

Contrast-Adaptive and Class-Balanced Transfer Learning for Multi-Stage Lung Cancer Classification from CT Images Using EfficientNetB1

Annahl Riadi

Department of Electrical Engineering, Faculty of Engineering, Universitas Hasanuddin, Gowa, Indonesia
| Department of Informatics, Faculty of Computer Science, Ichsan Sidenreng Rappang University, Indonesia
riadia22d@student.unhas.ac.id

Andani Achmad

Department of Electrical Engineering, Faculty of Engineering, Universitas Hasanuddin, Gowa, Indonesia
andani@unhas.ac.id (corresponding author)

Zahir Zainuddin

Department of Informatics, Faculty of Engineering, Universitas Hasanuddin, Gowa, Indonesia
zahir@unhas.ac.id

Andini Dani Achmad

Department of Electrical Engineering, Faculty of Engineering, Universitas Hasanuddin, Gowa, Indonesia
andini.achmad@unhas.ac.id

Irvan Muzakkir

Department of Multimedia and Network Engineering, Politeknik Negeri Ujung Pandang, Makassar, Indonesia
irvanmuzakkir@poliupg.ac.id

Received: 15 March 2026 | Revised: 20 April 2026 | Accepted: 30 April 2026

Licensed under a CC-BY 4.0 license | Copyright (c) by the authors | DOI: <https://doi.org/10.48084/etasr.18763>

ABSTRACT

The multi-stage classification of lung cancer based on CT images is challenging due to morphological similarities between subtypes, variations in image contrast, and class distribution imbalances in medical datasets. Although deep transfer learning approaches have shown promising results in CT-based lung cancer detection, most previous studies focused on binary classification and applied static contrast enhancement, thus limiting adaptive feature learning. This study presents a contrast-adaptive and class-balanced transfer learning framework using EfficientNetB1 for multi-stage classification of lung cancer. Gamma correction is integrated directly into the augmentation pipeline as an on-the-fly preprocessing function, so contrast variations can be dynamically studied during the training process. The proposed approach also applies an increase in input resolution to 240×240 pixels, as well as a calibrated partial fine-tuning strategy on the last 50 layers of EfficientNetB1 to improve domain adaptation while maintaining computational stability. To reduce bias due to class imbalance, class weighting is used in the optimization process. The model was evaluated on a CT dataset with four classes, Adenocarcinoma Ib, Large Cell Carcinoma IIIa, Squamous Cell Carcinoma IIIa, and Normal, achieving an overall accuracy of 97% with a macro F1-score of 0.97, indicating balanced performance across classes. The proposed framework enhances the ability to discriminate between subtypes that have visual similarities while maintaining strong generalization capabilities. These findings suggest that the integration of contrast-based adaptive

augmentation with calibrated learning transfer and class-balancing-based optimization can improve the resilience and stability of multi-stage classification of CT-based lung cancer.

Keywords-lung cancer; CT scan; EfficientNetB1; gamma correction; classification

I. INTRODUCTION

According to recent global cancer statistics, lung cancer is one of the leading causes of cancer death worldwide, with millions of new cases each year [1]. Its high mortality rate is strongly associated with delayed diagnosis, as many patients are identified in advanced stages when treatment options are more limited [2]. Therefore, accurate identification and staging of lung cancer are essential to support clinical decision-making, treatment selection, and therapeutic planning [3]. Previous work on EfficientNetB0-based staging has demonstrated that CT-based staging performance is influenced by preprocessing, particularly the choice between gamma correction and histogram equalization [3]. This motivates the need for a more adaptive contrast-aware transfer learning framework rather than a fixed preprocessing pipeline.

Computed Tomography (CT) is a key imaging modality for the diagnosis and staging of lung cancer because it provides high-resolution visualization of pulmonary structures [2, 4, 5]. However, the multi-stage classification of lung cancer based on CT images is a complex problem. In contrast to binary classification (cancer vs. non-cancer), multi-stage classification demands a more subtle discriminating ability between subtypes or stages that have morphological similarities. Subtypes such as adenocarcinoma, large cell carcinoma, and squamous cell carcinoma may present overlapping radiological characteristics, which can complicate both expert interpretation and automated classification [6, 7].

