AI-Assisted Radiology: Detecting Lung Cancer in CT-Scans.

DOMAIN: Healthcare AI

1. INTRODUCTION

Lung cancer is one of the leading causes of cancer-related deaths worldwide. Early detection through medical imaging techniques like CT scans significantly improves patient outcomes. However, manual diagnosis by radiologists is time-consuming and prone to human error. This project leverages Artificial Intelligence (AI) and Deep Learning techniques to assist radiologists in detecting lung cancer from CT scan images with high accuracy.

1.1 Problem statement

Traditional lung cancer detection methods rely on manual examination of CT scans, which is subjective and susceptible to inconsistencies. The increasing volume of medical imaging data necessitates automated and reliable solutions to improve diagnosis accuracy and efficiency. This project aims to develop an AI-assisted radiology system that utilizes deep learning for detecting lung cancer from CT scan images.

1.2 Objective

- To build an AI-based system capable of detecting lung cancer in CT scans using deep learning models.
- To utilize the **Multi Cancer Dataset - 8 Types of Cancer Images**, focusing on lung cancer detection.
- To implement data augmentation techniques to enhance model performance and generalization.
- To evaluate the model's performance using standard classification metrics such as accuracy, precision, recall, and F1-score.
- To provide a robust and efficient tool that can assist radiologists in making accurate diagnoses.

2. DATASET DETAILS

The dataset used for this project is the **Multi-Cancer Dataset - 8 Types of Cancer Images**, which contains medical images of eight different cancer types, including lung cancer. It is a comprehensive dataset compiled from various sources, providing high-quality images for machine learning applications in medical image classification. For this project, the focus is on **Lung and Colon Cancer** images, specifically the lung cancer-related subclasses. The dataset includes labeled CT scan images of both cancerous and non-cancerous lung tissues, which are essential for training a deep learning model to distinguish between healthy and diseased cases.

2.1 Data Source

The dataset is compiled from publicly available medical imaging datasets, primarily sourced from **Kaggle** (contributed by Biplob Dey and others). It includes images of various histopathological and radiological scans labeled for different cancer types.

2.2 Data Characteristics

The dataset consists of **15,000 images** categorized into different classes and subclasses. For lung cancer detection, the following subclasses were used:

Path	Subclass	Description
/lung_aca	Lung Adenocarcinoma	Cancerous cells of the lung
/lung_bnt	Lung Benign Tissue	Healthy lung tissues
/lung_scc	Lung Squamous Cell Carcinoma	Aggressive form of lung cancer

Each image in the dataset is labeled according to these subclasses, providing a structured dataset for supervised learning.

2.3 Preprocessing

To ensure high-quality input for the deep learning model, preprocessing techniques were applied, including:

- Image Resizing: All images were resized to 224x224 pixels to maintain uniformity.
- Data Augmentation: Various augmentation techniques were applied to increase dataset diversity and improve model generalization. The augmentation parameters used are:
    - Rotation: ±10 degrees
    - Width & Height Shift: ±10%
    - Shear & Zoom: 10% variation
    - Horizontal Flip: Random flipping
    - Brightness Adjustment: Range [0.2, 1.2]
- Renaming: All files were systematically renamed in the format <subclass>_<serial_number>.jpg to maintain consistency.

3. MODEL ARCHITECTURE

The model used for lung cancer detection in CT scans is based on the EfficientNet architecture, a state-of-the-art deep learning model optimized for image classification tasks. EfficientNet utilizes compound scaling to balance depth, width, and resolution, making it highly efficient in terms of computational resources while achieving superior accuracy.

3.1 Model Selection

Selecting the right model for lung cancer detection in CT scans is crucial to ensure high accuracy, computational efficiency, and generalization to unseen data. Several deep learning architectures were evaluated based on performance metrics, computational requirements, and suitability for medical image classification.

EfficientNetB3 was selected due to:

- **Superior Accuracy**: Achieves higher accuracy with fewer parameters compared to ResNet and VGG.
- **Lower Computational Cost**: Uses compound scaling, making it more efficient for large-scale image processing.
- **Pre-trained Weights**: Utilizes transfer learning from ImageNet, accelerating training and improving generalization.
- **Scalability**: EfficientNet can be scaled up (B4, B5, etc.) if higher accuracy is needed without drastically increasing computational demand.

3.2 Layers

Stage	Operator	Resolution	#Channels	#Layers
1	Conv3x3	224 × 224	32	1
2	MBConv1, k3x3	112 × 112	16	1
3	MBConv6, k3x3	112 × 112	24	2
4	MBConv6, k5x5	56 × 56	40	2
5	MBConv6, k3x3	28 × 28	80	3
6	MBConv6, k5x5	14 × 14	112	3
7	MBConv6, k5x5	14 × 14	192	4
8	MBConv6, k3x3	7 × 7	320	1
9	Conv1x1 & Pooling & FC	7 × 7	1280	1

4. IMPLEMENTATION

4.1 Tools & Technologies

- **Programming Language:** Python
- **Frameworks:** TensorFlow, Keras
- **Libraries:** NumPy, Pandas, OpenCV, Matplotlib, Seaborn
- **Development Environment**: Jupyter Notebook (Kaggle Notebook)

4.2 Training Configurations

- **Optimizer:** Adam
- **Loss Function:** Categorical Cross-Entropy
- **Metrics:** Accuracy, Precision, Recall
- **Epochs:** 30
- **Batch Size:** 32

