Deep Learning for Lung Cancer Staging: A Performance Evaluation of Gamma Correction vs Histogram Equalization Using EfficientNetB0

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ABSTRACT

An accurate classification of lung cancer stages is critical in supporting the appropriate clinical decision-making and treatment strategies. This study aimed to analyze and compare the performance of two image preprocessing techniques, namely Gamma Correction and Histogram Equalization, in improving the accuracy of lung cancer stage classification based on CT scan images using the EfficientNetB0 deep learning architecture. Both methods were implemented with identical training configurations, including the use of RMSprop optimizers, last 50-layer fine-tuning, and class weighting to address data imbalances. The experimental results showed that Gamma Correction performed better with a test accuracy of 95.23% and a loss of 0.1303, compared to Histogram Equalization, which achieved an accuracy of 94.45% and a loss of 0.1523. In addition, Gamma Correction showed excellence in macro-mean F1-score metrics, especially in improving detection sensitivity in Stage Ib Adenocarcinoma and Squamous Cell Carcinoma IIIa. The training curve shows a consistent convergence trend and no indication of overfitting, with Gamma Correction demonstrating better validation stability. The results of this study confirm that the selection of preprocessing techniques has a considerable influence on the efficacy of the lung cancer stage classification model. Gamma Correction is shown to be more effective in sharpening important morphological features in CT images, while maintaining a balance between increased contrast and noise control. These findings are an important foundation for the development of accurate and reliable CAD systems for automatic lung cancer staging.

Keywords-lung cancer; classification; EfficientNetB0; gamma correction; histogram equalization

I. INTRODUCTION

Lung cancer is a common disease and one of the leading causes of cancer death worldwide [1]. One of the primary factors contributing to the predominance of lung cancer in mortality statistics is its frequent undiagnosed status until the disease has reached advanced stages [2, 3]. Lung cancer has one of the worst survival rates among all cancers [1]. However, early detection of cancer using Computer Tomography (CT) scans can save hundreds of thousands of lives each year [4, 5]. The problem is that analyzing hundreds of thousands of scans is a huge burden for radiologists, who often experience observer fatigue that can lower their performance. Therefore, there is a need to read, detect, and evaluate CT scans efficiently.

CT scans are one of the main diagnostic tools for lung cancer [6]. The determination of the stage of lung cancer requires a high degree of expertise and can be subjective and prone to human error [7]. Human errors in reading CT scan results include observer fatigue, noise, aberration, etc. [8]. To mitigate this impact and optimize the use of imaging in lung cancer monitoring and assessment, automated tools are needed to facilitate efficient detection and staging of cancer. Therefore, the use of computer vision and automation technologies, such as deep learning-based classification models, can help in more accurate detection and staging of lung cancer. In contemporary research, Convolutional Neural Networks (CNNs) have demonstrated superior efficacy in a multitude of applications within the realm of computer vision [9].

In [10], the VGG19 architecture exhibited commendable efficacy in the classification of COVID-19 cases. Nevertheless, this architectural framework permits substantial enhancements through various modifications or even through the implementation of preprocessing techniques. An experimental condition can lack preprocessing steps. However, in the framework of proposing a comprehensive model, image preprocessing (for instance, through denoising) has proven to be significantly beneficial. In [11], it was shown that employing the Otsu algorithm for background elimination exhibited a comparatively elevated Dice Coefficient (DC). The preprocessing step aimed at eliminating noise (such as background within the labeled area) is imperative for model training across various challenges, irrespective of the architectural design of the network. In [12], it was shown that Histogram Equalization improved the brightness and contrast of images.

Deep learning has emerged as an exceptionally potent instrument for the examination and diagnosis of medical imagery, exhibiting superior efficacy in tasks including the detection of cancerous tissues and tumors [13, 14]. Deep learning is the latest technique that assists medical professionals in diagnosing diseases and helps radiologists find conditions that are difficult to diagnose, such as lung cancer [15]. CNNs have been proven to have outstanding performance in image segmentation, classification, and disease detection [7, 16, 17]. EfficientNet is one of the cutting-edge CNN models and is widely used in image classification [18, 19].