In recent years, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have shown promising performance in medical image analysis, including CT-based lung cancer detection and classification [8-12]. Transfer learning strategies, utilizing pretrained architectures such as ResNet, DenseNet, and EfficientNet, are widely used to overcome the limitations of medical datasets [9, 13]. However, many previous studies have focused on binary classification, which does not fully reflect the clinical complexity of multi-class or multi-stage discrimination [6, 8-11]

In addition, there are two important technical problems that are often not addressed systematically. First, variation in contrast and intensity distribution in CT images can affect the stability of feature extraction. Contrast enhancement techniques such as histogram equalization, CLAHE, and gamma correction have been used in medical imaging to improve image visibility and support feature learning [14]. However, in many previous workflows, contrast enhancement is applied as a fixed preprocessing step before training, limiting the model's exposure to contrast variability during optimization. In contrast, this study integrates the gamma correction directly into the augmentation pipeline as an on-the-fly transformation so that contrast variation can be learned dynamically during training.

Second, class imbalance in medical datasets often leads to predictive bias toward majority classes, thereby reducing sensitivity to minority but clinically important categories [15]. Although various techniques for treating imbalances have been proposed, the explicit incorporation of class-balancing mechanisms in multi-class lung cancer CT classification remains less consistently addressed in prior studies.

Based on the reviewed literature, limited attention has been paid to the combined use of adaptive contrast augmentation, calibrated partial fine-tuning, and class-balanced optimization within a single transfer-learning framework for multi-class lung cancer CT classification. To bridge this gap, this study proposes a contrast-adaptive and class-balanced transfer learning framework using EfficientNetB1 for multi-stage detection of lung cancer based on CT images. In contrast to conventional approaches, gamma correction is integrated directly into the augmentation pipeline as an on-the-fly preprocessing function, so that contrast variations are learned dynamically during the training process. In addition, the input resolution was increased to 240×240 pixels, and a partial fine-tuning strategy was used in the last 50 layers of EfficientNetB1 to balance domain adaptation and the stability of pretrained features. To overcome class imbalance, class weighting is used in the loss function so that sensitivity to classes that have morphological similarities can be increased. The main contributions of this research can be summarized as follows:

- Develops an adaptive augmentation strategy based on gamma correction that is integrated in the transfer learning pipeline.
- Implements EfficientNetB1 with higher input resolution and calibrated partial fine-tuning strategies for multi-stage classification of lung cancer.
- Implements class-balance-based optimization to increase sensitivity to categories that have visual similarities.
- Demonstrates stable classification performance with 97% accuracy and a macro F1-score of 0.97 on a four-class CT dataset.

A. Related Work and Research Gap

Table I presents a concise comparison to clarify the methodological position of this study within the existing CT-based lung cancer classification literature. Although deep learning has been widely applied to CT-based lung cancer classification, the reviewed studies reveal several methodological limitations that motivate this work. First, many previous pipelines applied contrast enhancement as a fixed preprocessing step before training rather than as an adaptive component of the augmentation process. This can limit the model's exposure to realistic contrast variability during optimization. Second, transfer-learning fine-tuning is commonly implemented through either extensive freezing or broad end-to-end retraining, with limited explanation of how much adaptation is appropriate for the target CT domain. Third,

in multi-stage classification, class imbalance and morphological similarity between subtypes are often not explicitly addressed in the optimization mechanism, which can reduce the stability of class-wise discrimination. Therefore, a framework that integrates contrast adaptation, calibrated fine-tuning, and class-balanced optimization is still needed to improve stability and generalization in CT-based multi-stage lung cancer classification.

TABLE I. LITERATURE REVIEW

Ref. Year	Focus	Method/model	Key findings
[1] 2024	Global statistics of lung cancer	Epidemiological analysis	Lung cancer is the highest cause of cancer death in the world.
[2] 2021	Clinical diagnosis and imaging of lung cancer	Clinical review and imaging	Early detection increases the chance of successful therapy.
[4] 2023	Deep learning for lung cancer CT	CNN	CNN improves the accuracy of CT-based automatic detection.
[6] 2025	Multi-class classification of lung cancer	CNN	Multi-class classifications are more complex than binaries.
[7] 2025	Evaluation of AI performance in thorax CT	Deep learning	Morphological similarity lowers the stability of the classification.
[8] 2024	Transfer learning for lung cancer detection	Hybrid transfer learning	Transfer learning accelerates convergence on limited datasets.
[9] 2023	EfficientNet on pulmonary CT classification	EfficientNet	EfficientNet has a good balance of accuracy and efficiency.
[16] 2024	Multi-class classification of lung cancer	CNN	Visual overlap between subtypes affects the accuracy of discrimination.
This study 2026	Multi-stage CT-based lung cancer classification	Contrast-adaptive and class-balanced transfer learning (EfficientNetB1 + gamma on-the-fly + partial fine-tuning + class weighting)	Improves discrimination stability between morphologically similar subtypes, achieving 97% accuracy and a macro F1-score of 0.97.

