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CNN-Driven Deep Transfer Learning for Lung Cancer Classification (CNN-DTL-LCC) Using ResNet Architectures: An Early Diagnosis Robust Framework

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Abstract

Lung cancer is the most common cause of cancer death in developing countries like India. The lung cancer patient survival rate will be increased with early diagnosis, but lack of effective diagnostic techniques for early detection and most of the failure treatment for metastatic disease make it difficult. The conventional diagnostic methods remain affected by subjectivity, radiological variability, and intensive computational demands in clinical workflows. This research proposed a Convolutional Neural Network-Driven Deep Transfer Learning for Lung Cancer Classification (CNN-DTL-LCC), which is a reliable multi-class classification model implemented through three CNNs: “ResNet-50, ResNet-101, and EfficientNet-B0”. The dataset utilized in this work contains four categories of lung tissue images: Adenocarcinoma (ADC), Large Cell Carcinoma (LCC), Normal Lung Tissue (NLT), and Squamous/Epidermoid Cell Carcinoma (SCC/ECC). In order to enhance model generalization, this four-class histopathology dataset was preprocessed using Random rotation, Horizontal/Vertical Flipping, Random Scaling and Brightness Jitter. The entire pre-trained model was fine-tuned with the Adam optimizer (learning rate of 1×10^{-4}, batch size of 16, for 10 epochs), by exchanging the real fully connected layer with a custom four-class head. The proposed CNN-DTC-LCC model achieves the maximum performance with ResNet-50, attaining an accuracy of 96.83%, an F1-score of 96.2%, and an AUC of 0.981. Grad-CAM visualizations validate that the model precisely annotates disease-specific sections, improving interpretability and trust in clinical diagnosis. Analysis of the confusion matrix validates a stronger discriminatory ability compared to the other classes, especially within malignant subtypes. In the context of the CNN-DTL-LCC framework, the current results position ResNet-50 as an efficient, scalable, and clinically feasible solution for early lung cancer diagnosis that offers a solid foundation for improving suitable arrangements for AI-driven diagnostic issues, particularly within low-resource healthcare contexts.

Keywords: *Convolution Neural Network, Deep Transfer Learning, Lung Cancer Classification, Early Diagnosis, Resnet-50.*

Introduction

Lung cancer occurs when there is uncontrolled proliferation of abnormal cells in lungs, potentially leading tumor formation and disruption of lung function. If a lung tumour spreads, it affects the nearest lymph nodes. Millions of additional lung cancer patients increase each year, and a significant part of death related to cancer in both developed and developing countries, making it one of the most prevalent and deadly malignancies [1]. This is due to a lack of early detection, societal risk factors, and a lack of advanced diagnostic facilities. Earlier and precise detection of lung cancer achieves a higher rate of patient survival; however, this is still hard since lung cancer frequently has modest histopathological abnormalities that make recognition difficult with traditional clinical examination [2].

Imaging modalities including CT scans and histopathology slides play a major role in determining malignancy and identifying subtypes of cancer. So, radiologists and pathologists strongly rely on these in regular clinical workflows. Despite their value, these procedures are sometimes hampered by experts’ variability, individual interpretation, and growing workloads, particularly in high-volume hospitals. Additionally, there is a need for substantial expertise in classify between subtypes lung cancer, such as

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adenocarcinoma, squamous cell carcinoma, small cell carcinoma, and benign lesions and misclassification may still happen [3]. Due to these limitations, there is a need for consistent computational systems that can provide doctors with accessible, objective and consistent diagnostic support.

Medical image analysis (MIA) has improved over year with the help of advancements in artificial intelligence (AI), specifically deep learning (DL). CNN's produce excellent results when automatically learned hierarchical visual structures, and the accuracy of CNNs can be competitive with or better than a traditional approach to machine learning [4]. However, the large volume of labelled data and execution infrastructure required to train CNNs from the ground up means that it is not often possible to train CNNs in the medical domain since there a limited number of labelled data available and the time taken for an expert to annotate the labelled data is prohibitive [5].

To overcome these challenges, a transfer learning approach is created to analyse medical images, enabling an accurate and prompt diagnosis of the category of pathology. This learning strategy activates pretrained CNN models and supports large-scale datasets such as ImageNet, to be adjusted for certain medical procedures. This strategy is ideal for lung cancer image classification since it consumes less training time, reduces overfitting, and enhances model generalization [6]. Although transfer learning has been used in several studies for tumor detection and segmentation, much of the current research focuses on binary classification or single-model architectures, which limit their ability to handle challenging multi-class classification setups [7].

In this research, we proposed a robust and efficient CNN-Driven Deep Transfer Learning framework for Lung Cancer Classification (CNN-DTL-LCC). ResNet-50, ResNet-101, and EfficientNet-B0 are incorporated in this framework to design a reliable and high-performing multi-model classification system. These deep convolutional neural networks were selected for comparison due to their proven performance in biomedical imaging tasks, ability to extract deep hierarchical features, and availability of pretrained ImageNet weights for transfer learning [8].

