Comparative Analysis of Lung Cancer Classification Models Using EfficientNet and ResNet on CT-Scan Lung Images

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Abstract

This study investigates the classification of lung cancer, a major global cause of mortality. The accurate diagnosis and classification of lung cancer through CT-Scan images demand significant expertise, precision, and time to ensure appropriate treatment for patients. Transfer learning has emerged as a beneficial technology to aid in this process by effectively classifying lung cancer-related patterns in CT-Scan images. In this research, a dataset of 1,000 lung CT-Scan images, divided into four categories—Adenocarcinoma, Large Cell, Squamous, and Normal—was employed. The study evaluated several transfer learning models, including ResNet50, ResNet101, EfficientNetB1, EfficientNetB3, EfficientNetB5, and EfficientNetB7. The findings revealed that the EfficientNetB3 model outperformed the others, achieving an accuracy of 97.78%, a precision of 97.34%, a recall of 98.33%, and an F1-Score of 97.78%. These results demonstrate that the EfficientNetB3 model enhances the accuracy of lung cancer classification in CT-Scan images more effectively than other transfer learning models. This research underscores the significant potential of EfficientNetB3 in facilitating early diagnosis, advancing the integration of machine learning in medical practices, and providing critical insights for the selection of transfer learning models in clinical applications. The implications of these findings suggest a substantial impact on improving diagnostic processes and outcomes in lung cancer management.

Keywords— Transfer Learning, EfficientNet, ResNet, CT-Scan

1. INTRODUCTION

Lung cancer is one of the most prevalent cancers and a leading cause of death globally. According to the World Health Organization (WHO) in 2020, there were 9.6 million deaths due to cancer, with lung cancer ranking second to breast cancer, accounting for 2.21 million cases. In that same year, lung cancer caused 1.80 million deaths, making it the most common cause of cancer-related mortality [1]. Data from Globocan (International Agency for Research on Cancer) reveals a significant rise in lung cancer cases in Indonesia, reporting 34.7 million cases and 30.8 million deaths in 2020 [2]. A major challenge is that many lung cancer patients are diagnosed at advanced stages, which adversely affects their prognosis and chances of recovery [3]–[5]. Several factors influence the prognosis of lung cancer, including the type of lung cancer, the stage at diagnosis, response to treatment, overall health, and other individual factors. The type of lung cancer plays a crucial role in determining the prognosis and treatment strategy. Non-small cell Lung Cancer (NSCLC) is the most prevalent type of lung cancer, which includes Squamous Cell Cancer (SCC), Large Cell Cancer, and Lung Adenocarcinoma[6], [7]. SCC occurs in the central part of the lungs and is often linked to smoking. Large-cell carcinoma is known for its aggressive nature and rapid spread [8]. Lung adenocarcinoma, the most common type, originates from glandular cells in the lungs [9]. Lung cancer generally develops through the growth and proliferation of malignant cells within lung tissue, initiated by genetic mutations that cause uncontrolled cell growth[10]. Therefore, early diagnosis and accurate detection are essential in managing lung cancer effectively. Computed Tomography (CT) Scan of the lungs is currently one of the primary methods used for early detection and evaluation of lung cancer[11]. Radiologists and pulmonologists can identify specific characteristics in CT-Scan images to detect suspicious masses or tumors and determine their size, location, condition, stage, and type [12]. Through CT-Scan procedures, doctors can obtain critical information necessary for accurate lung cancer diagnosis and appropriate treatment planning. However, interpreting lung CT-Scan images requires a high level of expertise and is time-consuming, as doctors must avoid errors to provide precise diagnoses [13]. Due to the required level of precision and reliability, technology that aids in classifying lung cancer CT-Scan images is needed to make the examination process more efficient and time-saving.