This study addresses this gap by combining on-the-fly gamma-based contrast adaptation, partial fine-tuning of the EfficientNetB1 backbone, and class-weighted optimization in a unified framework for four-class CT image classification. The unified framework achieved 97% accuracy and a macro F1-score of 0.97, indicating stable performance across visually similar classes within the experimental setting.

II. MATERIALS AND METHODS

A. Dataset Description

This study used a pulmonary CT image dataset consisting of four classes, which can be accessed at [17]. The data was augmented using Albumentations to a total of 5,958 images. Table II shows details on the data distribution for each class.

TABLE II. DATASET DISTRIBUTION FOR TRAINING, VALIDATION, AND TESTING

Category	Training	Validation	Testing
Adenocarcinoma Ib	1,170	408	408
Large Cell Carcinoma IIIa	690	216	216
Normal	888	204	198
Squamous Cell Carcinoma IIIa	930	318	312

B. Contrast Adaptive Augmentation

Variations in contrast in CT images can affect the stability of the features extracted by a CNN. To address this, gamma correction is integrated directly into the augmentation pipeline as an on-the-fly preprocessing function. Instead of statically applying contrast enhancement before training, these transformations are executed dynamically during the augmentation process using ImageDataGenerator. This approach allows the model to study contrast variations as part of the training data distribution. In addition to gamma correction, the augmentation used includes rotation up to 40°, horizontal and vertical shift up to 30%, zoom up to 30%, horizontal flipping, and brightness variation of 0.8–1.2. This approach aims to increase robustness against geometric variations and intensities.

C. Model Architecture

This study used an EfficientNetB1, pretrained with ImageNet weights. EfficientNet uses a compound scaling strategy to balance network depth, width, and input resolution. The model architecture consists of:

1. EfficientNetB1 backbone without the fully connected top layer
2. Global Average Pooling
3. Dropout (0.5)
4. Dense layer with Softmax activation

The input resolution is increased to 240×240 pixels to improve the spatial representation of features.

D. Calibrated Partial Fine-Tuning

A partial fine-tuning strategy is used to maintain a balance between domain adaptation and stability of pretrained features. Only the last 50 layers of EfficientNetB1 are set as trainable, while the rest are frozen. This approach allows the model to adapt high-level features to the characteristics of the CT imagery without undermining the representation of the basic features that have been learned from ImageNet.

E. Class-Balanced Optimization

Medical datasets often experience class distribution imbalances. To reduce bias towards the majority class, a class weighting approach is used. The class weight calculation is carried out based on the proportion of the number of samples in each class, so that misclassification in classes with less data will get a greater penalty during the training process. The following is the formula for class weight balancing:

$$\omega_c = \frac{N}{K \cdot n_c} \quad (1)$$

where N is the number of total samples (trained, according to y_{train}), K is the number of classes, and n_c is the number of samples in class c (trained). This weight is applied to the loss categorical cross-entropy function during the training process.

F. Optimization Algorithm

Model optimization was carried out using RMSprop. Training was performed for up to 40 epochs with EarlyStopping and adaptive learning-rate adjustment through ReduceLRonPlateau to improve generalization and maintain training stability.

G. Performance Evaluation

Model evaluation was carried out using accuracy, precision, recall, and F1-score. In addition, the confusion matrix and the accuracy and loss curves per epoch were used to assess classification stability and convergence behavior.