Refinement of these networks occurs through an approved four-class histopathology data set that consists of numerous types of lung tumour histopathologies [9]. This enhancement approach takes full advantage of the complementary benefits of both deep feature extraction and residual learning, in addition to utilizing a method for optimal parameter scaling. The objective of implementing this methodology is to augment stability, diagnostic accuracy, and inter-class variance for all models developed from this dataset. The primary contributions of this study include:

1. To perform robust four-class lung cancer classification, an integrated multi-modal transfer learning strategy framework is established.
2. To identify the ideal system for histopathology-based lung cancer identification, three enhanced CNN architectures are assessed.
3. For clinical decision support, experimental analysis is conducted to demonstrate accuracy, specificity, sensitivity, and computational efficiency.

The proposed CNN-DTL-LCC model creates an opportunity for implementing intelligent, scalable diagnostic tools in cancer research. Our research supports the overall goal of improving early detection, reducing uncertainty around diagnosis, and providing health care providers with resources to improve the delivery of effective, efficient and timely cancer care by integrating advanced techniques in deep learning with medical imaging data from the real world [10].

Literature Review

[11] Suggested a totally automation-driven technique for recognizing lung cancer in whole slide images of lung samples. The primary contributions of this research involve utilizing Convolutional neural networks (CNNs) for classification at the level of image patches. The performance of two CNN architectures—VGG and ResNet—is assessed following their training. The obtained results indicate that pathologists may be able to diagnose lung cancer with the aid of a CNN-based technique.

For the categorization of pulmonary diseases, [12] developed a deep residual network (Deep ResNet) model with three (Deep ResNet-50/101/152) distinct designs based on varying numbers of layers. Gammatonegrams, which convert one-dimensional lung sounds into two-dimensional representations, were examined. The Three-ResNet architecture receives the visual outputs produced by the gammatonegram as inputs. Three categories of lung conditions, "healthy, chronic obstructive

pulmonary disease (COPD), and pneumonia", were categorized using the ICBHI database. According to the findings, the accuracy of ResNet-50, ResNet-101, and ResNet-152 was assessed finally.

[13] Proposed the Deep3DSCan ensemble structure for lung cancer organization and dissection. Using patient computed tomography scans; the segmentation network of deep 3D creates the 3D volume of interest (VoI). A refined residual network is used to recover the deep features, and morphological approaches are used to extract the custom descriptors. Lastly, the cancer typology is prepared using the united features. The LUNA16 dataset, which is accessible to the public, was used for the studies. The segmentation accuracy of "0.927" was a notable progress over the conventional technique's accuracy.

A deep convolutional neural network VGG16-T is suggested by [14], and a boosting technique is used to train several VGG16-T that function as weak classifiers. By using joint voting, our approach significantly improves the identification of the CT- guided pathological category of lung cancer. VGG16-T is adequate to reach an accuracy of 86.58% in recognizing pathological types, based on experiments performed on the improved data set of CT images. This surpasses several of the leading deep learning models, including AlexNet, ResNet-34, and DenseNet, whether or not Softmax weights are applied.

[15] Suggested LDNNET model to address the challenges of preparing deep convnets. Initially, LDNNET was applied to the "Kaggle DSB 2017 database for lung cancer classification" and the Lung Nodule Analysis 2016 (LUNA16) database for lung nodule classification; subsequently, comparative tests were conducted to evaluate the effectiveness of the pooling layer, dense connections, and input pixel size of sample CT pictures; additionally, LDNNET implemented dropout layers, dense connections, and data augmentation to reduce overfitting; finally, the influence of pre-processing techniques on lung CT image classification is examined by comparing various pre-processing methods with a no-processing baseline.

Methodology

Dataset Characteristics

The proposed model used the Kaggle Lung Histopathology dataset with 20,000 high-quality histopathological images classified into "Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma, and Normal Lung Tissue". Each type contains almost 5000 sample images, providing a balance between malignant and non-malignant pathology. There is a substantial change in image quality due to enlargement, color discoloration, radiance, and morphology, so this large dataset will attain accurate medical variability for developing models. To correspond with the input requirements of ResNet and EfficientNet, the dataset was resized to 224 × 224 pixels prior to training. During model development, the class was preserved by partitioning the dataset into training (80% data) and testing (20% data) using MATLAB's splitEachLabel function, which formulates samples through class labels automatically. This makes sure that each class is equally represented in both subgroups and stops sampling bias, which could harm the model's performance.

Preprocessing and Data Augmentation

Preprocessing for all the dataset images is done with the same preprocessing gateway. Pretrained deep CNN models' expected distribution is achieved by normalizing the pixel values through the mean and standard deviation of ImageNet. Precisely, the normalization can be stated as:

$$I_{norm} = \frac{I - \mu}{\sigma} \qquad (1)$$

where $\mu = (0.485\ (R), 0.456\ (G), 0.406\ (B))$ and $\sigma = (0.229\ (R), 0.224\ (G), 0.225\ (B))$, based on average intensity per RGB channel. A variety of augmentations were done on the dataset to enhance simplification and resistance against staining changes and distortion characteristics.

