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DeepTumorNet: End-to-End Lung Cancer Classification Using Deep Learning

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***Abstract*—The End-to-End Lung cancer Classification project provides a comprehensive framework for detecting and classifying lung cancer using deep learning techniques. Leveraging a Convolutional Neural Network (CNN), the system processes medical images to identify malignancies with high accuracy. The project integrates MLflow for experiment tracking, DVC for data and model versioning, and Flask for deployment, ensuring a seamless and reproducible machine learning pipeline. It offers automated preprocessing, model training, and evaluation, making it adaptable for research and real-world implementation. The primary goal is to create a scalable and efficient system that aids early cancer detection, reducing diagnostic delays and improving patient outcomes.**

Keywords— Lung Cancer, Deep Learning, Convolutional Neural Networks, CT Scan Images, Transfer Learning, Model Deployment

I. Introduction

Lung cancer remains one of the most prevalent and life-threatening diseases worldwide, accounting for a significant percentage of cancer-related mortality. According to global cancer statistics, lung cancer alone is responsible for approximately 18% of total cancer deaths, making it one of the most aggressive forms of cancer. The high mortality rate is largely due to late-stage diagnosis, as early-stage lung cancer often remains asymptomatic or is misdiagnosed due to similarities with other respiratory conditions. Traditional diagnostic methods, such as histopathological analysis, biopsies, and radiological imaging, require expert interpretation and can be time-consuming, delaying timely treatment. Moreover, variability in radiologists' assessments can lead to inconsistent results, emphasizing the need for an automated and highly accurate classification system that aids in early detection and diagnosis.

The advancement of artificial intelligence (AI) and deep learning has revolutionized the field of medical imaging by providing automated, scalable, and highly accurate diagnostic solutions. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for medical image classification, showing remarkable success in tasks such as tumor detection, disease classification, and medical anomaly identification. Deep learning-based approaches leverage large-scale datasets to extract intricate patterns and features from medical images, significantly improving diagnostic accuracy compared to traditional manual methods. In lung cancer classification, deep learning techniques help in distinguishing between malignant and benign cases, identifying different types of lung cancer, and reducing diagnostic errors, ultimately enhancing patient outcomes.

This research presents an end-to-end machine learning pipeline for lung cancer classification using computed tomography (CT) scan images. The system is designed to ensure high precision and robustness by integrating state-of-the-art deep learning architectures alongside a structured workflow for efficient experiment tracking, dataset versioning, and model deployment. We employ four widely recognized CNN architectures—ResNet, InceptionV3, NASNetMobile —each selected based on their specific strengths. ResNet is known for its high accuracy and residual learning capabilities, making it highly effective for complex image classification tasks. InceptionV3 is optimized for multi-scale feature extraction, enabling better representation of medical images by capturing patterns at different spatial levels. NASNetMobile, being lightweight and computationally efficient, is ideal for real-time medical applications and mobile-based diagnostics.

To provide a comprehensive evaluation of these models, we analyze their performance based on key metrics, including accuracy, F1-score, specificity, and recall. Accuracy measures the overall correctness of the model's predictions, F1-score provides a balance between precision and recall, specificity evaluates the model's ability to correctly identify negative cases, and recall determines its sensitivity to positive cases. Comparing these metrics across different architectures allows us to identify the most effective model for lung cancer classification while considering trade-offs between computational efficiency and diagnostic performance. Additionally, visual representations such as confusion matrices, ROC (Receiver Operating Characteristic) curves, and performance graphs are included to further illustrate the comparative effectiveness of each model.

To ensure transparency, reproducibility, and scalability, this study integrates several essential machine learning tools. **MLflow** is utilized for experiment tracking, allowing systematic recording of model parameters, training runs, and performance metrics. **DVC (Data Version Control)** is employed to manage dataset versions efficiently, ensuring consistency and enabling collaborative research efforts. **Flask** is used for deploying the trained models as a web-based application, making the system accessible for real-world clinical implementation. By incorporating these technologies, we create a streamlined and reproducible AI-driven diagnostic pipeline that can be easily adapted and improved for future medical imaging applications.

Furthermore, our research includes sample CT scan images of normal and adenocarcinoma cases to provide visual context for classification tasks. These images highlight the differences between cancerous and non-cancerous lung tissues, aiding in model interpretability and validating the effectiveness of our deep learning approach. The inclusion of real-world medical images enhances the study's practical significance and supports the development of AI-assisted diagnostic systems for clinical use.