In contrast to most previous studies that only focused on the binary classification of lung cancer (i.e., cancer vs. non-cancer), this study focused on the classification of lung cancer stages based on CT scan images. In addition, this study uniquely compares the effectiveness of two image contrast enhancement techniques, namely Gamma Correction and Histogram Equalization, in the same deep learning workflow using the EfficientNetB0 architecture. The novelty of this research lies in the integration of: (i) Partial fine-tuning on the last 50 layers of the previously trained EfficientNetB0 model, (ii) Performance evaluation of two different image preprocessing schemes, and (iii) Application of class weighting and data augmentation to overcome class imbalances. This combined approach is still rarely explored directly in the context of lung cancer stage classification. This study aims to improve the efficiency and accuracy of diagnosis, allow for improved patient prognosis, and aid in the determination of more appropriate treatment options for patients with lung cancer.

II. LITERATURE REVIEW

Numerous prior investigations have examined the application of deep learning methods, specifically CNNs, in the classification of lung cancer [20]. Table I shows a summary of recent studies.

TABLE I. LITERATURE REVIEW

Ref.	Year	Focus of study	Method/model	Key findings
[18]	2024	Comparison of CNN models for lung abnormality classification	ResNet50 vs. EfficientNet-B0	EfficientNet-B0 outperformed ResNet50
[21]	2024	Enhancement of image contrast using histogram equalization	Optimized Histogram Equalization	Significantly improved global contrast while avoiding over-enhancement and preserving image detail.
[22]	2025	Enhancement of low-light image quality using gamma correction	Localized Gamma Correction	Preserved edge smoothness and natural low-frequency components in the Y channel of the input image.

A systematic analysis of the literature reveals several research gaps:

- Most studies focus on binary (cancer vs. non-cancerous) detection, rather than clinically relevant cancer stage classification.
- There are no direct comparative studies between Gamma Correction and Histogram Equalization to improve the performance of deep learning classification of lung cancer stages.
- Partial fine-tuning on pretrained models has not been optimally explored in this domain, although it offers computational efficiency.

This study fills the gap by:

- Systematically comparing two major preprocessing methods (Gamma Correction vs Histogram Equalization) in the task of stage classification of lung cancer using EfficientNetB0.
- Using a partial fine-tuning strategy (last 50 layers) that is optimal for medical datasets with limited image counts.

This research combines the evaluation of preprocessing techniques, a modern CNN architecture, and an efficient fine-tuning strategy to address real problems in classifying lung cancer stages, which have not been highlighted in the previous literature.

III. MATERIALS AND METHODS

The system proposed in this study classifies lung cancer using the CNN architecture of EfficientNetB0 and the preprocessing techniques of Gamma Correction and Histogram Equalization. Figure 1 presents the implementation stages for lung cancer detection and stage classification.

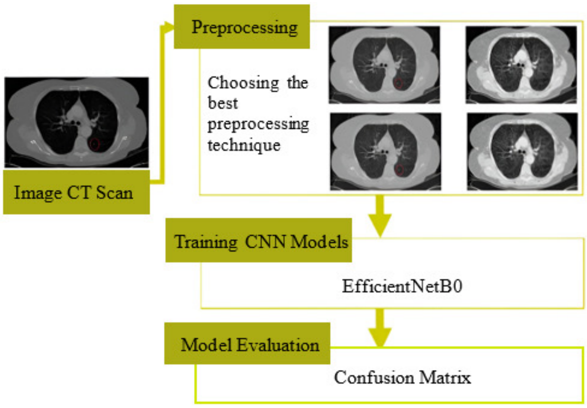

Fig. 1. Architecture of the proposed system

A. Dataset

The initial stage involved collecting CT images from patients who had been diagnosed with lung cancer. These images are the basic data for the preprocessing stage and further analysis. The dataset used in this study is publicly available in [23] and contains images in .png format. To increase the diversity of the data and the generalization capabilities of the model, data augmentation was performed using the Albumentations library, resulting in a total of 5,958 images. The dataset is then classified into four main classes. Table II presents details on the data distribution for each class.

TABLE II. DATASET DISTRIBUTION

	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. Preprocessing Techniques

Based on the initial evaluation, the best preprocessing techniques were selected for use on CT scan image data. This selection was based on how well each technique improves the quality of the image and makes it easier to classify. Each CT image was resized to 224×224 pixels to match the input of the CNN model.

1) Gamma Correction

This technique is used to adjust the intensity of light in an image so that details in areas that are dark or too bright can be enhanced.

2) Histogram Equalization

This technique is used to improve the contrast of the image by flattening the distribution of pixel intensity, so that important features become more prominent.

C. Model Architecture

This study used the EfficientNetB0 model, which is known to have a good balance between accuracy and computational efficiency. Its architecture consists of:

- Multiple convolution layers with ReLU activation.
- Global Average Pooling.
- Batch Normalization and Dropout for regularization.
- Fully Connected Layer with Softmax for 4-class classification (stage I–IIIa).