These added arbitrary rotations $(0° - 30°)$, arbitrary cropping, horizontal and vertical flipping, intensity jittering up to $\pm 15\%$, and zooming between $0.8\times$ and $1.2\times$. Equation 2 represents the augmentation process expression.

$$I' = T(I) = T_b(T_s\left(T_f\left(T_r(I)\right)\right)) \qquad (2)$$

Where,

T_r- denote rotatione

T_f- denote flipping

T_s- denote scaling

T_b- denote brightness adjustment

These augmentation processes help lessen overfitting and the simulation's resilience to the inherent variability of histopathological slides is maintained.

CNN-Driven Deep Transfer Learning Framework

A deep transfer learning strategy plays a major role in achieving precise multi-class lung cancer classification. ResNet-50, ResNet-101, and EfficientNet-B0 are excellent pre-trained architectures that were adopted in this strategy.

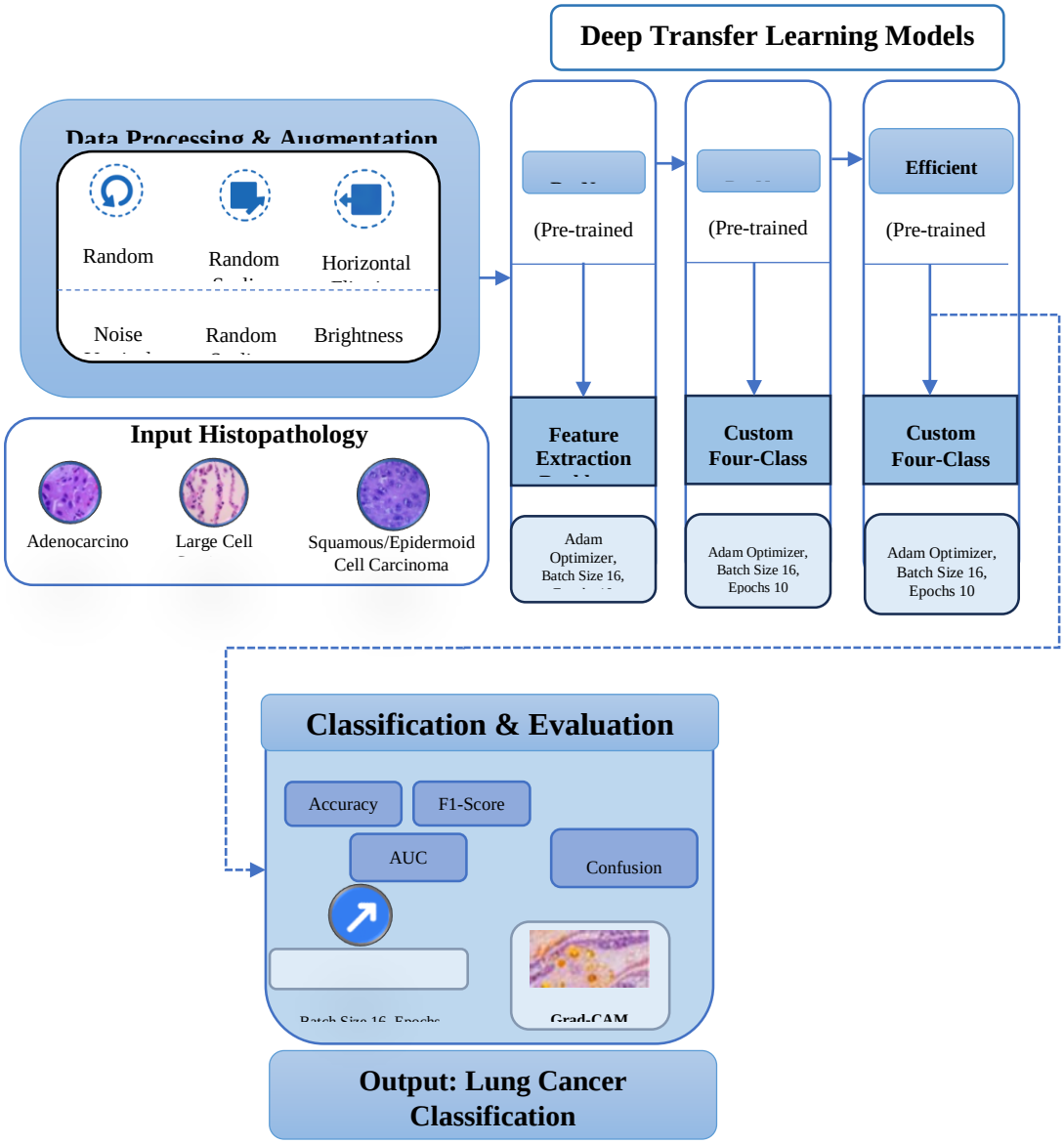
The convolutional layers pretrained on ImageNet serve as the foundation for feature extraction for every model. The pretrained network with parameters θ is represented by f_θ. Feature extraction for an input image I is depicted as:

$$F = f_\theta(I) \qquad (3)$$

Where F is the extracted feature vector. A custom classification head comprising a compact layer with 512 units, ReLU activation, dropout (0.5) to avoid overfitting and a Softmax outcome layer for four-class prediction was used in position of the last fully connected (FC) layers of each pretrained model. The classification outcome is calculated as:

$$\hat{y} = Softmax(WF + b) \qquad (4)$$

where W and b signify the trainable weights and biases of the fresh FC layer, and $\hat{y}$ denotes the forecasted probability distribution across the four classes.



