results indicate that modified EfficientNetB1 attained the highest accuracy of 99.1% and 98.0%, respectively. The results also show that modified EfficientNetB6 attained the highest performance obtaining an overall accuracy of 90.3% using the LIDC-IDRI dataset. Fig. 7(a)–(c) illustrates the advancement of the training/validation accuracy and loss for the models utilizing the IQ-OTH/NCCD, chest CT scan, and LIDC-IDRI datasets, respectively.

The findings also indicate that the modified EfficientNetB1 attained an average sensitivity and precision of 98.7% each for the IQ-OTH/NCCD dataset. Moreover, in the case of the chest scan dataset, the top-performing model achieved an average sensitivity of 98.3% and precision of 97.8%, respectively. Additionally, the modified EfficientNetB6 demonstrated an average sensitivity and precision of 90.5% each for the LIDC-IDRI dataset. As classification models primarily aim to enhance sensitivity, which signifies the victory or hit rate, the obtained values of these metrics how the strength of the presented model. Based on the accuracy measure, it is clear from Table VII that the presented model has demonstrated superior effectiveness compared to other techniques on the identical dataset.

Among the evaluated models, ModifiedEfficientNetB1 consistently achieved the highest classification accuracy across the IQ-OTH/NCCD (99.5%) and Chest CT-scan (98.0%) datasets. This superior performance can be attributed to specific architectural modifications made to the EfficientNetB1 variant. (1) EfficientNetB1 strikes an optimal balance between depth, width, and resolution scaling, making it more efficient in extracting discriminative lung nodule features while avoiding overfitting, which can occur in deeper variants (B4–B7), (2) The inclusion of additional CNN layers and attention mechanisms in ModifiedEfficientNetB1 likely improved its ability to capture subtle texture variations in lung cancer CT images, leading to better classification performance and (3) Compared to smaller variants (B0) and deeper variants (B3–B7), B1 demonstrated better generalization, potentially due to its moderate parameter count and reduced risk of overfitting, which is crucial when working with limited medical imaging datasets. In general, these factors suggest that ModifiedEfficientNetB1 provides an optimal trade-off between model complexity, feature extraction capability, and computational efficiency, making it the best-performing model for lung cancer classification in this study.

E. Statistical Assessment of the Proposed Model Using Accuracy

To further validate the robustness of our proposed model, we conducted statistical significance testing on the classification results. Specifically, we computed 95% confidence intervals (CIs) for the accuracy. For the IQ-OTH/NCCD dataset, the proposed model achieved an accuracy of 99.5% (95% CI: 99.2%–99.8%), indicating high confidence in its performance. The model attained 98.0% accuracy (95% CI: 97.6%–98.4%) for the Chest CT-scan dataset, confirming its consistency across multiple evaluations. However, for the LIDC-IDRI dataset, the accuracy was 90.3% (95% CI: 89.5%–91.1%), showing a relatively broader range, likely due to the dataset's complexity and fewer training samples compared to the others. Table VIII provides a p-value from hypothesis testing of the proposed approach with others in the literature. The table shows that there is a significance difference between the proposed and other methods that utilized IQ-OTH/NCCD and Chest CT-scan dataset. However, the p-value indicates no significance difference between this work and those that utilized LIDC-IDRI.

TABLE VIII. P-VALUES PRODUCED BY THE T-TEST FOR THE THREE DATASETS

Work	Dataset	*p*-value
Shalini *et al* [8]	CT scan dataset	0.00055
Ibrahim *et al.* [11]	CT scan dataset	0.0151
Nigudgi and Bhyri [12]	IQ-OTH/NCCD	0.00089
Narin and Onur in [13]	IQ-OTH/NCCD	0.0515
AL-Huseiny and Sajit [14]	IQ-OTH/NCCD	<0.0001
Al-Yasriy *et al.* [15]	IQ-OTH/NCCD	<0.0001
Pascal [22]	IQ-OTH/NCCD	0.00012
Bushara *et al.* [23]	LIDC-IDRI	0.1588
Raza *et al.* [24]	IQ-OTH/NCCD	0.566
Liu *et al.* [26]	LIDC-IDRI	<0.0001

V. CONCLUSION

This research work employed three lung cancer CT-scan datasets (IQ-OTH/NCCD, chest-CT dataset, and LIDC-IDRI datasets) to developed an enhanced lung cancer classification model using eight modified EfficientNet framework. The proposed algorithm has been proven to achieve higher accuracy rates of 99.1% and 98.0% for the IQ-OTH/NCCD and chest-CT datasets, respectively, when compared to the original algorithm suggested using these datasets. However, for the LIDC-IDRI datasets, the proposed framework achieved the lowest accuracy of 90.3% in contrast to other works presented using the same dataset. These results indicate that the proposed approach can be better suited for multi-classification of lung cancer rather than binary classification.

