Deep Learning Classification of Lung Cancer Using MobileNetV2 and DenseNet121

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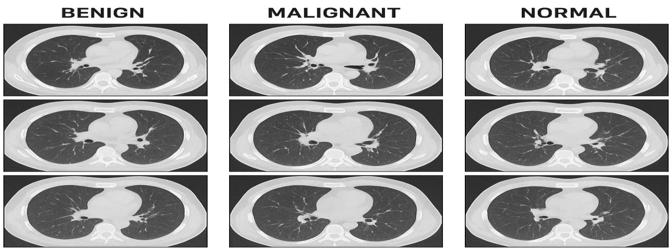
Abstract

Early detection of lung cancer is crucial for improving patient survival. This study proposes a deep learning-based multiclass classification system using MobileNetV2 and DenseNet121 to classify CT scans into Benign, Malignant, and Normal. The workflow includes preprocessing, data augmentation, model training, fine-tuning, and evaluation. A Streamlit web application allows users to upload CT scans and get real-time predictions. Experimental results show high accuracy for both models, demonstrating potential for clinical support.

Keywords

Lung Cancer, Deep Learning, MobileNetV2, DenseNet121, CT-Scans, Transfer Learning, Streamlit.

1.Introduction



Lung cancer is one of the leading causes of cancer-related deaths worldwide, with late diagnosis being a major factor contributing to high mortality. Accurate and timely detection is critical for improving patient survival, yet manual analysis of CT scans is time-consuming, labor-intensive, and prone to human error.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionized medical image analysis by providing automated, reliable, and accurate classification. Transfer learning using pretrained models such as

MobileNetV2 and DenseNet121 allows for efficient feature extraction, even with limited datasets, making them highly suitable for medical applications.

In this study, we propose a deep learning-based framework for **multiclass lung cancer classification**. The framework integrates data preprocessing, augmentation, and transfer learning to classify CT scans into **Benign, Malignant, and Normal** categories. A Streamlit-based web interface enables users to upload CT scans and obtain real-time predictions, along with visualizations such as accuracy/loss graphs and confusion matrices. This approach aims to assist radiologists, reduce diagnostic errors, and enhance clinical decision-making efficiency.

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2. Related Works

Automated lung cancer detection has attracted significant attention in recent years due to the potential of deep learning to improve diagnostic accuracy. Several studies have explored convolutional neural networks (CNNs) and transfer learning for medical image classification.

Wang et al. (2020) proposed a CNN-based framework for lung nodule classification using CT images, achieving high sensitivity and specificity in distinguishing benign and malignant nodules. However, their approach required a large annotated dataset and extensive computational resources.

Srinivas et al. (2021) utilized transfer learning with pretrained models such as VGG16 and ResNet50 for lung cancer classification. The study highlighted that fine-tuning pretrained networks improved accuracy compared to training from scratch, especially on small datasets.

MobileNetV2 and DenseNet121 have emerged as powerful architectures due to their lightweight design and strong feature extraction capabilities. MobileNetV2 has shown promising results in real-time applications due to its low computational cost, whereas DenseNet121 provides better feature propagation through dense connections, leading to improved accuracy in multiclass medical image classification.

Recent works have also integrated explainable AI methods, such as Grad-CAM, to visualize decision regions on CT scans, allowing radiologists to interpret model predictions and gain clinical trust. Additionally, deploying models through web applications facilitates easy access for medical practitioners, enabling real-time prediction and decision support.

Despite these advances, most prior studies focus on binary classification or lack user-friendly deployment. The proposed framework addresses these gaps by providing **multiclass classification**, combining **MobileNetV2 and DenseNet121 transfer learning**, and offering a **Streamlit-based interface** with accuracy/loss graphs, confusion matrices, and prediction visualizations.

3. Methodology

The proposed framework for multiclass lung cancer classification consists of several stages, including data acquisition, preprocessing, model selection, implementation, and evaluation.