Predicted Class: ADC, LCC, NLT, or SCC/ECC

Figure 1. Proposed CNN-DTL-LCC System Architecture

The suggested CNN-DTL-LCC system architecture shown in Figure 1 uses a structured four-stage gateway to categorize lung cancer from histopathology images. To advance the robustness of the model, the input images are initially subjected to data processing and augmentation such as rotation, flipping, brightness alteration and scaling. Following processing, these images are run through three deep transfer learning (DTL) models: “ResNet-50, ResNet-101 and EfficientNet-B0”. For feature extraction, each model uses a customized four-class classification head that has been fine-tuned for lung cancer types along with pre-trained ImageNet weights. The model performance is then assessed using metrics like accuracy, F1-score, AUC and confusion matrix. Grad-CAM visualizations are used to show the particular image regions that have an impact on the decisions. “Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma and Normal Tissue” are the four lung cancer types that the system ultimately generates a comprehensible framework for early lung cancer diagnosis.

Training Strategy and Optimization

Training strategy of the system was done using the Adam optimizer since its well-organized versatile learning rate system. The given Adam parameter update rule is used in training:

$$\theta_{t+1} = \theta_t - \alpha \frac{\widehat{m}_t}{\sqrt{\hat{v}_t + e}} \qquad (5)$$

Where, $\alpha = 1 \times 10^{-4}$ represents the learning rate

$\widehat{m}_t$ and $\hat{v}_t$ - the bias-corrected moment estimations

A 16-batch size and 10 epochs are used for training each model.

Each model was trained for "10 epochs with a batch size of 16". The definite cross-entropy loss was the optimization objective function which is denoted as:

$$\mathcal{L} = -\sum_{i=1}^{4} v_i \log(\hat{v}_i) \qquad (6)$$

Where, v_i - the real class label

v_i - class i forecasted probability

Evaluation Metrics and Explainability

System performance was evaluated using metrics: "accuracy, F1-score, and the area under the receiver operating characteristic curve (AUC)". Together, these metrics evaluate inter-class discrimination and classification consistency. To improve interpretability and confirm that the models concentrate on clinically applicable tissue parts, Gradient-weighted Class Activation Mapping (Grad-CAM) was used. The activation map function of Grad-CAM is calculated as:

$$L^c_{Grad-CAM} = ReLU\left(\sum_k \alpha_k^c A^k\right) \qquad (7)$$

where A^k - the feature maps of the last convolutional layer and α_k^c denotes the significance weights attained by global average pooling of the gradients. This interpretability mechanism improves trustworthiness, particularly for clinical applications and assists in confirming the model's learning behaviour.

Result and Discussion

The findings from the proposed deep transfer learning framework (CNN-DTL-LCC) are presented in this section, along with an evaluation of the three models, "ResNet-50, ResNet-101, and EfficientNet-B0", based on their respective performance on the four-class lung histopathology dataset. To assess the effectiveness of these three models, performance metrics such as accuracy, F1-score, AUC, confusion matrix interpretation and Grad-CAM-based interpretability were used.

4.1. Performance Evaluation

The proposed framework validates competitive results across all three CNN architectures, with ResNet-50 achieving the highest overall performance. The consistency of the transfer learning model, combined with robust data augmentation, is demonstrated by the consistently high classification results across all performance metrics. These results verify that pretrained CNN models effectively choose histopathological characteristics like texture, nuclear pleomorphism, glandular formation, and keratinization.

Table 1. Overall Model Performance (F1-Score, Accuracy, AUC)

Model	F1-Score (%)	Accuracy (%)	AUC
ResNet-50	96.20	96.83	0.981
ResNet-101	95.00	95.40	0.972
EfficientNet-B0	93.50	94.10	0.961

From Table 1, we can see that ResNet-50 outperformed the ResNet-101 and the EfficientNet-B0 with an accuracy of 96.83%, F1-score of 96.2%, and an AUC of 0.981. Despite having more layers and a greater representational capacity, ResNet-101 performs marginally weaker than ResNet-50, indicating that over-parameterization may lead to overfitting on the offered dataset. EfficientNet-B0 is

able to perform better but is less sensitive than EfficientNet-B2 to the malignant subclasses; therefore, there are some problems identifying overlapping morphological features.