Our experiments clearly demonstrate that the integration of CNN and attention mechanisms into EfficientNet yields a performance improvement of with a statistical significance as shown in Tables VII and VIII across all major metrics compared to established State of the art models. This validates the significance of our architectural enhancements and supports our claim of improved diagnostic accuracy in lung cancer classification.

The practical implications of this work extend to real-world clinical applications, where automated lung cancer classification can assist radiologists in early and precise diagnosis. The proposed model can be integrated into Computer-Aided Diagnosis (CAD) systems, reducing diagnostic errors and expediting decision-making in clinical settings. Furthermore, its adaptability to multi-class classification suggests potential use in personalized treatment planning and telemedicine applications. Future research could focus on incorporating advanced data augmentation techniques, such as Generative Adversarial Networks (GANs), to generate high-quality synthetic medical images and mitigate data scarcity challenges. Additionally, exploring other pre-trained deep learning models and representation learning approaches, such as autoencoders, could further enhance feature extraction and classification accuracy. Further optimization through hyperparameter tuning and transfer learning strategies may improve model adaptability across diverse datasets. Additionally, investigating alternative augmentation methods, such as self-supervised learning and domain adaptation techniques, could help refine the model's generalizability for real-world clinical applications.

Conflict of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

Author Contributions

NA, IHH, ARK; methodology: IHH, ARK, ARM; software: AMH, TS, IHH; validation: NA, AMS; writing–original draft preparation, IHH, NA, AMS, ARK; writing–review and editing, IHH, NA, AMS; visualization, NA, ARK supervision: AMS, ARK; project administration, AMS, ARK. All authors have read and agreed to the published version of the manuscript.

Acknowledgment

The authors would like to acknowledge AIDA Lab CCIS Prince Sultan University, Riyadh Saudi Arabia for APC support.

References

[1] R. Javed, T. Saba, T. J. Alahmadi, S. Al-Otaibi, B. AlGhofaily, and A. Rehman, "EfficientNetB1 deep learning model for microscopic lung cancer lesion detection and classification using histopathological images," *Comput., Mater. Contin.*, vol. 81, no. 1, pp. 1–18, 2024.

[2] T. Saba, A. Sameh, F. Khan, S. A. Shad, and M. Sharif, "Lung nodule detection based on ensemble of hand crafted and deep features," *J. Med. Syst.*, vol. 43, pp. 1–12, 2019.

[3] T. Saba, "Automated lung nodule detection and classification based on multiple classifiers voting," *Microsc. Res. Tech.*, vol. 82, no. 9, pp. 1601–1609, 2019.

[4] A. Rehman *et al.*, "Detection of lungs tumors in CT scan images using convolutional neural networks," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 21, no. 4, pp. 769–777, 2023.

[5] T. Saba, M. Kashif, H. Alaskar, and E. Afzal, "Lung cancer detection and diagnosis with deep learning models evaluation," in *Proc. Artificial Intelligence and Internet of Things*. Boca Raton, FL, USA: CRC Press, 2021, pp. 167–188.

[6] S. A. Khan *et al.*, "Lungs nodule detection framework from computed tomography images using support vector machine," *Microsc. Res. Tech.*, vol. 82, no. 8, pp. 1256–1266, 2019.

[7] S. Dodia, B. Annappa, and P. A. Mahesh, "Recent advancements in deep learning-based lung cancer detection: A systematic review," *Eng. Appl. Artif. Intell.*, vol. 116, 105490, 2022.

[8] W. Shalini and S. Vigneshwari, "A novel hybrid deep learning method for early detection of lung cancer using neural networks," *Healthc. Anal.*, vol. 3, 100195, 2023.