Machine Learning (ML) is a promising technology that can assist in detecting different types of lung cancer [14], monkeypox disease [15], and brain tumor [16] by allowing computers to learn complex patterns from data using multi-layered neural networks. One of the most successful deep learning methods for image processing is the Convolutional Neural Network (CNN). CNNs have been proven effective in image analysis and are widely used for detecting lung cancer in CT-Scan images [17]. Specifically designed for 2D image recognition, CNNs can classify important patterns in images, making them highly effective tools for analyzing and classifying lung CT-Scan images [18]. However, developing an accurate CNN model typically requires large datasets and significant computational time for training. Thus, transfer learning techniques become highly relevant for developing CNN models for lung cancer classification. Transfer learning leverages pre-trained models' knowledge to reduce computational resources needed for training new tasks. This approach enables the use of patterns learned from large datasets, such as shape and texture recognition, to aid in detecting and diagnosing lung cancer in CT-Scan images. Transfer learning leverages the existing knowledge from pre-trained models on extensive datasets to perform new tasks while maintaining high accuracy. This approach is not limited to CNN models; it can be applied to various types of machine-learning models, including CNNs, RNNs, and others. This technique reduces the time needed to develop accurate and efficient models for specific tasks. The benefits of using transfer learning include time savings, faster data processing without sacrificing accuracy, and the ability of the model to understand complex patterns in new data. Therefore, this study developed and evaluated lung cancer classification models using transfer learning techniques on CT-Scan images. This study aims to contribute to the early detection and management of lung cancer by providing insights into selecting EfficientNet and ResNet models for lung cancer classification in CT scan images.

2. RESEARCH METHODS

The research commences by acquiring data from a Kaggle dataset comprising CT-Scan images of lung cancer [19]. Following data collection, various preprocessing techniques are employed for feature extraction. Both ResNet and EfficientNet models are employed simultaneously using transfer learning to enhance learning speed and improve classification accuracy across four distinct categories: "adenocarcinoma," "squamous," "normal," and "large-cell." Evaluation of model performance includes the use of a confusion matrix to assess key metrics such as accuracy, recall, precision, and F1-score. The final phase of the study involves the development of a user-friendly web application for uploading images and visualizing accuracy results generated by the pre-trained models. Figure 1 illustrates the structured research methodology encompassing these sequential steps, ensuring a comprehensive approach to lung cancer classification using deep learning techniques.

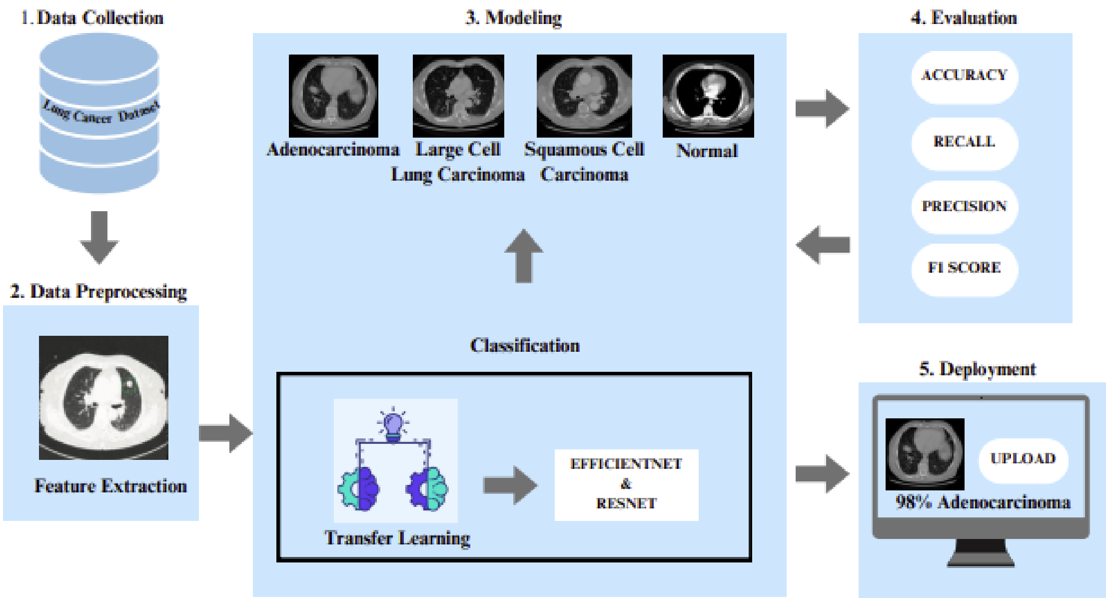

Figure 1. Research Design

2.1. Data Collection

The dataset is structured into three main folders: data_train, data_test, and data_valid, with each folder containing subfolders for three types of lung cancer (adenocarcinoma, large cell carcinoma, squamous cell carcinoma) and one subfolder for normal CT-Scan images. Each of these subfolders holds a portion of the total 1,000 images in JPG or PNG format, with 61.3% of images in data_train, 31.5% in data_test, and 7.2% in data_valid.