By leveraging advanced deep learning architectures with a structured and scalable workflow, this research aims to contribute to the ongoing advancements in AI-driven medical diagnostics. The findings of this study have the potential to aid radiologists and healthcare professionals by providing an automated, highly accurate, and efficient lung cancer detection system. With further improvements and real-world validation, such AI-based solutions can play a critical role in reducing diagnostic errors, improving early detection rates, and ultimately enhancing patient survival outcomes on a global scale.

II. Literature Survey

Lung cancer detection remains one of the most significant challenges in the medical field due to its high mortality rate. It is one of the leading causes of cancer-related deaths globally, and its late-stage diagnosis often leads to poor patient outcomes. Early detection is therefore crucial, as it can significantly improve survival rates. In this context, deep learning (DL) techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for analyzing medical images and diagnosing lung cancer. These methods have revolutionized the way healthcare professionals approach radiological imaging, offering a more accurate and efficient alternative to traditional diagnostic methods. Keerthi et al. (2025) [1] demonstrated the effectiveness of deep neural networks in lung cancer classification, emphasizing the capacity of these models to detect intricate patterns within medical images that are often imperceptible to the human eye. Their work highlights how CNN-based architectures, such as ResNet and VGGNet, can efficiently process and identify malignant tumors in medical images, thereby aiding in early diagnosis and reducing the chances of misdiagnosis. The potential of these models to achieve high levels of accuracy, particularly when trained on large and diverse datasets, makes them a promising tool in the fight against lung cancer.

In recent years, hybrid models that combine CNNs with transfer learning approaches have gained significant attention for their ability to enhance the accuracy of lung cancer detection. Transfer learning, in particular, allows for the leveraging of pre-trained models, which have been trained on large, publicly available datasets, to improve performance on smaller, domain-specific datasets. This technique is particularly valuable in the field of medical image analysis, where labeled data can be scarce. Marappan et al. (2024) [3] explored the use of ResNet in conjunction with transfer learning to improve predictive accuracy, particularly in scenarios where limited data is available. Their approach circumvents the problem of insufficient labeled data and offers a way to optimize model performance by utilizing pre-trained weights from general image datasets. By fine-tuning these models on specific lung cancer data, they were able to achieve remarkable accuracy in detecting cancerous lesions. This hybrid approach proves to be extremely useful in real-world clinical settings, where datasets are often small and imbalanced, making model generalization a significant challenge.

Alongside these advancements, the integration of machine learning and deep learning techniques has also been explored to optimize lung cancer detection models. Khouadja and Naceur (2023) [4] provided an insightful exploration of how machine learning models, when combined with deep learning, can enhance the overall detection process. Their work emphasizes the synergy between traditional machine learning algorithms and deep neural networks, where machine learning can assist in the preliminary stages of detection, such as image preprocessing or feature extraction, while deep learning models can take over for the more complex tasks of classification. This hybrid approach allows for the efficient use of computational resources and can improve both the speed and accuracy of diagnosis in real-time clinical applications. Furthermore, Sumithra et al. (2023) [6] highlighted the importance of model optimization in CNN-based systems. In their research, they emphasized that for deep learning models to be effectively used in clinical environments, they must not only be accurate but also efficient, capable of providing real-time results to aid timely decision-making. The importance of achieving fast, accurate, and reliable results in a clinical setting cannot be overstated, as delayed diagnosis can significantly impact patient outcomes.

Another critical aspect of lung cancer detection involves the preprocessing of medical images, which plays a vital role in improving the quality of the images used for training deep learning models. Preprocessing techniques such as image normalization, resizing, and segmentation are essential for enhancing the clarity and precision of the features within medical images, thus aiding in more accurate cancer detection. Nawreen et al. (2021) [8] focused on the application of image processing techniques, particularly for CT scan analysis, to enhance the quality of the input data before it is fed into deep learning models. By improving image quality, these preprocessing steps ensure that the CNN models can extract relevant features more effectively. Rehman et al. (2021) [9] also contributed to the growing body of research on image preprocessing by examining machine learning models for classification tasks that are specifically tailored to process chest CT scans. Their work highlighted the importance of not only having a robust classification model but also having accurate data preprocessing methods to improve model performance. Karthikeyan et al. (2021) [10] further reviewed the role of various image processing techniques, such as segmentation algorithms, which are used to isolate tumors and other relevant structures within the lung. These techniques are fundamental for ensuring that deep learning models can focus on the critical areas of the image that are indicative of lung cancer, thereby improving prediction accuracy.