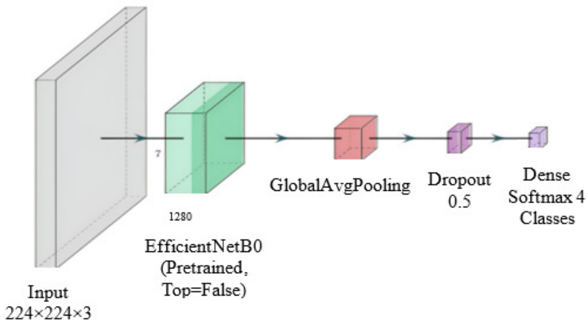

Fig. 2. EfficientNetB0.

D. Optimization Algorithm

The RMSprop optimization algorithm was used. Each model was trained for a maximum of 40 epochs with early stopping and ReduceLROnPlateau to prevent overfitting and optimize learning.

E. Performance Evaluation

Model evaluation was carried out using the Accuracy, Precision, Recall, and F1-score metrics (1-4). In addition, a confusion matrix and the accuracy and loss graphs per epoch were used to assess the stability and convergence of the model.

$$\text{Accuracy} = \frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{TN}+\text{FP}+\text{FN})} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})} \quad (2)$$

$$\text{Recall} = \frac{TP}{(TP+FN)} \quad (3)$$

$$F1-\text{score} = 2 \times \frac{\text{Precision x Recall}}{\text{Precision + Recall}} \quad (4)$$

where TP denotes the number of true positive predictions, TN denotes the number of true negative predictions, FP denotes the number of false positive predictions, and FN denotes the number of false negative predictions.

F. Experimental Setup

The model was trained and evaluated using CT scan images that had been divided into training, validation, and testing data. Some details of the experiment setup are as follows:

- The entire training experiment was conducted using Google Colab Pro with the support of the NVIDIA Tesla T4 GPU.
- The implementation was carried out using Python and TensorFlow.
- The Albumentations library was used for image augmentation, providing flexible and efficient preprocessing capabilities.
- The model was trained using the RMSprop optimizer with a learning rate of 0.0001 and a batch size of 32.
- The maximum number of epochs was set at 40, and the EarlyStopping and ReduceLROnPlateau mechanisms were applied to prevent overfitting and dynamically adjust the pace of learning during the training process. This setting was chosen to ensure an optimal convergence process while maintaining generalization capabilities, especially in the face of unbalanced medical data.

IV. RESULTS AND DISCUSSION

A. Performance of Gamma Correction with EfficientNetB0

Figure 3 shows the results of the evaluation of the EfficientNetB0 classification model with Gamma Correction preprocessing on 1,154 test images of four classes. Table III shows the performance of this approach per class.

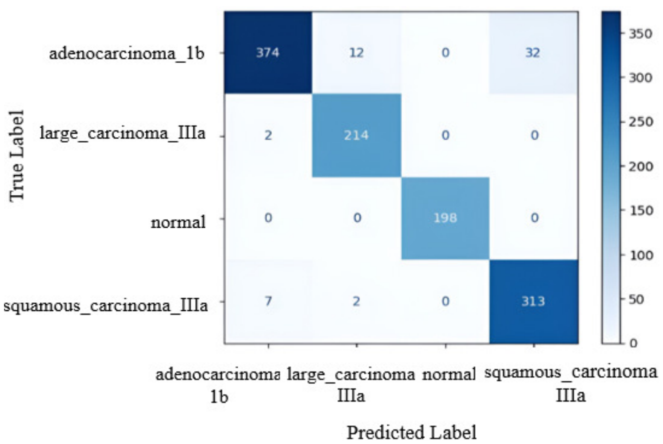

Fig. 3. Confusion matrix for Gamma Correction with EfficientNetB0.

TABLE III. PERFORMANCE OF GAMMA CORRECTION WITH EFFICIENTNETB0

Class	Precision	Recall	F1-score	Support
Adenocarcinoma_1b	0.98	0.89	0.93	418
Large_carcinoma_IIIa	0.94	0.99	0.96	216
Normal	1.00	1.00	1.00	198
Squamous_carcinoma_IIIa	0.91	0.97	0.94	322