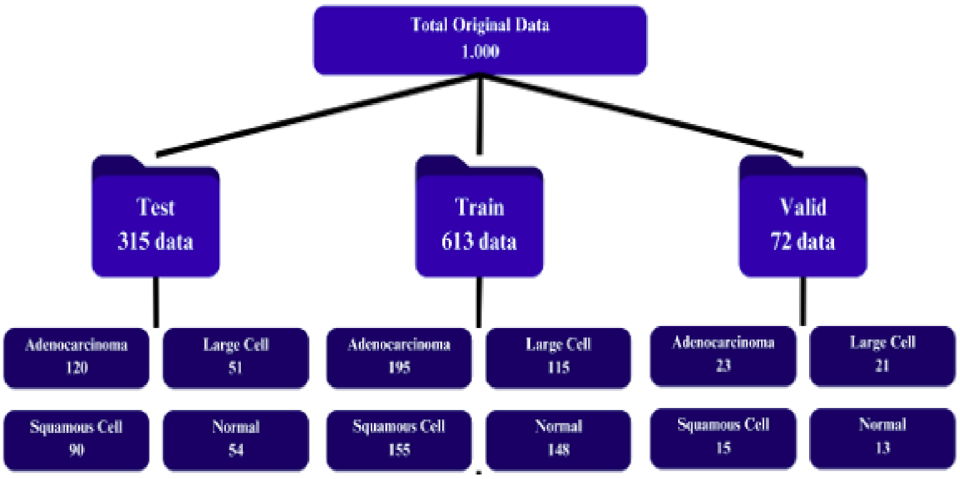

Figure 2. Data Distribution

2.2. Data Preprocessing

Data preprocessing in our study involves extensive use of data augmentation techniques aimed at strengthening the robustness and performance of our classification model, as illustrated in Figure 3. These techniques include standardizing image sizes to 440x300 pixels and applying rotations, horizontal flips, and vertical flips within specified angles to introduce variability and improve the model's ability to recognize patterns from different orientations. Additionally, adjustments in brightness and contrast are applied to simulate various lighting conditions, while the incorporation of blur and noise enhances the model's resilience to variations in image quality. These preprocessing steps are crucial as they effectively expand the training dataset, enabling our model to learn more effectively and accurately classify a diverse range of lung conditions such as adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal lung images. This comprehensive approach ensures that the model can generalize well and perform robustly when faced with real-world data challenges.