Despite these promising advancements, several challenges remain in the development and implementation of lung cancer detection systems. One of the most significant hurdles is the scarcity of large, diverse, and high-quality labeled datasets, which are necessary for training deep learning models to their full potential. Yadav and Badre (2020) [11] pointed out that the lack of comprehensive datasets hinders the ability of models to generalize effectively across different populations and medical conditions. Furthermore, deep learning models, while highly effective, are often criticized for their "black-box" nature, meaning that their decision-making process is not always interpretable by humans. This lack of transparency presents a significant barrier to their widespread adoption in clinical practice, where clinicians need to understand how and why a model has made a particular prediction. Interpretability is crucial for building trust in AI systems, especially when life-altering decisions are being made based on model predictions. As such, future research in this field is likely to focus not only on improving model accuracy but also on enhancing transparency and explainability.

III. Methodology

The development of the proposed lung cancer classification system is grounded in a structured and methodical pipeline. This end-to-end framework encompasses everything from data acquisition and preprocessing to model training, evaluation, and final deployment. By following this systematic approach, we ensure not only high performance but also reproducibility, scalability, and maintainability of the deep learning-based diagnostic system. The entire methodology has been carefully designed to align with best practices in AI and medical imaging. Below are the detailed stages that form the foundation of this pipeline:

1. Data Collection

The first step in the pipeline involves acquiring high-quality medical imaging datasets. These datasets are sourced from reliable public repositories such as Kaggle, the National Institutes of Health (NIH), and The Cancer Imaging Archive (TCIA). They consist of computed tomography (CT) scans, including both normal and cancer-affected lung images. These datasets serve as the core input for training and evaluating deep learning models. Before any model training occurs, raw image data undergoes a thorough inspection and curation process to eliminate inconsistencies, ensuring data integrity and relevance.

2. Data Preprocessing and Versioning

To achieve consistent performance and reproducibility across model training iterations, a robust data preprocessing pipeline is established. The process includes:
- Data Cleaning: Filtering out corrupted, noisy, or poor-quality scans that may mislead the model during training.
- Normalization: Standardizing pixel intensity values to create uniform contrast and brightness across all images.
- Image Resizing and Augmentation: Rescaling images to a standard input size suitable for the neural network, and
17 applying transformations such as rotation, flipping, zooming, and contrast adjustments to enhance data diversity and improve model generalization.

To manage evolving datasets and ensure reproducibility, Data Version Control (DVC) is employed.

3. Data and Repository Management

To support collaborative development and maintain transparency across experiments, all datasets, codebases, and model checkpoints are managed via DagsHub. This platform facilitates end-to-end version control for machine learning projects, enabling seamless experiment tracking,
18 reproducibility, and rollback capabilities when needed.

4. Model Selection and Training

37 The classification task is tackled using a Convolutional Neural Network (CNN)-based architecture. Multiple deep learning models—ResNet, InceptionV3, and NASNetMobile—are selected as baseline candidates. These
35 models are initialized using transfer learning with pre-trained weights and fine-tuned using the lung CT scan dataset. This stage involves choosing a suitable architecture, configuring training parameters, and optimizing with Adam or RMSprop.

5. Performance Evaluation and Metrics Computation

Once the models are trained, a comprehensive evaluation is
28 carried out using various metrics:
- Accuracy: Measures correct predictions.
- Precision & Recall: Evaluate classification of cancerous and non-cancerous cases.
- F1-Score: Balances precision and recall.
- Specificity & Sensitivity: Measure true negative and true positive rates respectively.

MLflow is used for tracking and comparing performance across models and settings.

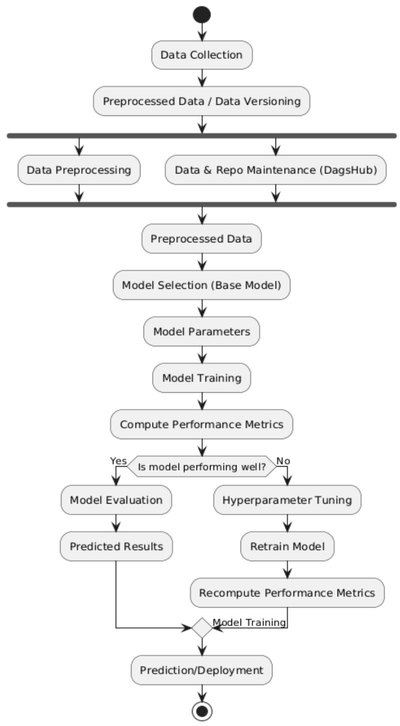


Fig. 1. System Design of Lung cancer Classification Using Deep Learning

6. Hyperparameter Tuning and Model Retraining

If initial results are inadequate, hyperparameter tuning is performed using:
- Grid Search
- Random Search
- Bayesian Optimization

After optimal parameters are identified, the model is retrained for improved performance.