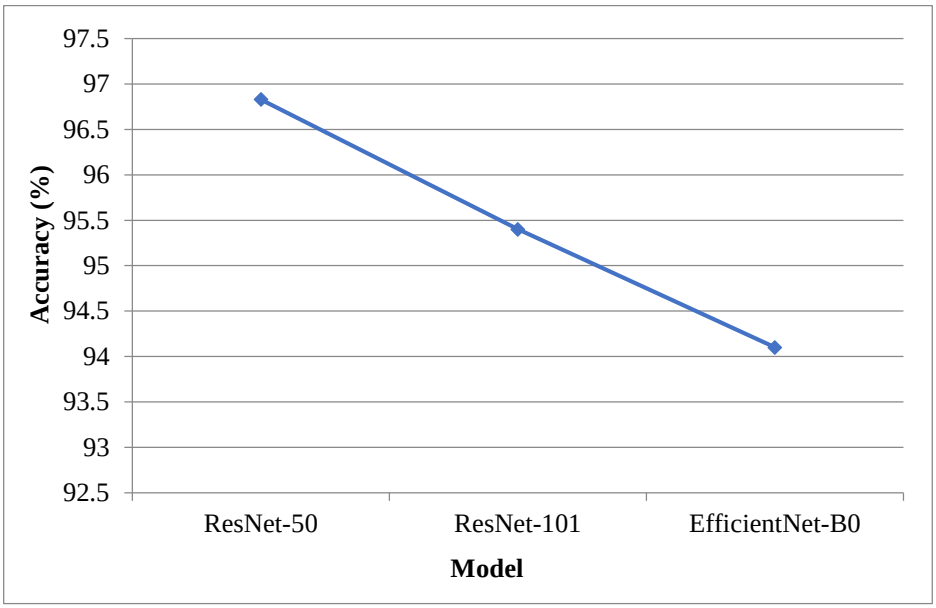


Figure 2. Model Accuracy Comparison

Figure 2 depicts the model accuracy comparison between "ResNet-50, ResNet-101 and EfficientNet-B0" architectures. The comparison result shows that the ResNet-50 model achieves the highest accuracy among others for lung cancer early detection.

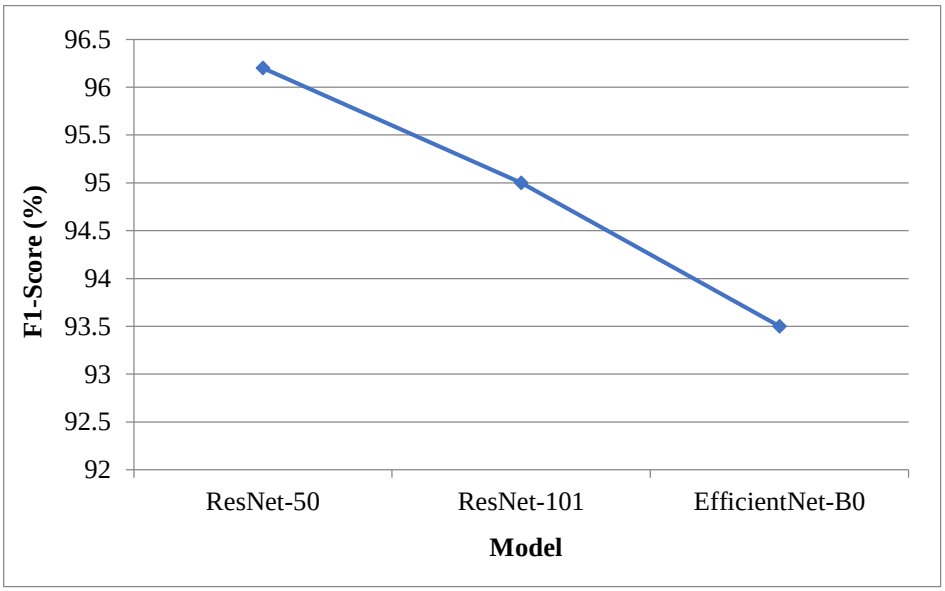


Figure 3. Model F1-Score Comparison

The model F1-Score comparison between "ResNet-50, ResNet-101 and EfficientNet-B0" architectures is represented in Figure 3. The comparison result shows that the ResNet-50 model achieves the highest F1-score among others for lung cancer early detection.