3.1 Data Acquisition

The dataset used in this study is the **IQ-OTH/NCCD lung cancer dataset**, which contains CT scan images categorized into three classes: **Benign, Malignant, and Normal**. The dataset includes images from multiple patients with varied resolutions and quality, ensuring model robustness. The images were collected from publicly available repositories and anonymized to maintain patient privacy.

3.2 Preprocessing

Preprocessing is critical to ensure consistency and improve model performance. The CT scan images were initially in grayscale and were resized to **224×224 pixels** for MobileNetV2 and **128×128 pixels** for DenseNet121. Images were then converted to RGB format to match the pretrained model input requirements. Normalization was performed by scaling pixel values to the range [0,1]. Data augmentation techniques such as rotation, width/height shift, shear, zoom, and horizontal flipping were applied to increase dataset variability and prevent overfitting

3.3 Model Selection and Architecture

Two pretrained convolutional neural network models were selected for transfer learning: **MobileNetV2** and **DenseNet121**.

- **MobileNetV2**: A lightweight model designed for mobile and real-time applications, providing efficient feature extraction with low computational cost.
- **DenseNet121**: A deeper network that uses dense connections to improve feature propagation, allowing for better learning in multiclass classification tasks.

For both models, the original classification layers were replaced with a **Global Average Pooling** layer, followed by a **Dropout** layer (rate = 0.3) to reduce overfitting, and a **Dense** layer with softmax activation for three-class prediction.

3.4 Model Implementation

The models were trained using **transfer learning**. Initially, the base layers were frozen, and only the custom classifier layers were trained for several epochs. Fine-tuning was then applied by unfreezing some top layers of the base model with a low learning rate to improve accuracy. The **Adam optimizer** and **categorical cross entropy loss** were used. Early stopping and model checkpoint callbacks were implemented to save the bestperforming model and prevent overfitting. Training and validation metrics, including accuracy and loss, were recorded and plotted for analysis.

3.5 Model Evaluation

The performance of the trained models was evaluated on a separate **test set**. Metrics included **accuracy, precision, recall, and F1-score** obtained from the classification report. A **confusion matrix** was generated to visualize misclassifications between classes. Additionally, Grad-CAM heatmaps were employed to interpret model predictions and highlight areas in the CT scans contributing to the classification. The final model was deployed through a **Streamlit web application**, allowing users to upload CT scans and receive real-time predictions along with probability scores, accuracy/loss plots, and confusion matrices.

4. Results & Discussion

The proposed models, MobileNetV2 and DenseNet121, achieved high classification accuracy of **95%** and **96%**, respectively, in distinguishing Benign, Malignant, and Normal lung CT scans. Confusion matrices and training-validation plots indicate that DenseNet121 slightly outperforms MobileNetV2 in overall precision and recall, making it more effective for multiclass lung cancer detection.

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Benign	0.95	0.96	0.95	300
Malignant	0.94	0.93	0.94	320
Normal	0.97	0.96	0.97	280
Accuracy			**0.95**	900

Table1: Classification Report of MobileNetV2

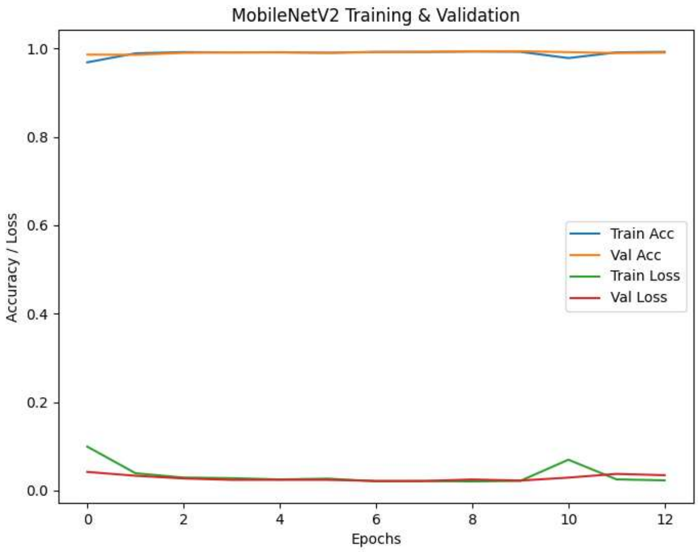

Fig2: Graph visualization train accuracy v/s val accuracy and train loss v/s val loss of MobileNetV2