The normal class showed perfect precision and recall (1.00), indicating that the model was able to recognize images of healthy lungs very accurately without any misclassification. Large_carcinoma_IIIa was also very well classified (recall = 0.99), indicating that the model had a high sensitivity to this type of cancer. Adenocarcinoma_1b had a slightly lower recall value (0.89), with 32 samples classified as Squamous Carcinoma_IIIa and 12 as Large Carcinoma_IIIa. This suggests a visual ambiguity between the classes that may be due to morphological similarities in some CT scan images. Squamous_carcinoma_IIIa has a high recall (0.97) but slightly lower precision (0.91), as some images from other classes (such as adenocarcinoma) were detected as squamous carcinoma. Figure 4 shows the loss and accuracy curves for the number of epochs during the training process of the EfficientNetB0-based lung cancer stage classification model. The graph on the left shows the decrease in the loss in the training data (Train loss) and validation data (Val loss), while the graph on the right shows the increase in the accuracy of the training and validation data. Stable and well-converged loss and accuracy curves indicate that the model is not only fit for training data, but also has a high generalization ability against new data. The absence of a large gap between train and validation accuracy indicates that the model is not overfitting, making it suitable for application in real-world environments or clinical decision support systems. Training strategies such as ReduceLROnPlateau and EarlyStopping have proven effective in keeping the model's performance stable throughout the training process.

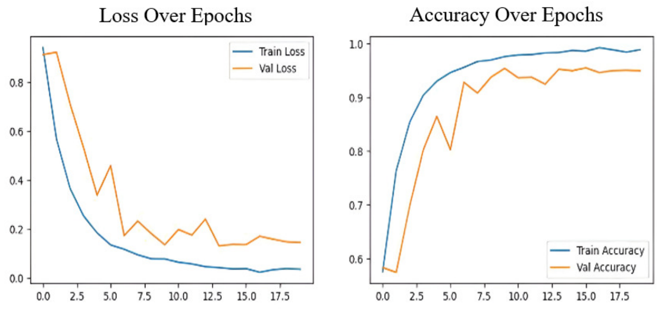

Fig. 4. Accuracy and loss curves.

A validation accuracy greater than 95% also supports the claim that the EfficientNetB0 architecture, when combined with preprocessing techniques such as Gamma Correction, can be used effectively for multi-stage classification of lung cancer based on CT images.

B. Performance of Histogram Equalization with EfficientNetB0

The lung cancer classification model developed using the EfficientNetB0 architecture with Histogram Equalization preprocessing and the RMSprop optimizer showed a test accuracy of 94.45% and a test loss of 0.1523. These results indicate that the model performs very well in recognizing and distinguishing the four main classes of lung cancer in the CT scan dataset. Based on the confusion matrix in Figure 2, Table IV shows the classification performance of this model per class.

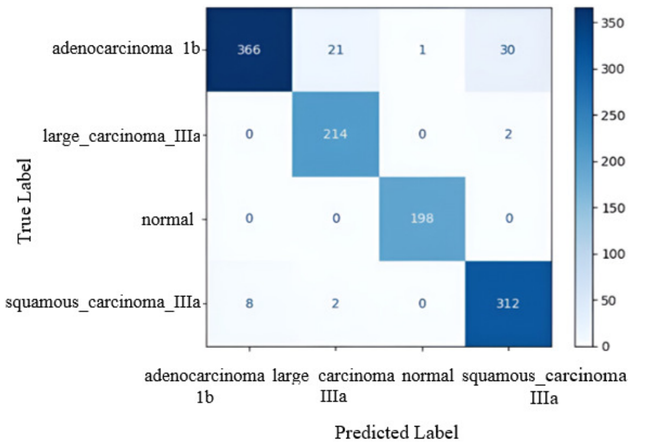

Fig. 5. Confusion matrix for Histogram Equalization with EfficientNetB0.

TABLE IV. PERFORMANCE OF CLASS HISTOGRAM EQUALIZATION WITH EFFICIENTNETB0

Class	Precision	Recall	F1-score	Support
Adenocarcinoma_1b	0.98	0.88	0.92	418
Large_carcinoma_IIIa	0.90	0.99	0.94	216
Normal	0.99	1.00	1.00	198
Squamous_carcinoma_IIIa	0.91	0.97	0.94	322

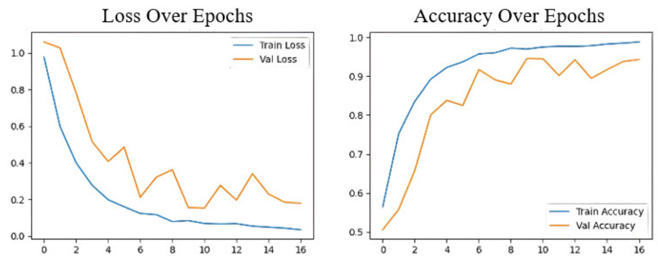

Fig. 6. Accuracy and loss curves.