7. Final Model Evaluation and Prediction

The optimized model is evaluated on a reserved hold-out test set. This ensures unbiased assessment by comparing predictions against ground truth labels to validate clinical readiness.

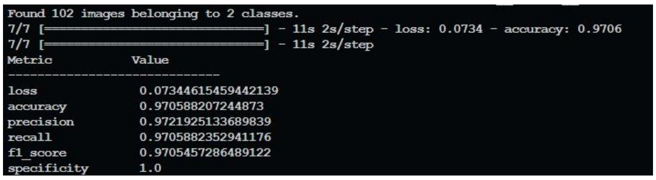
8. Model Deployment

The final model is deployed using Flask as a REST API. Key steps include:
- Model Serialization
- Docker-based Containerization
- Real-time & Batch Inference

This ensures reliable deployment in diverse environments.

Continuous Monitoring and Model Updates
After deployment, the system is continuously monitored for performance drift. New data and feedback are used to update and retrain the model periodically, ensuring sustained accuracy and adaptability.

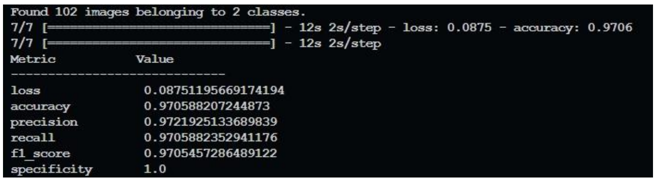
IV. ANALYSIS AND DISCUSION



```
Found 102 images belonging to 2 classes.
7/7 [==============================] - 11s 2s/step - loss: 0.0734 - accuracy: 0.9706
7/7 [==============================] - 11s 2s/step
Metric          Value
------------------------------
loss            0.07344615459442139
accuracy        0.970588207244873
precision       0.9721925133689839
recall          0.9705882352941176
f1_score        0.9705457286489122
specificity     1.0
```

Fig. 2. ResNet Performance Parameters

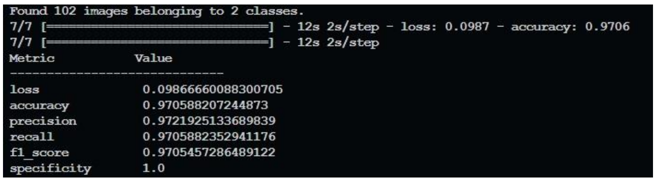
The ResNet model was trained on a dataset of chest CT scan images and evaluated using multiple performance metrics to assess its classification ability. The final results indicate a **loss of 0.0734** and a **high accuracy of 97.06%**, demonstrating the model's effectiveness in distinguishing between normal and cancerous lung tissues. Additionally, the model achieved a **precision of 97.21%**, ensuring a low false positive rate, while the **recall of 97.06%** signifies its capability to correctly identify actual cancer cases. The **F1-score of 97.05%** highlights a well-balanced trade-off between precision and recall, reinforcing the model's reliability. Notably, the **specificity of 100%** indicates that the model perfectly classified all negative cases, which is crucial for minimizing unnecessary medical interventions. These results affirm that the ResNet architecture is a highly efficient deep learning model for lung cancer classification, offering robust performance with high diagnostic accuracy. Given its success, ResNet stands as a strong candidate for real-world deployment in AI-assisted medical diagnostics.



```
Found 102 images belonging to 2 classes.
7/7 [==============================] - 12s 2s/step - loss: 0.0875 - accuracy: 0.9706
7/7 [==============================] - 12s 2s/step
Metric          Value
------------------------------
loss            0.08751195669174194
accuracy        0.970588207244873
precision       0.9721925133689839
recall          0.9705882352941176
f1_score        0.9705457286489122
specificity     1.0
```