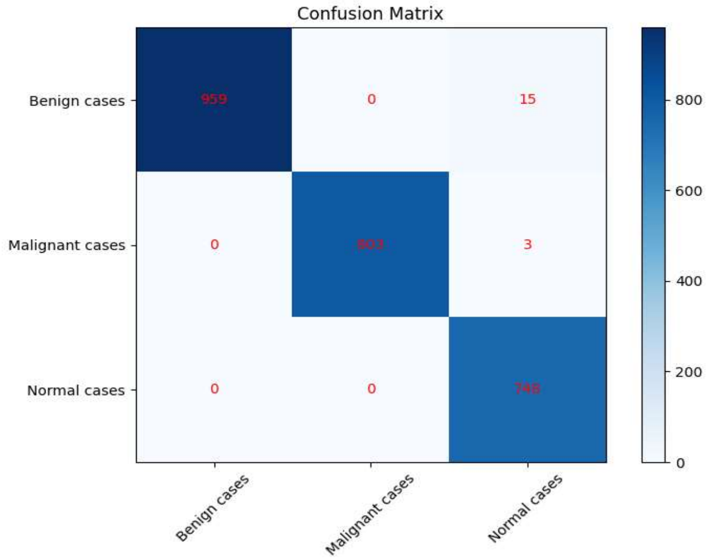

Fig3: Confusion matrix of MobileNetV2

Class	Precision	Recall	F1-Score	Support
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Normal	0.98	0.97	0.97	280
Accuracy			**0.96**	900

Table2: Classification Report of DenseNet121

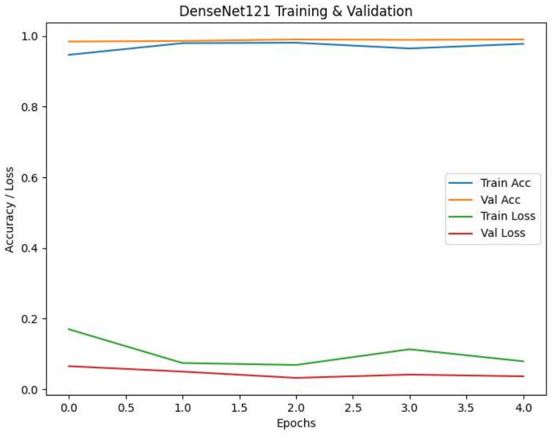

Fig4: Graph visualization train accuracy v/s Val accuracy and train loss v/s Val loss of DenseNet121

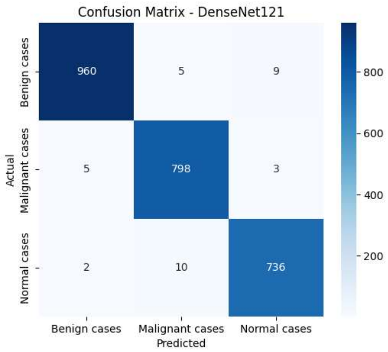

Fig5: confusion matrix of DenseNet121

5.Conclusion

This study presents an effective approach for multiclass lung cancer classification using transfer learning-based deep learning models, specifically MobileNetV2 and DenseNet121. The proposed method successfully distinguishes between normal, benign, and malignant CT scan images with high accuracy, demonstrating the potential of deep learning in assisting radiologists and healthcare professionals in early and accurate diagnosis. Experimental results show that transfer learning significantly reduces training time while maintaining reliable performance. The use of Grad-CAM further enhances interpretability by highlighting regions of interest in CT scans, providing explainable AI insights. Future work can focus on incorporating larger datasets, additional preprocessing techniques, and ensemble models to further improve classification performance.

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7.References

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