The Normal class obtained a perfect classification performance with an F1-score of 1.00, demonstrating the model's ability to distinguish between healthy lung conditions and cancer with great accuracy. Large Carcinoma IIIa was also very well detected (recall = 0.99), indicating high sensitivity to this type of cancer. Adenocarcinoma_1b experienced a decrease in recall (0.88), with some cases being misclassified as Squamous Carcinoma or Large Carcinoma. This suggests the possibility of textural similarities in image features between these types of cancer. Squamous_carcinoma_IIIa has a high recall (0.97), but some erroneous predictions of Adenocarcinoma lowered its precision to 0.91. The difference in loss values between the training and validation data remains within a reasonable range, indicating that the model is not significantly overfitting. Although training accuracy was slightly higher than that of validation, the gap was very small and showed that the model was well optimized without losing generalization capabilities. This curve illustrates that the training process with Histogram Equalization, EfficientNetB0, and RMSprop optimizer runs optimally. Strategies such as the use of class weights, EarlyStopping, and ReduceLROnPlateau have proven to be effective in avoiding overfitting and ensuring training efficiency.

C. Comparison of Gamma Correction vs Histogram Equalization Performance

This study presented two image preprocessing approaches to improve the accuracy of EfficientNetB0-based lung cancer stage classification, namely Gamma Correction and Histogram Equalization. Both approaches were tested with the same training architecture and configuration (RMSprop optimizer, 1e-4 initial learning rate, and fine-tuning the last 50 layers), to ensure that the differences in pure results came from preprocessing techniques. As shown in Table V, Gamma Correction slightly outperformed Histogram Equalization in terms of accuracy and loss, suggesting that non-linear contrast adjustment via gamma can retain important features more subtly without magnifying noise, compared to a global histogram equalization. Table VI shows the F1-score metrics per class for the two methods.

TABLE V. COMPARISON OF TEST ACCURACY AND LOSS

Method	Test accuracy	Test loss
Gamma Correction	95.23%	0.1303
Histogram Equalization	94.45%	0.1523

TABLE VI. . EVALUATION METRICS PER CLASS

Class	F1-score (Gamma)	F1-score (HistEq)
Adenocarcinoma_1b	0.93	0.92
Large Cell Carcinoma_IIIa	0.96	0.94
Normal	1.00	1.00
Squamous Carcinoma_IIIa	0.95	0.94

Although the F1-score difference only ranges from 0.01 to 0.02, the consistency of Gamma Correction's performance in maintaining higher sensitivity and precision makes it practically superior, especially in the more visually difficult classes of adenocarcinoma and squamous cell carcinoma. Both methods show a stable and convergent training pattern. In Gamma Correction, the validation loss drops steadily and the accuracy increases consistently, demonstrating efficient learning. In Histogram Equalization, although the trend also shows convergence, there is a slight fluctuation in the validation loss after the 6th epoch, indicating a sensitivity to noise that may be exacerbated by the histogram leveling process.

Based on the experimental results, Gamma Correction consistently shows better performance than Histogram Equalization, determined by the higher classification accuracy (95.23% vs. 94.45%), lower loss values (0.1303 vs. 0.1523), and superior average F1-scores in all cancer stage classes. Gamma Correction also results in a more stable accuracy and loss curve during training, demonstrating better generalization capabilities and lower overfitting rates. This technique can effectively increase local contrast without magnifying the noise. In contrast, Histogram Equalization applies contrast enhancement globally, which can lead to artifacts and excessive contrast. These results show that the selection of preprocessing techniques greatly affects the performance of deep learning models in the classification of medical images, such as CT scans.

V. CONCLUSION AND FUTURE WORK

The results of this study show that Gamma Correction is more effective as a preprocessing method for the classification of lung cancer stages using EfficientNetB0, with higher accuracy and better training stability. However, Histogram Equalization is still a powerful alternative, especially when the initial dataset has low contrast lighting artifacts. The Histogram Equalization technique has been shown to improve the clarity of tissue structure in CT scan images, helping the model extract important features. In the future, it is necessary to compare the proposed method with ResNet and DenseNet, as well as explore explainable AI methods (such as Grad-CAM) to provide a visual interpretation of classification decisions. Advanced studies can evaluate this model in a real clinical setting with real-world data from different hospitals. Finally, the combination of preprocessing with a modern CNN architecture was able to achieve a validation accuracy of more than 94%, which indicates the success of the proposed approach.

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