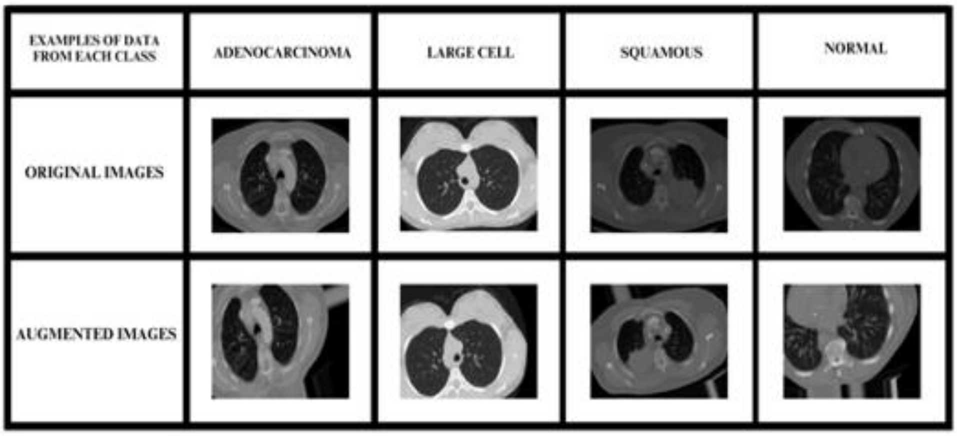

Figure 3. Data Augmentation

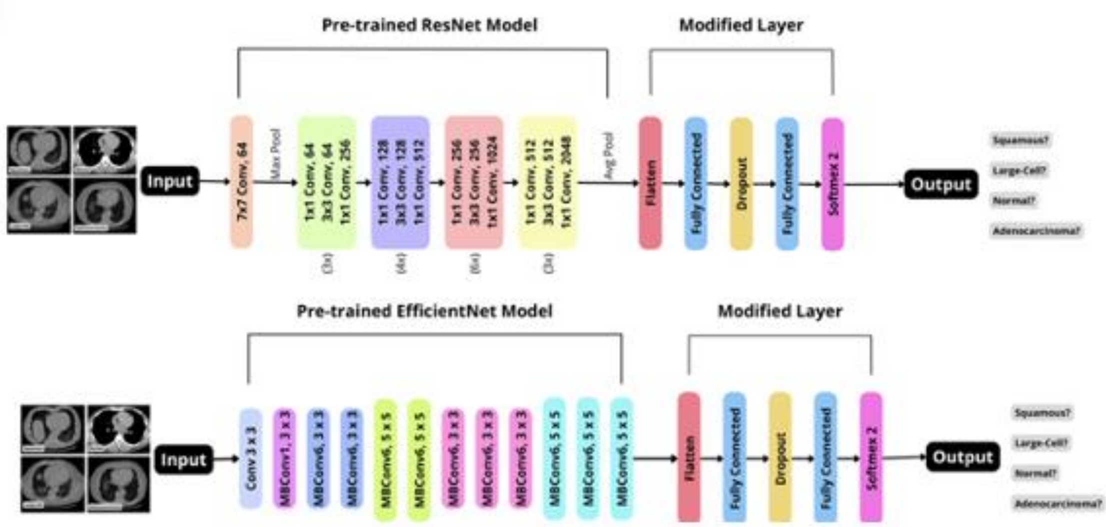

Figure 4. Modified Layer ResNet and EfficientNet

2.3. *Modeling*

In the modeling phase, we retained the basic architectures of the ResNet and EfficientNet models. Subsequently, we conducted feature extraction from lung cancer CT-Scan images at the convolutional layer and utilized max pooling. We contributed by modifying layers following ResNet and EfficientNet to achieve improved accuracy, as demonstrated in the proposed layer modifications. This process of maintaining and modifying the model architecture occurred towards the end, as depicted in Figure 4. Furthermore, we conducted experiments based on two designed scenarios, detailed in Table 1 as parameters. In Scenario 1, using a batch size of 10, models ResNet (depth 50 and 101) and EfficientNet (B1, B3, B5, and B7) were employed. The loss function utilized was Categorical Crossentropy, and three optimizers—Adam, SGD, and RMSProp—were tested over 30 epochs with a fixed learning rate (LR) of 0.001. In Scenario 2, the batch size was increased to 20, while maintaining the same model specifications and optimizers as in Scenario 1. Both scenarios employed Categorical Crossentropy as the loss function, ran for 30 epochs, and utilized a learning rate of 0.001. The choice of a fixed learning rate (LR) of 0.001 for our experiments was deliberate to ensure stable and controlled training of ResNet (depth 50 and 101) and EfficientNet (B1, B3, B5, B7) models on lung cancer CT-Scan images.

Table 1. The Parameters Used in Each Scenario

Scenario	***Batch Size***	***Model***	***Loss Function***	***Optimizer***	***Epoch***	***LR***
Scenario 1	10	*ResNet (50 &101) EfficientNet (B1, B3, B5 & B7)*	*Categorical Crossentropy*	*Adam, SGD*, dan *RMSProp*	30	0.001
Scenario 2	20	*ResNet (50 &101) EfficientNet (B1, B3, B5 & B7)*	*Categorical Crossentropy*	*Adam, SGD*, dan *RMSProp*	30	0.001

2.4. Model Evaluation

Model evaluation is a crucial aspect of machine learning, encompassing the assessment of how well a trained model performs on unseen data. It relies on fundamental metrics such as accuracy, precision, recall, and the F1 score. Accuracy, represented by the formula:

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \tag{1}$$

measures the ratio of correctly predicted instances to the total number of instances. Precision, calculated as

$$Precision = \frac{\text{TP}}{\text{FP+TP}} \tag{2}$$

evaluates the proportion of correctly predicted positive instances among all instances predicted as positive. Recall, or sensitivity, is computed using

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

indicating the model's ability to correctly identify all positive instances. The F1 score,

$$F1\text{-}Score = \frac{\text{2 x Recall x Precision}}{\text{Recall+Precision}} \tag{4}$$

harmonizes precision and recall into a single metric, providing a balanced measure of a model's performance. These metrics collectively provide insights into a model's capability to generalize to new data and its effectiveness in real-world applications across diverse domains such as healthcare, finance, and natural language processing.

