Detection of Lung Cancer using CT Scan Images

Abstract Lung cancer is one of the most prevalent and fatal cancers worldwide, necessitating fast, accurate, and reliable diagnostic tools to enhance early detection and treatment outcomes. This study explores a deep learning-based approach for classifying lung cancer cases using CT scan images. By leveraging the EfficientNet-B0 architecture and transfer learning techniques, our proposed model demonstrates impressive accuracy when fine-tuned on lung cancer datasets. The study employs data augmentation to improve model generalization and prevent overfitting. The experimental results show a classification accuracy of 89% for the VGG16 model and 87% for EfficientNet-B0. These findings highlight the potential of AI-assisted diagnostics in supporting healthcare professionals.

1. Background and Motivation

Lung cancer remains a leading cause of cancer-related mortality worldwide, accounting for a significant burden on global healthcare systems. Early detection is crucial for improving survival rates, but the lack of accessible diagnostic tools in resource-constrained settings remains a challenge. CT scan images provide a reliable method for detecting lung abnormalities, but their manual interpretation is time-consuming and prone to error.

Recent advancements in artificial intelligence (AI) and deep learning have transformed medical diagnostics by enabling automated, data-driven solutions. Convolutional Neural Networks (CNNs) have shown promise in analyzing complex patterns in medical images, making them an effective tool for lung cancer detection. This study aims to harness these technologies to improve early detection of lung cancer.

1.1 Background Lung cancer is categorized into benign, malignant, and normal cases. Early diagnosis often involves analyzing CT scan images to identify abnormalities. However, the complexity of medical imaging necessitates robust tools to differentiate between cases accurately. Deep learning, specifically CNNs, offers significant potential for improving diagnostic precision by learning intricate features from medical images.

1.2 Motivation Traditional diagnostic approaches rely heavily on expert interpretation, which can delay detection and treatment. With the increasing availability of CT scan datasets, leveraging deep learning models can automate the process, providing faster and more accurate results. This research focuses on developing a scalable, efficient model for lung cancer classification using real-world data, addressing the need for reliable diagnostics in underserved regions.

2. Aim and Research Questions

2.1 Aim The study aims to develop a deep learning-based framework for classifying lung cancer cases from CT scan images. By employing EfficientNet-B0 and VGG16 architectures, the research seeks to enhance the classification of benign, malignant, and normal cases, overcoming limitations posed by scarce labeled data and improving robustness and accuracy.

2.2 Research Questions

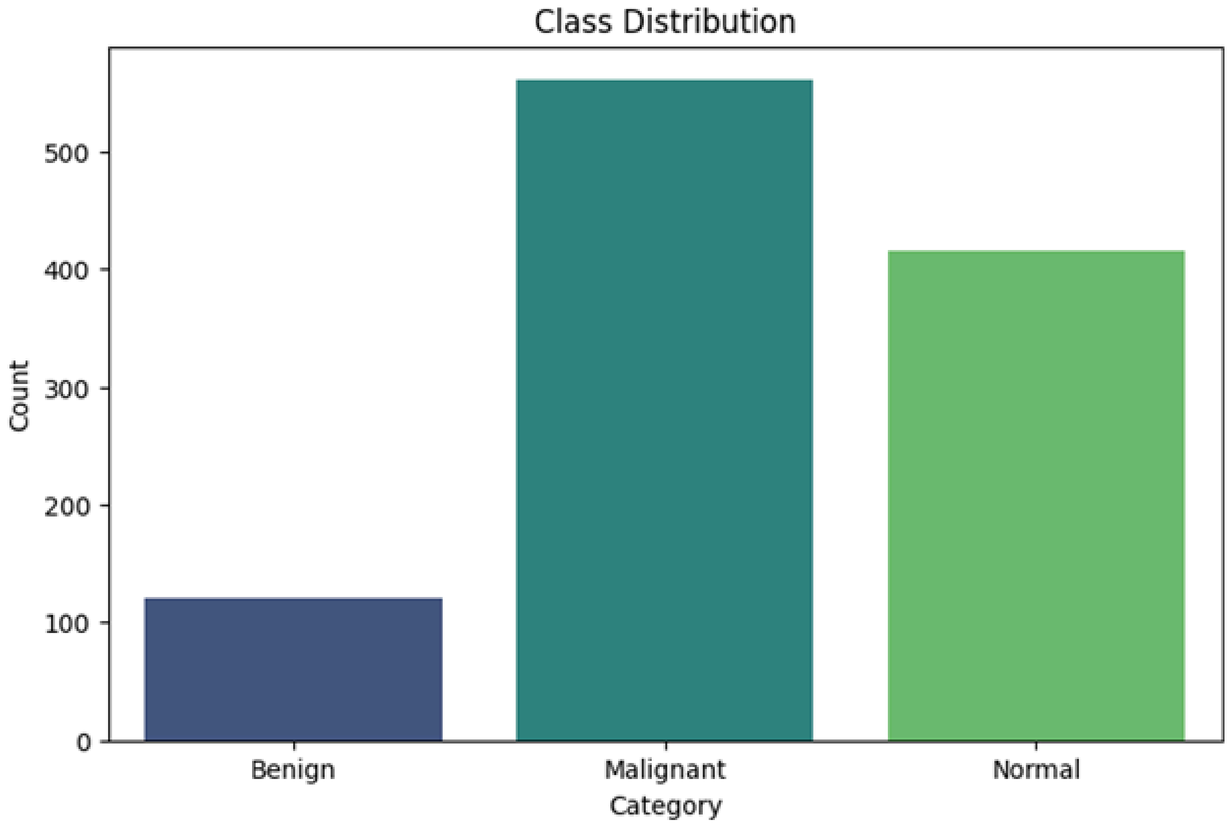
1. Can transfer learning-based deep learning models effectively detect lung cancer from CT scan images?