H. Experimental Setup

Experiments were conducted in Google Colab using TensorFlow/Keras. The four-class CT dataset is organized in a train/test directory and loaded with the ImageDataGenerator at 240x240 resolution. Adaptive contrast is applied using gamma correction ($\gamma = 1.5$) on-the-fly on the generator pipeline, along with rotation, translation, zoom, flip, and brightness augmentation for training data. EfficientNetB1, pretrained on ImageNet, is used as a backbone with a classification head (GAP-Dropout 0.5-Softmax). Partial fine-tuning is applied to the last 50 layers. Class imbalance is handled using class weighting. The model was trained for up to 40 epochs using RMSprop ($lr = 1e - 4$) with ReduceLRonPlateau and EarlyStopping.

III. RESULTS AND DISCUSSION

A. Overall Classification Performance

The proposed model was evaluated on a four-class CT dataset with a total of 1,154 test samples. The evaluation results showed an overall accuracy of 97%, with a macro F1-score of 0.97, indicating balanced performance across classes. Table III presents the class-wise precision, recall, and F1-score of the proposed contrast-adaptive and class-balanced EfficientNetB1 model on the four-class CT dataset. Figure 1 visualizes the confusion matrix. A macro F1-score of 0.97 indicates that the model not only achieves high overall accuracy but also maintains relatively consistent performance in minority classes and classes with morphological similarities. Figure 2 shows training and validation curves.

TABLE III. PERFORMANCE OF GAMMA CORRECTION WITH EFFICIENTNETB1

Class	Precision	Recall	F1-score	Support
Adenocarcinoma 1b	0.97	0.94	0.95	418
Large Carcinoma IIIa	0.90	1.00	0.95	216
Normal	1.00	1.00	1.00	198
Squamous Carcinoma IIIa	0.99	0.96	0.97	322

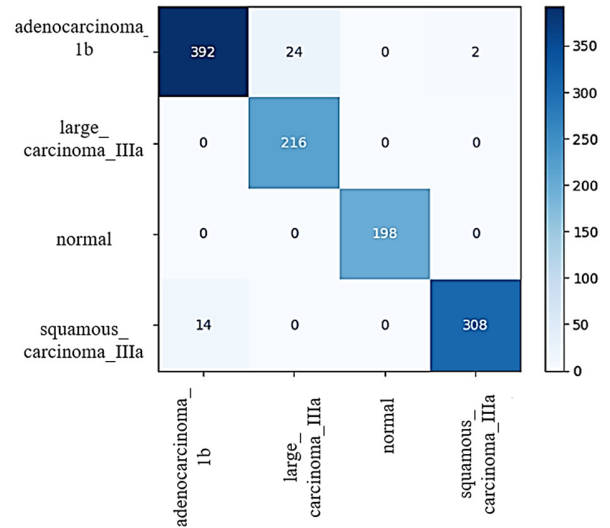


Fig. 1. Confusion matrix of gamma correction with EfficientNetB1.

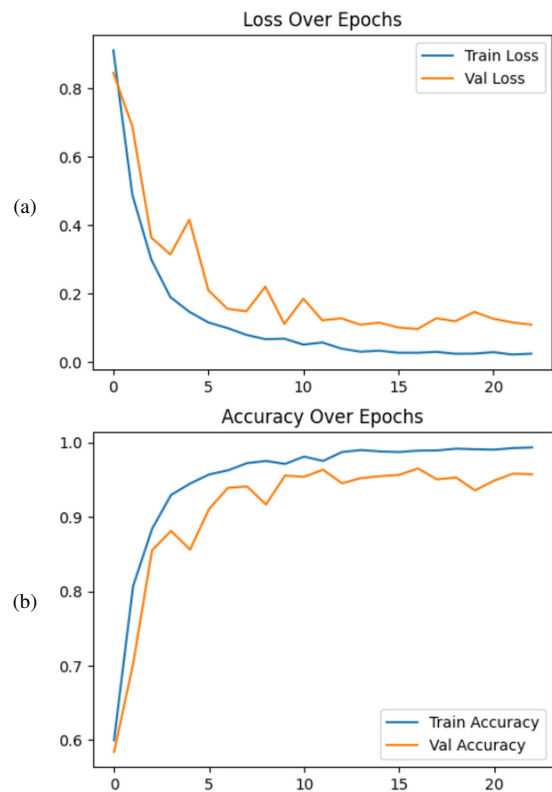


Fig. 2. Training and validation loss (a) and accuracy (b) curves.