2.5. Deployment

During the deployment phase, we developed a simple web system capable of classifying lung cancer CT-Scan images. The web interface allows users to upload lung CT-Scan images and displays accurate results for classifying 4 classes: three types of lung cancer (adenocarcinoma, squamous, and large cell) and one normal lung category. This web system was constructed using the Flask framework and operates solely in a local environment.

3. RESULT AND DISCUSSION

3.1. Comparative Evaluation of the Best Performing Transfer Learning Models

Table 2 summarizes key performance metrics of deep learning models for lung cancer classification using CT-Scan images. Models like ResNet50, ResNet101, EfficientNetB1, B3, B5, and B7 were evaluated in two scenarios. Optimizer and loss function choices significantly affect accuracy: ResNet50 achieved 94.60% with ADAM in Scenario 1, while ResNet101 reached 81.59% using SGD, highlighting ADAM's faster convergence. In Scenario 2, EfficientNetB1 and B3 achieved 95.56% and 97.78% accuracy respectively with RMSprop, showing its effectiveness. EfficientNet consistently outperformed ResNet, with EfficientNetB3 reaching 97.78% accuracy in Scenario 2, highlighting its superior feature extraction from CT-Scan images. Scenario 2 generally yielded better results, indicating the impact of parameter adjustments on model performance. Optimizing model selection and parameters is crucial for enhancing lung cancer classification accuracy from CT-Scan data.

Table 2. Comparative Evaluation of the Best Performing Transfer Learning Models (ResNet50, ResNet101, EfficientNetB1, B3, B5, and B7)

Model	***Optimizer***	***Loss Function***	***Accuracy***	***Scenario***
ResNet50	ADAM	Categorial	94.60%	1
ResNet101	SGD	Categorial	81.59%	1
EfficientNetB1	RMSprop	Categorial	95.56%	2
EfficientNetB3	**RMSprop**	**Categorial**	**97.78%**	**2**
EfficientNetB5	ADAM	Categorial	92.38%	1
EfficientNetB7	ADAM	Categorial	94.29%	1

3.2. Comparative Evaluation of Transfer Learning Model in Two Scenarios

Tables 3 and 4 analyze deep learning models for lung cancer classification using CT-Scan images in two scenarios. In Scenario 1 with a batch size of 10, models like ResNet (50 & 101) and EfficientNet (B1, B3, B5, B7) were tested with different optimizers (Adam, SGD, RMSProp) and categorical cross-entropy loss over 30 epochs at a 0.001 learning rate. EfficientNetB3 excelled with Adam, achieving 97.46% accuracy, along with strong precision (95.78%), recall (95.56%), and F1-score (95.57%), indicating its robust performance in lung cancer classification. RMSProp yielded mixed results, with EfficientNetB3 achieving 95.87% accuracy but showing variability in precision, recall, and F1-score metrics across models.

Table 3. Confusion Matrix in Scenario 1

Optimizer	***Model***	***Confusion Matrix***			
		Accuracy	***Precision***	***Recall***	***F1-Score***
Adam	ResNet50	94.60%	94.87%	94.60%	94.63%
	ResNet101	74.60%	81.55%	74.60%	73.58%
	EfficientNetB1	93.97%	94.05%	37.97%	93.98%
	EfficientNetB3	**97.46%**	**95.78%**	**95.56%**	**95.57%**
	EfficientNetB5	92.38%	92.97%	92.38%	92.35%
	EfficientNetB7	94.29%	94.42%	94.29%	94.27%
SGD	ResNet50	78.73%	79.42%	78.73%	78.74%
	ResNet101	**81.59%**	**83.79%**	**81.59%**	**81.41%**
	EfficientNetB1	64.44%	63.91%	64.44%	63.72%
	EfficientNetB3	68.89%	69.49%	68.89%	68.35%
	EfficientNetB5	**81.59%**	**81.85%**	**81.59%**	**81.66%**
	EfficientNetB7	58.73%	63.04%	58.73%	57.78%
RMSProp	ResNet50	46.98%	47.57%	46.98%	46.92%

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	ResNet101	57.14%	49.92%	57.14%	52.95%
	EfficientNetB1	93.65%	94.61%	93.65%	93.71%
	EfficientNetB3	**95.87%**	**95.96%**	**95.87%**	**95.89%**
	EfficientNetB5	91.43%	93.12%	91.43%	91.61%
	EfficientNetB7	85.71%	90.67%	85.71%	86.60%

In Scenario 2, using a batch size of 20, ResNet (50 & 101) and EfficientNet (B1, B3, B5, B7) were assessed under the same optimizers and loss function as in Scenario 1. EfficientNetB3 maintained its top performance, achieving 97.78% accuracy with the RMSProp optimizer, alongside strong precision (97.91%), recall (97.78%), and F1-score (97.80%) in classifying lung cancer from CT-Scan images. This underscores EfficientNetB3's consistent excellence across scenarios. In contrast, models like ResNet101 with RMSProp exhibited lower accuracy and precision, reflecting varied performance influenced by optimizer choice.