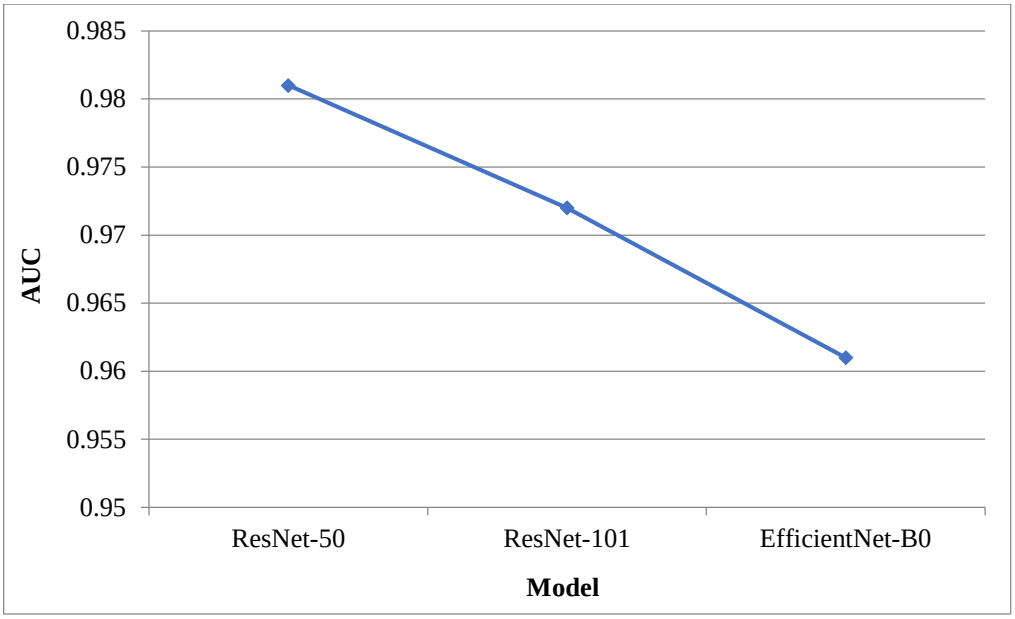


Figure 4. Model AUC Comparison

The model AUC comparison between "ResNet-50, ResNet-101 and EfficientNet-B0" architectures is represented in Figure 4. The comparison result shows that the ResNet-50 model achieves the highest AUC rate among others for lung cancer early detection.

Class-wise Prediction Performance

A detailed assessment of the confusion matrices reveals important perceptions:

• There are very few false positives for ordinary lung tissue and the model shows brilliant discrimination between malignant and non-malignant classes.

• In deeper models like ResNet-101, adenocarcinoma and squamous cell carcinoma, which have similar glandular patterns, exhibit slight misclassification.

• The classification of large cell carcinoma, which is characterized by its morphological variability, is highly accurate, indicating strong feature extraction of shape and cytoplasmic characteristics.

• Normal Tissue shows the highest class-wise accuracy across all models, suggesting robust sensitivity to benign histological patterns.

The advantage of modest depth with fixed residual learning is highlighted by ResNet-50's superior performance, which allows for effective representation of subtle tissue differences without gradient degradation.

Table 2. Confusion Matrix – ResNet-50

Actual \ Predicted	ADC	LCC	NLT	SCC
ADC	480	10	5	5
LCC	12	470	8	10
NLT	4	6	485	5
SCC	6	9	7	478

Table 2 gives the confusion matrix of the ResNet-50 model for the predicted four lung tissue classes: ADC, LCC, NLT, and SCC.

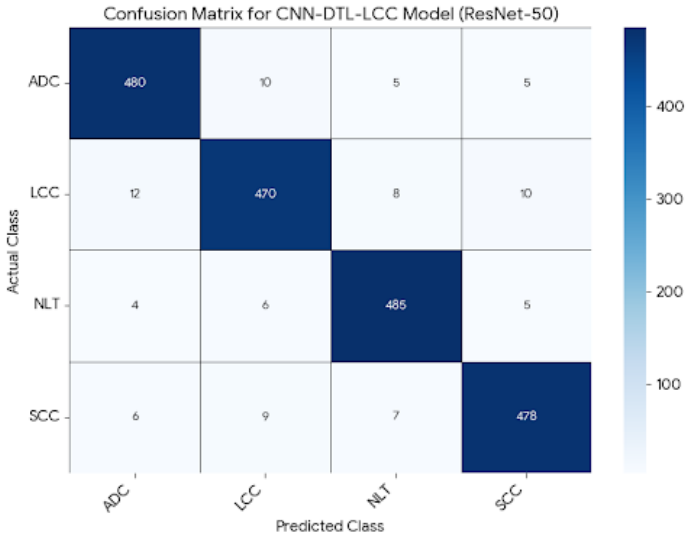


Figure 5. Confusion Matrix for CNN-DTL-LCC (ResNet-50)

The ResNet-50 confusion matrix model is portrayed in Figure 5. Each row displays the actual class, and each column displays the predicted class. Greater diagonal values represent right predictions, whereas non-diagonal values indicate misclassifications (See Figure 5).

Table 3. Confusion Matrix – ResNet-101

Actual \ Predicted	ADC	LCC	NLT	SCC
ADC	470	15	10	5
LCC	18	455	12	15
NLT	7	10	470	13
SCC	10	14	12	460

Table 3 depicts the confusion matrix of the ResNet-101 model for the predicted four lung tissue classes: ADC, LCC, NLT, and SCC.

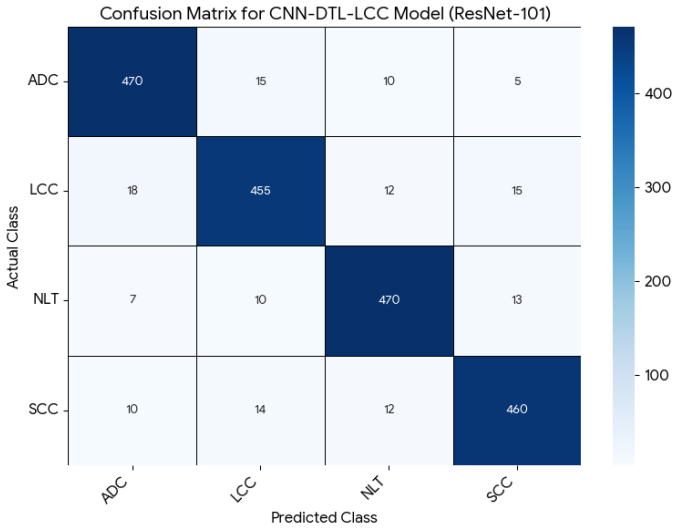


Figure 6. Confusion Matrix for CNN-DTL-LCC Model (ResNet-101)