B. Class-wise Analysis

1) Adenocarcinoma 1b

Adenocarcinoma class 1b achieved a precision of 0.97 and a recall of 0.94 with an F1-score of 0.95. A major misclassification occurred when 24 samples were predicted as Large Cell Carcinoma IIIa and 2 samples as Squamous Cell Carcinoma IIIa. This error can be explained by the similarity in the texture pattern and distribution of nodules on CT images,

which often exhibit overlapping radiological characteristics. However, the recalls remain high (94%), indicating that the class balancing strategy helps maintain sensitivity to this class.

2) Large Cell Carcinoma IIIa

This class shows optimal performance with a perfect recall (1.00) and an F1-score of 0.95, having no classification errors. These results indicate that the features studied at the high-level layer of EfficientNetB1, after partial fine-tuning, are able to stably capture the typical visual characteristics of Large Cell Carcinoma IIIa.

3) Normal

The Normal class achieved perfect precision and recall (1.00) with an F1-score of 1.00, having no prediction errors. This stability suggests that the model is able to distinguish normal lung tissue from pathological lesions consistently, which is important in Computer-Aided Diagnosis (CAD) systems.

4) Squamous Cell Carcinoma IIIa

This class obtained a precision of 0.99 and a recall of 0.96 with an F1-score of 0.97. A total of 14 samples were misclassified as adenocarcinoma Ib, which indicates a morphological overlap between the two subtypes. However, the still high recall rate suggests that the combination of contrast-based adaptive augmentation and calibrated fine-tuning helps improve discrimination between similar subtypes.

C. Impact of Contrast-Adaptive and Class-Balanced Learning

The results obtained indicate that on-the-fly integration of gamma correction contributes to improved feature stability against variations in image intensity. In contrast to static preprocessing, the adaptive approach allows the model to learn a more varied contrast distribution during training.

In addition, the use of class weighting has been proven to maintain a balance of performance between classes, which is reflected in the macro value of F1 being almost identical to the weighted F1. This shows that the model is not biased towards the majority class.

The partial fine-tuning strategy of the last 50 layers of EfficientNetB1 also plays a role in maintaining a balance between domain adaptation and pre-trained feature stability, resulting in stable convergence without significant overfitting.

D. Comparative Interpretation with Prior Studies

Most previous CT-based lung cancer classification studies reported high performance in binary classification scenarios or relied on fixed preprocessing and conventional fine-tuning strategies. In multi-stage classification, however, performance is more easily affected by subtype similarity and class imbalance. The proposed framework differs by combining on-the-fly gamma correction, calibrated partial fine-tuning, and class-weighted optimization in a single EfficientNetB1-based pipeline. With a macro F1-score of 0.97, the results indicate more stable class-wise discrimination than approaches that emphasize only backbone selection or static preprocessing.

E. Discussion on Generalization

The results show that misclassifications only occur in classes with morphological similarities, not due to class distribution bias. This indicates that the model has good generalization capabilities for the distribution of test data. The integration of three main components, namely contrast-adaptive augmentation, calibrated partial fine-tuning, and class-balanced optimization, forms a more robust system than the conventional approach. Figure 3 provides some prediction examples.

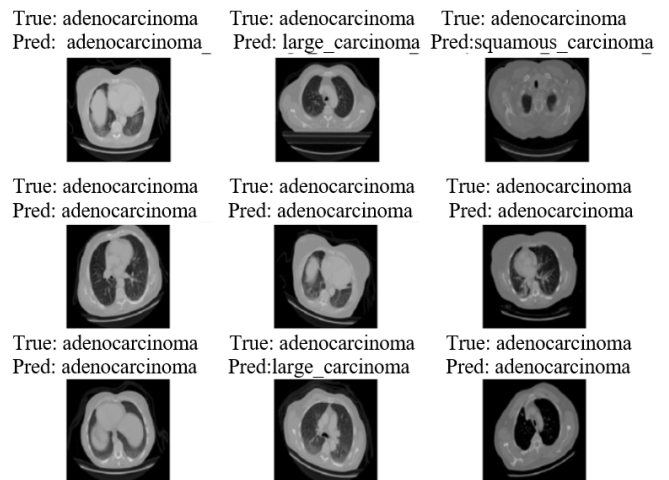


Fig. 3. Model prediction examples.