Table 4. Confusion Matrix in Scenario 2

Optimizer	***Model***	***Confusion Matrix***			
		Accuracy	***Precision***	***Recall***	***F1-Score***
Adam	ResNet50	89.21%	90.38%	89.21%	89.20%
	ResNet101	74.29%	82.34%	74.29%	71.07%
	EfficientNetB1	**94.92%**	**95.54%**	**94.92%**	**94.97%**
	EfficientNetB3	93.02%	94.40%	93.02%	93.16%
	EfficientNetB5	91.11%	91.15%	91.11%	91.10%
	EfficientNetB7	90.79%	92.30%	90.70%	90.88%
SGD	**ResNet50**	**89.84%**	**90.63%**	**89.84%**	**89.78%**
	ResNet101	80.00%	83.38%	80.00%	79.24%
	EfficientNetB1	64.13%	65.21%	64.13%	63.61%
	EfficientNetB3	65.08%	65.18%	65.08%	63.97%
	EfficientNetB5	57.46%	57.15%	57.46%	56.40%
	EfficientNetB7	85.08%	86.82%	85.08%	84.86%
RMSProp	ResNet50	47.62%	53.14%	47.62%	44.98%
	ResNet101	52.70%	64.36%	52.70%	48.38%
	EfficientNetB1	95.56%	95.75%	95.56%	95.57%
	EfficientNetB3	**97.78%**	**97.91%**	**97.78%**	**97.80%**
	EfficientNetB5	91.11%	92.57%	91.11%	91.14%
	EfficientNetB7	87.94%	89.86%	87.94%	87.95%

3.3. The Best Training and Validation Loss/Accuracy in Scenario 1 and 2

The analysis compares the performance of two scenarios over 30 epochs, focusing on training and validation loss, as well as accuracy. Figure 5 provides insights into the learning dynamics, generalization capabilities, and potential overfitting of deep learning models, crucial for assessing their effectiveness in real-world applications. In Figure 5(A), the left graph illustrates a consistent decrease in both training loss (red line) and validation loss (green line), converging towards similar values by the end of training, indicating effective learning without overfitting. The blue dot highlights the best epoch at 10. On the right, training accuracy (red line) rises rapidly, nearing 100% early on, while validation accuracy (green line) steadily increases to about 95%, demonstrating good generalization. In Figure 5(B), the left graph shows training loss (red line) starting low and decreasing smoothly, whereas validation loss (green line) initially spikes and then gradually reduces with more fluctuations, stabilizing slightly higher than training loss. The best epoch for loss, indicated by the blue dot, occurs at 25. On the right, training accuracy (red line) quickly reaches near 100%, but validation accuracy (green line) fluctuates more and stabilizes around 90%. The best epoch for accuracy is at 15. These figures provide a detailed view of how each model learns and generalizes, highlighting nuances in training dynamics and performance across epochs, which are essential for evaluating their reliability in practical applications.