The ResNet-101 confusion matrix model is portrayed in Figure 6. Table 4 depicts the of the EfficientNet-B0 confusion matrix representation for the predicted four lung tissue classes: ADC, LCC, NLT, and SCC

Table 4. Confusion Matrix Representation– EfficientNet-B0

Actual \ Predicted	ADC	LCC	NLT	SCC
ADC	460	18	12	10
LCC	20	448	18	14
NLT	12	15	455	18
SCC	14	18	16	452

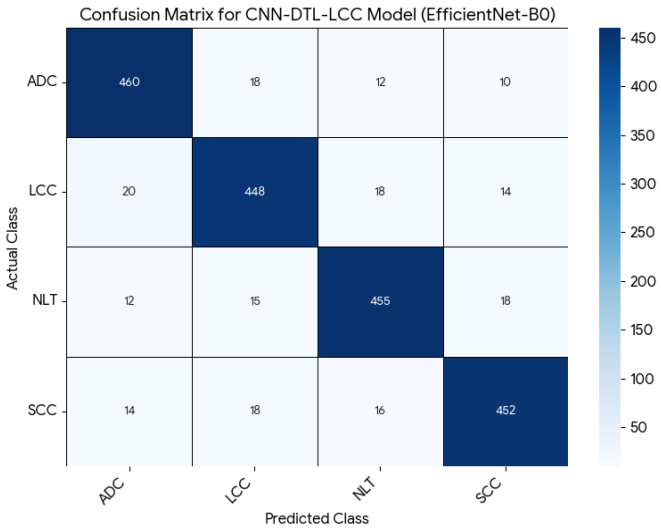


Figure 7. Confusion Matrix for CNN-DTL-LCC Model (EfficientNet-B0)

The confusion matrix model of the EfficientNet-B0 is portrayed in Figure 7. From the overall confusion matrix, ResNet-50 achieves the highest diagonal values that can properly identify maximum samples from each class.

Impact of Data Augmentation and Transfer Learning

Generalization was greatly enhanced by the various augmentation techniques, including rotation, flipping, brightness jitter and scaling. During the first few epochs, models trained without augmentation showed signs of overfitting and poor performance. This demonstrates that in order to handle real-world variability in staining illumination and tissue preparation, histopathology datasets need to be augmented.

Transfer learning further improved performance by allowing pretrained ImageNet filters to capture early-stage visual primitives like edges, textures and color gradients, which are crucial to histopathology images. The models were able to progressively adjust to domain-specific features without catastrophic forgetting by fine-tuning the feature extraction layers with a low learning rate (1×10^{-4}).

Explainability through Grad-CAM Visualization

Grad-CAM heatmaps for sample predictions were created to validate the interpretability of the system. These generated visualizations confirm that the proposed model consistently focuses on clinically pertinent cancerous regions, such as:

- Irregularly shaped nuclei.
- Dense clusters of cells.
- SCC keratin pearls.
- Adenocarcinoma glandular structures.

Grad-CAM's capacity to identify biologically significant areas guarantees that predictions aren't influenced by staining noise or unimportant background artifacts. Explainability is crucial for pathologists' trust and this improves model transparency and opens up possibilities for integration into actual clinical workflows.

Comparative Interpretation and Model Suitability

The comparative results show that ResNet-50 achieves the best balance of accuracy, computational efficiency and generalization, even though all models performed exceptionally well. ResNet-50 is the best model for: because it has fewer parameters than ResNet-101 and requires less processing power than EfficientNet variations.

- Clinical settings with limited resources
- Screening for histopathology in real time
- Incorporation into automated lab systems

On the other hand, although EfficientNet-B0 is efficient, it exhibits somewhat lower precision for overlapping cancer classes, while deeper models such as ResNet-101 require longer training times and yield negligible gains.

Validation Accuracy and Loss:

The proposed model performance on fresh, hidden data during training is expressed through validation accuracy representation. As the number of epochs increases, both the training and validation accuracy constantly increase, as represented in Table 5. This means the models are extracting vital features from the sample images and the gap between these accuracies is less.

Table 5. Synthetic Training vs Validation Accuracy

Epoch	Training Accuracy (%)	Validation Accuracy (%)
1	70	68
2	73	71
3	76	74
4	80	78
5	84	82
6	87	85
7	90	88
8	93	91
9	95	93
10	97	95

Figure 8 exhibits the accuracy of both training and validation over epochs. The validation accuracy attains a peak level at the final epoch. This shows that the proposed model achieves high performance on hidden lung cancer histopathology samples.