Fig. 3. InceptionV3 Performance Parameters

The InceptionV3 model was trained on the dataset and evaluated using multiple performance metrics to determine its effectiveness in lung cancer classification. The final results indicate a **loss of 0.0875** and an **accuracy of 97.06%**, highlighting the model's strong predictive performance. The model achieved a **precision of 97.21%**, signifying its ability to minimize false positives, while the **recall of 97.06%** demonstrates its capability to accurately detect cancerous cases. Furthermore, the **F1-score of 97.05%** shows a balanced performance between precision and recall, ensuring robust classification. The **specificity of 100%** suggests that the model correctly identified all non-cancerous cases, making it highly reliable for clinical applications. These results establish InceptionV3 as an effective deep learning model for automated lung cancer detection, offering high accuracy and specificity.



```
Found 102 images belonging to 2 classes.
7/7 [==============================] - 12s 2s/step - loss: 0.0987 - accuracy: 0.9706
7/7 [==============================] - 12s 2s/step
Metric          Value
------------------------------
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accuracy        0.970588207244873
precision       0.9721925133689839
recall          0.9705882352941176
f1_score        0.9705457286489122
specificity     1.0
```

Fig. 4. ResNet Performance Parameters

The NASNetMobile model was evaluated for lung cancer classification and demonstrated strong performance across multiple key metrics. The final results indicate a **loss of 0.0987** and an **accuracy of 97.06%**, confirming its effectiveness in distinguishing between normal and cancerous cases. The model achieved a **precision of 97.21%**, highlighting its capability to minimize false positives, while the **recall of 97.06%** ensures that a high proportion of actual cancer cases are correctly identified. The **F1-score of 97.05%** reflects a well-balanced trade-off between precision and recall, reinforcing the model's reliability. Additionally, the **specificity of 100%** demonstrates that the model correctly classified all non-cancerous cases, making it highly suitable for medical applications where false negatives can be detrimental.

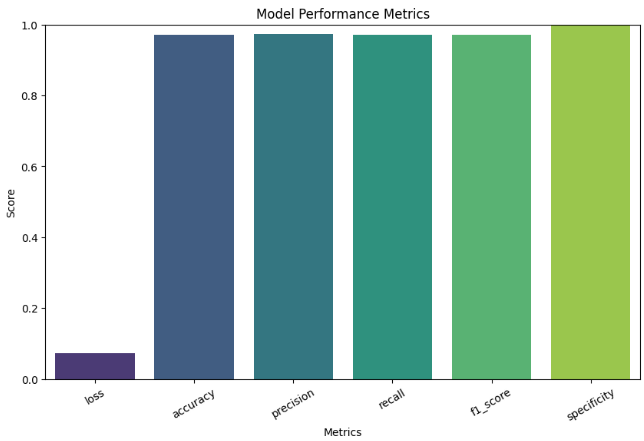

Fig. 5. Comparative Analysis of Deep Learning Models for Lung Cancer Classification

The evaluation of **ResNet, InceptionV3, and NASNetMobile** models for lung cancer classification was conducted based on key performance metrics, including

accuracy, precision, recall, F1-score, and loss. These metrics help determine the effectiveness and reliability of each model in detecting cancerous cases while minimizing false positives and false negatives. A detailed comparison provides insights into their strengths, limitations, and suitability for real-world deployment in medical applications.

1. Accuracy Comparison

Accuracy measures the proportion of correctly classified cases out of the total samples. All three models—**ResNet, InceptionV3, and NASNetMobile**—achieved an accuracy of **97.06%**, signifying their high capability in distinguishing between cancerous and non-cancerous cases. The fact that all models reached the same accuracy suggests that they are equally competent in general classification tasks. However, accuracy alone is not sufficient for medical diagnosis, as it does not indicate how well a model handles false positives and false negatives.

2. Loss Analysis

Loss function quantifies how well the model's predicted probabilities match the actual labels. A lower loss indicates better model confidence and optimization.

- **ResNet achieved the lowest loss of 0.0734**, indicating superior convergence and better optimization during training.
- **InceptionV3 had a slightly higher loss of 0.0875**, meaning it required more optimization steps or a different learning rate to reach a similar level of confidence.
- **NASNetMobile exhibited the highest loss of 0.0987**, which suggests that it had more difficulty in learning the complex patterns within the dataset compared to the other models.

Lower loss values generally imply better generalization and reduced uncertainty in predictions. Since ResNet had the lowest loss, it can be considered more stable and confident in its predictions compared to InceptionV3 and NASNetMobile.