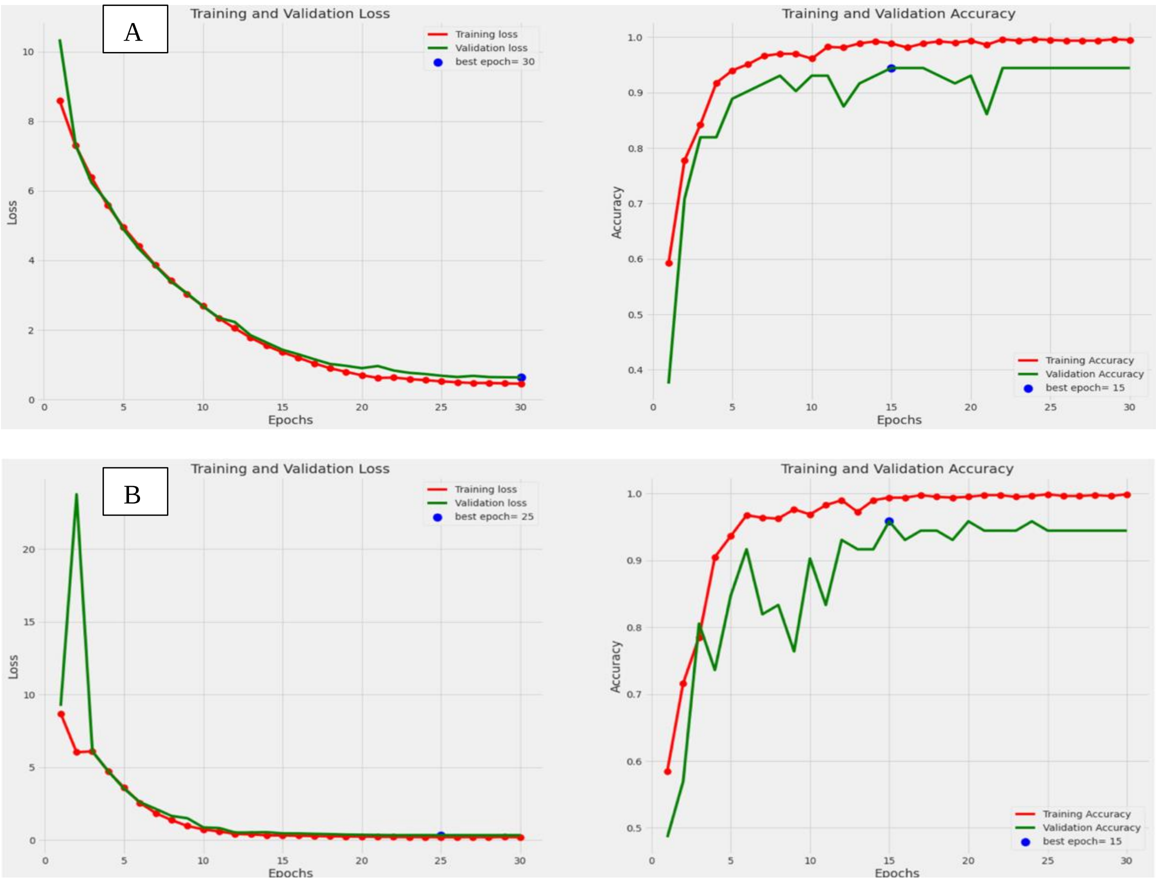

Figure 5. The Best Training and Validation Loss/Accuracy in Scenario 1 (A) and 2 (B)

3.4. Comparison of Models with Related Research

Table 5 summarizes recent research utilizing deep learning models for medical image classification tasks related to lung cancer across various datasets. Our study represents a significant advancement in this field, conducting a comparative analysis against existing research and demonstrating superior performance. Utilizing ResNet50, ResNet101, and EfficientNet variants (B1, B3, B5, B7) on chest CT-Scan images from Kaggle, our method aims to leverage the strengths of these architectures to enhance diagnostic accuracy for lung conditions. EfficientNetB3 emerged as the top-performing model in our study, achieving an impressive 97.78% accuracy by effectively extracting intricate features from CT images crucial for identifying lung diseases. By integrating multiple state-of-the-art models, our approach provides a robust solution capable of handling complexities in medical imaging datasets. These results underscore the effectiveness of transfer learning and careful model selection in advancing diagnostic capabilities for medical professionals analyzing CT-Scan data.

Table 5. Deep Learning Models and Their Highest Accuracy Results in Lung Image Classification Studies

Related Research	Model	Dataset	Best Model Accuracy Result
Wang et al. (2020) [20]	AlexNet, VGG16, DenseNet, and DRNN	Lung cancer dataset collected in Shan- dong Provincial Hospital.	DRNN (85.71%)
Saha et al. (2024) [21]	VER-Net (VGG19 + EfficientNetB0 + ResNet101)	Chest CT-Scan Images Dataset from Kaggle.	VER-Net (91.00%)
Mamun et al. (2022)[22]	CNN, RestNet50, InceptionV3, and Xception	LIDC-IDRI data set, which is accessible to the general public, is used for the experiment.	CNN (92.00%)
Hamdalla et al. (2020) [23]	AlexNet with CNN	IQ-OTH/NCCD lung cancer dataset	AlexNet (93.54%)
Muayed et al., 2021 [24]	GoogLeNet DNN	IQ-OTH/NCCD lung cancer dataset	GoogLeNet DNN (94.38%)
Proposed Method	ResNet50, ResNet101, EfficientNet (B1, B3, B5, & B7)	Chest CT-Scan Images Dataset from Kaggle.	EfficientNetB3 **(97.78%)**