[9] T. T. Al-Shouka and K. M. A. Alheeti, "A transfer learning for intelligent prediction of lung cancer detection," in *Proc. Al-Sadiq Int. Conf. Commun. Inf. Technol.*, Baghdad, Iraq, 2023, pp. 1–6.

[10] M. Mamun *et al.*, "LCDCTCNN: Lung cancer diagnosis of CT scan images using CNN based model," in *Proc. 10th Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Noida, India, 2023, pp. 1–5.

[11] M. S. Ibrahim *et al.*, "A deep learning algorithm for lung cancer detection using EfficientNet-B3," *Wasit J. Comput. Math. Sci.*, vol. 2, no. 4, pp. 68–76, 2023.

[12] S. Nigudgi and C. Bhyri, "Lung cancer CT image classification using hybrid-SVM transfer learning," *Soft Comput.*, vol. 27, pp. 9845–9859, 2023.

[13] D. Narin and T. Ö. Onur, "The effect of hyper parameters on the classification of lung cancer images using," *J. Sci. Technol.*, vol. 15, no. 1, pp. 258–268, 2022.

[14] M. S. Al-Huseiny and A. S. Sajit, "Transfer learning with GoogLeNet for detection of lung cancer," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 22, no. 2, pp. 1078–1086, 2021.

[15] H. F. Al-Yasriy, M. S. AL-Husieny, F. Y. Mohsen, E. A. Khalil, and Z. S. Hassan, "Diagnosis of lung cancer based on CT scans using CNN," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 881, 012034, 2020.

[16] M. Hammad, M. ElAffendi, M. Asim, A. A. Abd El-Latif, and R. Hashiesh, "Automated lung cancer detection using novel genetic TPOT feature optimization with deep learning techniques," *Results Eng.*, vol. 24, 103448, 2024.

[17] R. Jain, P. Singh, M. Abdelkader, and W. Boulila, "Efficient lung cancer detection using computational intelligence and ensemble learning," *PLoS ONE*, vol. 19, no. 9, e0310882, 2024.

[18] M. A. Alkhonaini *et al.*, "Detection of lung tumor using ASPP-Unet with whale optimization algorithm," *CMC-Comput. Mater. Contin.*, vol. 72, no. 2, pp. 3511–3527, 2022.

[19] H. Alyasriy and A. Muayed, "The IQ-OTHNCCD lung cancer dataset," *Mendeley Data*, vol. 1, pp. 1–3, 2020.

[20] Anon. (2023). IQ-OTH/NCCD lung cancer dataset—Kaggle. [Online]. Available: https://www.kaggle.com/datasets

[21] H. M. Fahad, M. U. G. Khan, T. Saba, A. Rehman, and S. Iqbal, "Microscopic abnormality classification of cardiac murmurs using ANFIS and HMM," *Microsc. Res. Tech.*, vol. 81, no. 5, pp. 449–457, 2018.

[22] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," arXiv preprint, arXiv:1512.03385, 2015.

[23] A. R. Bushara, K. R. S. Vinod, and S. S. Kumar, "LCD-Capsule network for the detection and classification of lung cancer on computed tomography images," *Multimedia Tools Appl.*, vol. 82, pp. 37573–37592, 2023.

[24] R. Raza, F. Zulfiqar, M. O. Khan, M. Arif, A. Alvi, M. A. Iftikhar and T. Alam, "Lung-EffNet: Lung cancer classification using EfficientNet from CT-scan images," *Eng. Appl. Artif. Intell.*, vol. 126, 106902, 2023.

[25] T. Mahmmod, N. Ayesha, M. Mujahid, and A. Rehman, "Customized deep learning framework with advanced sampling techniques for lung cancer detection using CT scans," in *Proc. 2024 Seventh International Women in Data Science Conference at Prince Sultan University*, 2024, pp. 110–115.

[26] M. Liu, J. Dong, X. Dong, H. Yu, and L. Qi, "Segmentation of lung nodule in CT images based on mask R-CNN," in *Proc. 9th Int. Conf. Aware. Sci. Technol. (iCAST)*, Fukuoka, Japan, 2018, pp. 1–6.

[27] U. I. Maijeddah, S. A. Yusuf, M. Abdullahi, and I. H. Hassan, "A hybrid transfer learning model with optimized SVM using honey badger optimization algorithm for multi-class lung cancer classification," *Sci. World J.*, vol. 19, no. 4, pp. 977–986, 2024.