2. How can the accuracy of lung cancer classification models be improved using data augmentation and clinical metadata?

3. Methodology

3.1 Dataset The dataset consists of 1,097 CT scan images, categorized as benign (120 cases), malignant (561 cases), and normal (416 cases). Images were sourced from publicly available repositories. Preprocessing steps include:

- Resizing images to 224x224 pixels.
- Normalizing pixel values to the range [0, 1].
- Splitting the dataset into training (70%), validation (20%), and test (10%) subsets.
- Applying data augmentation techniques like rotation, zooming, and flipping to improve generalization.



3.2 Machine Learning Models

3.2.1 EfficientNet-B0 EfficientNet-B0 is a scalable CNN architecture optimized for computational efficiency and accuracy. Pre-trained on ImageNet, the model was fine-tuned for lung cancer classification. Key components include:

- GlobalAveragePooling2D for dimensionality reduction.
- Fully connected layers with 256 neurons and Dropout for regularization.
- Softmax activation for multi-class classification.

3.2.2 VGG16 VGG16 is a widely used CNN architecture known for its simplicity and effectiveness. It uses:

- 16 weight layers with 3x3 convolutional filters.
- Batch normalization and Dropout for improved stability.
- Fully connected layers tailored for lung cancer classification.

4. Findings and Results

4.1 Findings

- **VGG16 Model:** Achieved an accuracy of 89%, with precision, recall, and F1-score values above 88%.
- **EfficientNet-B0 Model:** Achieved an accuracy of 87%, demonstrating a balance between computational efficiency and classification performance.

4.2 Results

- True Positives (Malignant Cases): Both models accurately identified malignant cases, with EfficientNet-B0 showing fewer false positives.
- True Negatives (Normal Cases): Both models demonstrated reliable detection of normal cases, ensuring specificity.
- Misclassifications: VGG16 outperformed EfficientNet-B0 in minimizing false negatives, critical for reducing missed diagnoses.

VGG16 Classification Report:

	precision	recall	f1-score	support
Benign cases	0.64	0.54	0.58	13
Malignant cases	0.97	1.00	0.98	57
Normal cases	0.86	0.86	0.86	42
accuracy			0.89	112
macro avg	0.82	0.80	0.81	112
weighted avg	0.89	0.89	0.89	112

Efficient Net B0 classification report:

	precision	recall	f1-score	support
Benign cases	0.25	0.15	0.19	26
Malignant cases	0.99	0.97	0.98	117
Normal cases	0.75	0.87	0.81	77
accuracy			0.84	220
macro avg	0.66	0.67	0.66	220
weighted avg	0.82	0.84	0.83	220

5. Result Validation and Explainability The limited dataset size and reliance on pre-trained ImageNet weights constrained model performance. Future efforts should focus on:

1. Curating diverse datasets covering various demographics.
2. Pre-training on medical imaging-specific datasets for better feature extraction.

3. Integrating clinical metadata for multi-modal learning.

6. Conclusion This research highlights the potential of deep learning in lung cancer detection. The EfficientNet-B0 and VGG16 models achieved high accuracy, demonstrating their viability for clinical applications. These findings support the integration of AI-driven diagnostics in telemedicine and resource-limited settings, enabling early detection and improved healthcare outcomes.

7. Future Work Future studies should:

- Explore hybrid architectures combining CNNs with RNNs for temporal analysis of patient data.
- Develop multi-modal systems incorporating clinical history and imaging data.
- Address the "black-box" nature of deep learning through explainable AI techniques.
- Build scalable systems for real-time diagnostics and personalized treatment planning.

References

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