The confusion matrix shows that most prediction errors occurred between classes with high visual similarity. This suggests that the remaining classification difficulty is more closely related to inter-class resemblance than to severe dominance of a single class in prediction outcomes. Within the held-out test set used in this study, the model showed stable performance, indicating reasonable internal generalization.

The prediction examples also show that many samples were classified consistently with their ground-truth labels. However, some Adenocarcinoma Ib images were still predicted as Large Carcinoma IIIa or Squamous Carcinoma IIIa. This may reflect overlap in visually discriminative patterns between subtypes. In several difficult cases, lesion appearance seemed closer to features represented in other classes, which may have increased latent feature overlap. These errors appeared more frequently in images that visually showed lower contrast or more heterogeneous texture. However, this observation would require further verification through explainability analysis or expert radiological assessment. Therefore, while the proposed contrast-adaptive and class-balanced framework showed stable classification performance, similarity in radiological appearance between classes remains an important challenge.

IV. CONCLUSION

This study addressed the knowledge gap in CT-based lung cancer classification, where many previous works focused on binary detection, static contrast preprocessing, or transfer-learning strategies without explicit class-balanced optimization.

To address this gap, this study developed a contrast-adaptive and class-balanced transfer learning framework based on EfficientNetB1 for four-class lung cancer CT classification. The key methodological steps consisted of integrating gamma correction as an on-the-fly augmentation component, increasing the input resolution to 240×240 pixels, applying calibrated partial fine-tuning to the last 50 layers of EfficientNetB1, and using class-weighted categorical cross-entropy to reduce bias toward majority classes. These steps were designed to improve feature robustness against contrast variation while maintaining stable adaptation of the pretrained representations to the CT domain. The proposed model achieved 97% overall accuracy and a macro F1-score of 0.97 on the held-out test set. Class-wise analysis showed perfect performance for the Normal class, strong sensitivity for Large Cell Carcinoma IIIa, and limited misclassification mainly between Adenocarcinoma Ib and Squamous Cell Carcinoma IIIa or Large Cell Carcinoma IIIa. This pattern indicates that the remaining errors were primarily associated with morphological overlap between subtypes rather than severe prediction bias toward a dominant class.

The novelty of this study lies in the unified combination of on-the-fly gamma-based contrast adaptation, calibrated EfficientNetB1 fine-tuning, and class-balanced optimization for multi-stage CT image classification. Compared with prior studies that rely mainly on binary classification settings, fixed preprocessing, or non-calibrated fine-tuning, the proposed framework provides a more stable class-wise performance profile for visually similar lung cancer categories. These findings suggest that adaptive contrast handling and balanced optimization are important components for improving multi-class CT-based lung cancer classification, although broader external validation is still required before making claims of clinical deployment readiness.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests in this paper.

ACKNOWLEDGMENT

Not applicable in this study.

DATA AVAILABILITY

The dataset used in this study is publicly available at [17].

ETHICS STATEMENT

This study used a publicly available dataset of anonymized CT images and did not involve direct interaction with human participants.