3.5. Web System for Lung Cancer Classification Using CT Scan Images

In the Deployment phase, following the development and evaluation of our deep learning model, we implemented a simple web system, depicted in Figure 6, to showcase its performance. The selected model for deployment is EfficientNetB3, which achieved the highest accuracy of 97.78% in Scenario 2 using the RMSProp optimizer. This web system allows users to upload images for real-time predictions using the model. It classifies images into categories such as "Adenocarcinoma," "Large Cell," "Squamous," and "Normal," facilitating the practical application of the classification model. While not yet publicly accessible via the internet, this system offers an initial demonstration of the model's reliability and potential in medical image classification, laying the groundwork for future recommendations to lung medical professionals.

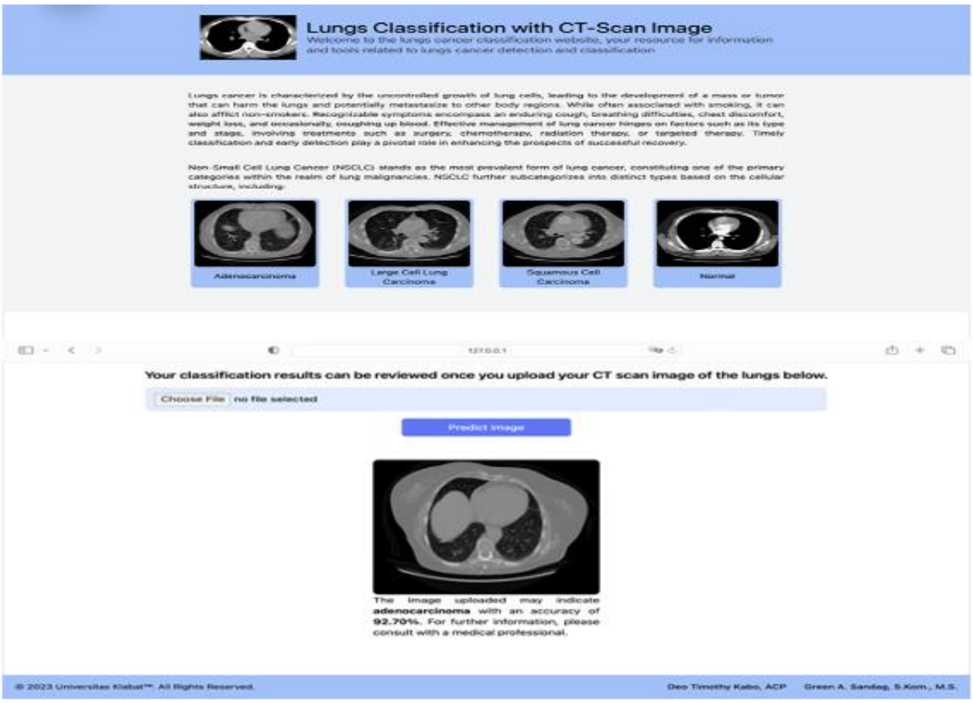

Figure 6. Web System for Lung Cancer Classification Using CT Scan Images

4. CONCLUSION

In conclusion, this study underscores the significant impact of employing Convolutional Neural Networks (CNNs) with a Transfer Learning approach on the classification of lung cancer and normal lung CT-Scan images. The research highlights EfficientNetB3 as the most effective model, achieving an impressive accuracy of 97.78%. Comparative analysis across EfficientNet architectures (B1, B3, B5, and B7) consistently shows EfficientNetB3's superiority in both Scenario 1 and Scenario 2, setting a benchmark for future model selections. The findings confirm that leveraging transfer learning from EfficientNet models enhances the ability to discern lung cancer CT-Scan images, surpassing the performance of traditional ResNet models. Optimizing hyperparameters such as a learning rate (lr) of 0.001, batch sizes of 10 and 20, and employing categorical entropy loss function were crucial contributors to achieving promising outcomes. Ultimately, the EfficientNetB3 transfer learning model emerges as an optimal choice, offering robust potential for developing dependable diagnostic solutions for accurately classifying lung cancer and normal lung CT-Scan images.

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