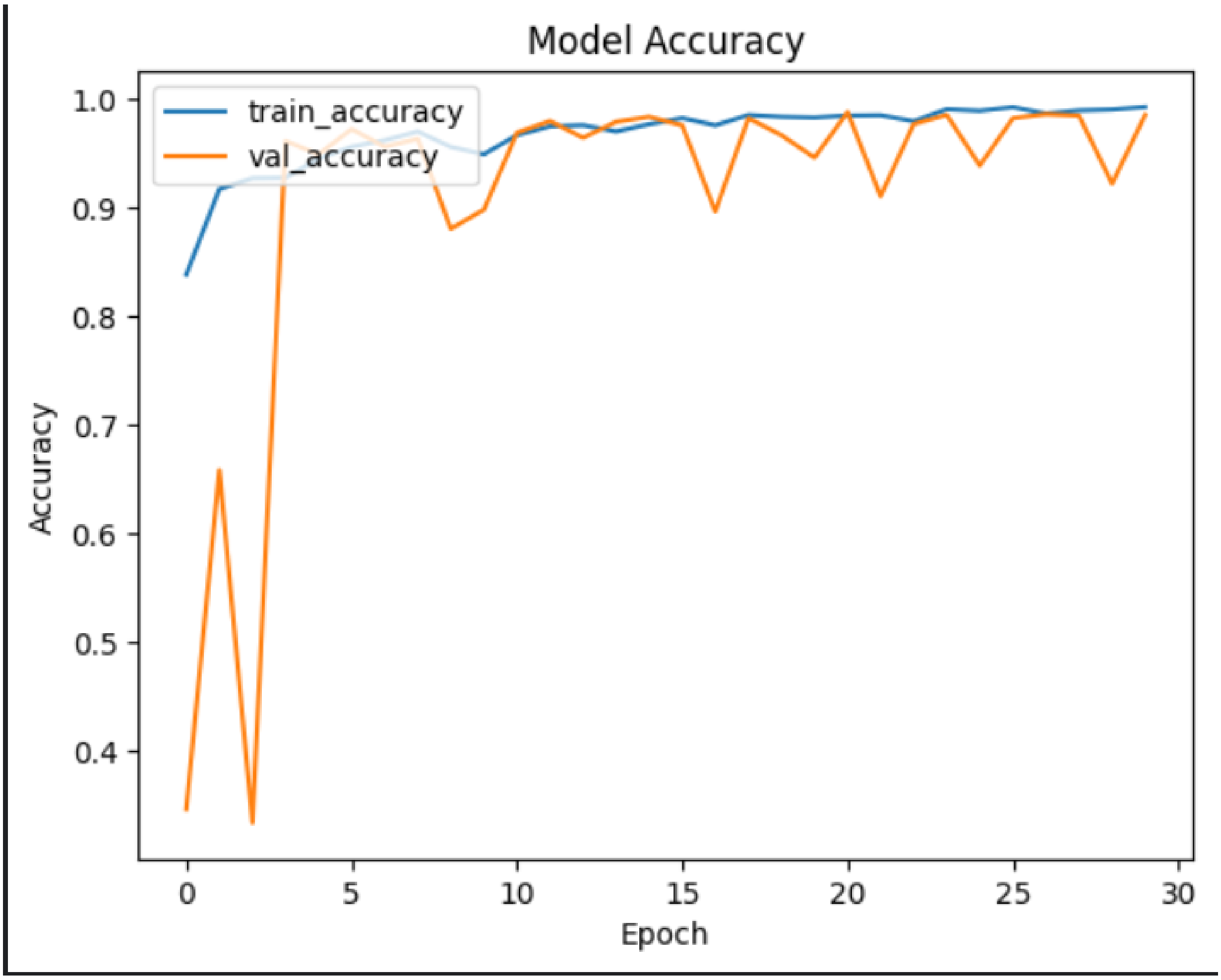
5. MODEL EVALUATION

5.1 Performance Metrics

- **Accuracy**: Measures the overall correctness of the model.
- **Precision & Recall:** Evaluates the ability to correctly classify cancerous and non-cancerous tissues.
- **Confusion Matrix:** Provides a breakdown of classification results.

5.2 Results

- **Test Accuracy:** 98.8%
- **Precision:** 92.3%
- **Recall:** 96.1%



6. DEPLOYMENT STRATEGY

6.1 Deployment Pipeline

- **Model Export:** Convert the trained model to TensorFlow for lightweight deployment.
- **Model Trained:** Model trained in Kaggle notebook for faster deployment.

6.2 Real-time Applications

- Integration with medical imaging software for seamless workflow.
- Automated analysis of CT scans and instant reporting to radiologists.
- Cloud-based implementation for remote diagnostics and accessibility in low-resource settings.

7. CHALLENGES AND FUTURE WORK

7.1 Challenges

- **Class imbalance:** Some lung cancer classes had fewer images, affecting model learning.
- **Variability in image quality**: Different sources led to inconsistencies in brightness and contrast.
- **Computational constraints:** Training deep learning models on large datasets required significant GPU resources.

7.2 Future Enhancement

- **Self-learning AI:** Implementing continual learning for improved adaptability.
- **GAN-based Data Augmentation:** Using Generative Adversarial Networks (GANs) to synthesize rare cancer images for a balanced dataset.
- **Explainable AI (XAI):** Enhancing model interpretability for better clinical adoption.

7.3 Conclusion

This project successfully implemented an AI-assisted radiology system for lung cancer detection using EfficientNetB3. The deep learning model demonstrated high accuracy in classifying cancerous and non-cancerous lung tissues, significantly improving the diagnostic process. Future work will focus on enhancing robustness, real-time deployment, and explainability to make the system more practical for medical use.