REFERENCES

- [1] F. Bray *et al.*, "Global cancer statistics 2022: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries," *CA: A Cancer Journal for Clinicians*, vol. 74, no. 3, pp. 229–263, May 2024, <https://doi.org/10.3322/caac.21834>.
- [2] R. Nooreldeen and H. Bach, "Current and Future Development in Lung Cancer Diagnosis," *International Journal of Molecular Sciences*, vol. 22, no. 16, Aug. 2021, Art. no. 8661, <https://doi.org/10.3390/ijms22168661>.
- [3] A. Riadi, A. Achmad, Z. Zainuddin, and H. A. Putrawan, "Deep Learning for Lung Cancer Staging: A Performance Evaluation of Gamma Correction vs Histogram Equalization Using EfficientNetB0," *Engineering, Technology & Applied Science Research*, vol. 15, no. 6, pp. 28719–28724, Dec. 2025, <https://doi.org/10.48084/etasr.13252>.
- [4] M. A. Thanoon, M. A. Zulkifley, M. A. A. Mohd Zainuri, and S. R. Abdani, "A Review of Deep Learning Techniques for Lung Cancer Screening and Diagnosis Based on CT Images," *Diagnostics*, vol. 13, no. 16, Aug. 2023, Art. no. 2617, <https://doi.org/10.3390/diagnostics13162617>.
- [5] I. Naseer, S. Akram, T. Masood, A. Jaffar, M. A. Khan, and A. Mosavi, "Performance Analysis of State-of-the-Art CNN Architectures for LUNA16," *Sensors*, vol. 22, no. 12, June 2022, Art. no. 4426, <https://doi.org/10.3390/s22124426>.
- [6] K. Abdullahi, K. Ramakrishnan, and A. B. Ali, "Deep Learning Techniques for Lung Cancer Diagnosis with Computed Tomography Imaging: A Systematic Review for Detection, Segmentation, and Classification," *Information*, vol. 16, no. 6, May 2025, Art. no. 451, <https://doi.org/10.3390/info16060451>.
- [7] H. M. Cheo, C. Y. G. Ong, and Y. Ting, "A Systematic Review of AI Performance in Lung Cancer Detection on CT Thorax," *Healthcare*, vol. 13, no. 13, June 2025, Art. no. 1510, <https://doi.org/10.3390/healthcare13131510>.
- [8] A. Saha, S. M. Ganie, P. K. D. Pramanik, R. K. Yadav, S. Mallik, and Z. Zhao, "VER-Net: a hybrid transfer learning model for lung cancer detection using CT scan images," *BMC Medical Imaging*, vol. 24, no. 1, May 2024, Art. no. 120, <https://doi.org/10.1186/s12880-024-01238-z>.
- [9] R. Raza *et al.*, "Lung-EffNet: Lung cancer classification using EfficientNet from CT-scan images," *Engineering Applications of Artificial Intelligence*, vol. 126, Nov. 2023, Art. no. 106902, <https://doi.org/10.1016/j.engappai.2023.106902>.
- [10] G. Mohandass, G. Hari Krishnan, D. Selvaraj, and C. Sridhathan, "Lung Cancer Classification using Optimized Attention-based Convolutional Neural Network with DenseNet-201 Transfer Learning Model on CT image," *Biomedical Signal Processing and Control*, vol. 95, Sept. 2024, Art. no. 106330, <https://doi.org/10.1016/j.bspc.2024.106330>.
- [11] U. Muñoz-Aseguinolaza, I. Fernandez-Iriondo, I. Rodríguez-Moreno, N. Aginako, and B. Sierra, "Convolutional neural network-based classification and monitoring models for lung cancer detection: 3D perspective approach," *Heliyon*, vol. 9, no. 11, Nov. 2023, Art. no. e21203, <https://doi.org/10.1016/j.heliyon.2023.e21203>.
- [12] G. Pezzano, V. Ribas Ripoll, and P. Radeva, "CoLe-CNN: Context-learning convolutional neural network with adaptive loss function for lung nodule segmentation," *Computer Methods and Programs in Biomedicine*, vol. 198, Jan. 2021, Art. no. 105792, <https://doi.org/10.1016/j.cmpb.2020.105792>.
- [13] A. Bouamrane *et al.*, "Toward Robust Lung Cancer Diagnosis: Integrating Multiple CT Datasets, Curriculum Learning, and Explainable AI," *Diagnostics*, vol. 15, no. 1, Dec. 2024, Art. no. 1, <https://doi.org/10.3390/diagnostics15010001>.
- [14] M. N. Nguyen, "A scoping review of deep learning approaches for lung cancer detection using chest radiographs and computed tomography scans," *Biomedical Engineering Advances*, vol. 9, June 2025, Art. no. 100138, <https://doi.org/10.1016/j.bea.2024.100138>.
- [15] M. Salmi, D. Atif, D. Oliva, A. Abraham, and S. Ventura, "Handling imbalanced medical datasets: review of a decade of research," *Artificial Intelligence Review*, vol. 57, no. 10, Sept. 2024, Art. no. 273, <https://doi.org/10.1007/s10462-024-10884-2>.
- [16] M. Q. Shatnawi, Q. Abuein, and R. Al-Quraan, "Deep learning-based approach to diagnose lung cancer using CT-scan images," *Intelligence-Based Medicine*, vol. 11, 2025, Art. no. 100188, <https://doi.org/10.1016/j.ibmed.2024.100188>.
- [17] "Chest CT Scan Image Lung." Kaggle, [Online]. Available: <https://www.kaggle.com/datasets/diayrudip/carinocroma>.