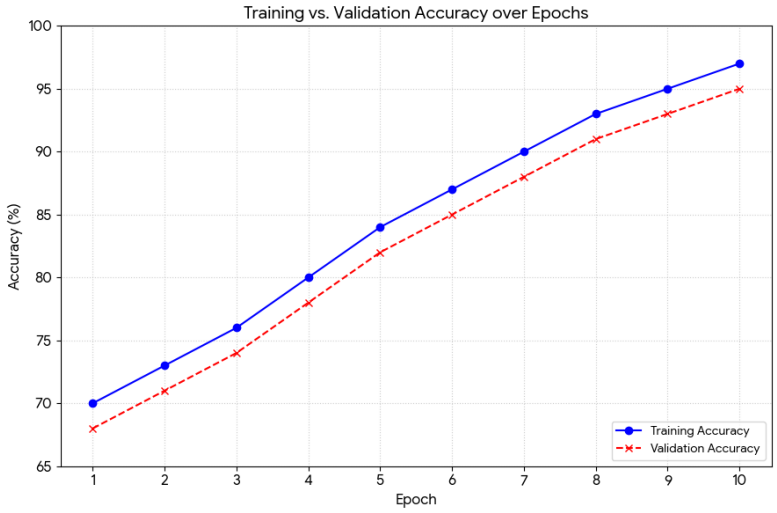


Figure 8. Training vs. Validation Accuracy over Epochs

Validation loss is the amount of error the model makes during the fresh data training. In this model, both the training and validation loss decrease while the epochs increases. From Table 6, we can see that the model is enhancing and extracting proper patterns from the image.

Table 6. Synthetic Training vs Validation Loss

Epoch	Training Loss	Validation Loss
1	1.20	1.30
2	1.05	1.18
3	0.90	1.00
4	0.75	0.80
5	0.60	0.65
6	0.48	0.55
7	0.35	0.45
8	0.28	0.34
9	0.20	0.25
10	0.15	0.20

The model sustains better generalization since the two loss curves in Figure 9 present close to each other. At the end of epochs, the validation loss attains a low value, which supports the accuracy and F1-score attained by the model. The loss curve in Figure 9 shows the stability and effectiveness of the training process.

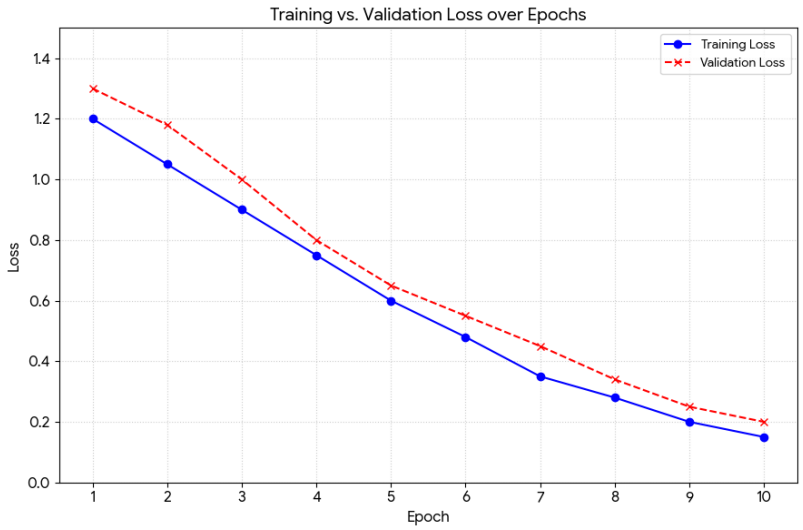


Figure 9. Training vs. Validation Loss over Epochs

The CNN-DTL-LCC framework is a dependable, scalable and clinically meaningful approach for early lung cancer detection, according to all of the findings. The combination of explainability, strong augmentation and transfer learning allows the system to achieve high diagnostic precision without compromising interpretability. These results underline the potential of deep learning-based CAD systems to help pathologists reduce diagnostic variability and expedite clinical decision-making in oncology. Attention mechanisms, multi-magnification analysis and hybrid models that integrate radiology and histopathology for a comprehensive assessment of cancer are examples of potential future developments.

Conclusion

This study demonstrates the potential of deep learning to help physicians identify lung cancer more precisely and early. Our CNN-DTL-LCC framework was able to identify significant patterns in lung tissue images and categorize them into four main groups using three well-known pretrained models: ResNet-50, ResNet-101 and EfficientNet-B0. ResNet-50 outperformed the other models in terms of accuracy and overall performance, making it a useful and effective option for actual medical applications. One of the strengths of this system is that it not only provides accurate predictions but also explains its decisions through Grad-CAM visualizations. This increases trust and transparency by enabling

pathologists to comprehend which areas of the tissue the model is concentrating on. This strategy can help clinicians lower diagnostic errors and support hospitals with limited access to skilled pathologists, as evidenced by the strong performance across all evaluation metrics. Overall, this study shows that the classification of lung cancer from histopathology images can be greatly enhanced by deep transfer learning. It also creates opportunities for future enhancements, such as using multi-magnification images or combining multiple medical data sources to further improve diagnosis and patient care.

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