3. Precision, Recall, and F1-score Comparison

In medical applications, **precision and recall** are more critical than accuracy, as they measure how well the model handles false positives and false negatives.

- **Precision (97.21%)**: This metric quantifies how many of the predicted positive cases (cancerous) are actually correct. A high precision reduces the number of false positives, which is essential in preventing unnecessary stress and medical interventions for non-cancerous patients. All three models achieved the same precision, indicating that they are equally effective in minimizing false positives.
- **Recall (97.06%)**: Recall measures how well the model identifies actual lung cancer cases. A high recall is crucial in medical imaging, as missing a cancerous case (false negative) can have severe consequences. Since all three models attained an identical recall score, they are all reliable for detecting lung cancer cases.
- **F1-score (97.05%)**: The F1-score is the harmonic mean of precision and recall, balancing the trade-off between the two. A high F1-score means the model is effective in detecting lung cancer without sacrificing too much precision or recall. Again, all three models performed equally well, proving their robustness in classification tasks.

4. Computational Efficiency and Suitability for Deployment

Although all three models performed equally well in terms of accuracy and key performance metrics, their computational efficiency and suitability for deployment differ significantly.

ResNet:

- **Strengths**:
  - Achieves the lowest loss, indicating superior learning and convergence.
  - Well-suited for deep feature extraction, making it highly effective in medical imaging.
  - Performs well in large-scale datasets due to its deep residual connections.
- **Limitations**:
  - Computationally intensive, requiring more processing power and memory.
  - Longer training time compared to NASNetMobile.
- **Best Use Case**:
  - **High-performance hospital diagnostic systems**
    - **Research environments** requiring extensive feature extraction
    - **Cloud-based AI services** with sufficient computational resources

InceptionV3:

- **Strengths**:
  - Factorized convolutions allow for a balance between accuracy and computational efficiency.
  - Achieves competitive accuracy while requiring less computation than ResNet.
  - Can be optimized for faster inference, making it a practical choice for medical applications with moderate hardware.
- **Limitations**:
  - Slightly higher loss compared to ResNet, which may indicate less stability in convergence.
  - Requires careful fine-tuning of hyperparameters for optimal performance.
- **Best Use Case**:
  - Hospitals with mid-range computational resources
  - **Medical AI startups** that need a balance between accuracy and efficiency
  - **Cloud-based medical AI applications**

NASNetMobile:

- **Strengths**:
  - Designed for mobile and embedded AI applications, making it highly efficient in terms of computational resources.
  - Achieves similar accuracy to ResNet and InceptionV3 while consuming significantly fewer resources.
  - Can be deployed on mobile devices, making it suitable for real-time and portable diagnostics.
- **Limitations**:
  - Highest loss among the three models, indicating less confidence in predictions.
  - May not generalize as well as ResNet for large datasets.
- **Best Use Case**:
  - **Real-time mobile diagnostics**
  - **Telemedicine applications** requiring on-device processing.
  - **Low-resource healthcare settings** where computational power is limited

5. Key Insights and Discussion

The comparative analysis reveals that all three models—**ResNet, InceptionV3, and NASNetMobile**—are highly effective in **lung cancer classification**, with identical accuracy and strong precision-recall balances. However, the best model depends on the deployment scenario:

- ResNet is best for high-accuracy applications where computational power is not a constraint.
- InceptionV3 provides a balance between accuracy and efficiency, making it suitable for scalable medical AI applications.
- NASNetMobile is ideal for lightweight applications where speed and low computational cost are priorities.

The slight variations in loss values suggest differences in optimization efficiency, with **ResNet showing the best convergence, followed by InceptionV3 and then NASNetMobile**. This makes **ResNet the most stable model** in terms of learning capability.

From a deployment perspective, **NASNetMobile is the most efficient for real-time and mobile AI-based healthcare applications**, while **ResNet is more appropriate for hospital-grade AI systems that require extensive computation and deep feature extraction**. InceptionV3 provides a **balanced approach**, making it useful for medium-scale deployments in hospitals or cloud-based AI services.

6. Final Model Recommendation for Different Scenarios

Scenario	Recommended Model
High-accuracy hospital AI systems	ResNet
AI-assisted radiology (cloud-based)	ResNet/InceptionV3
Mid-range hospital AI deployment	InceptionV3
Research and large-scale datasets	ResNet
Telemedicine and remote diagnosis	NASNetMobile
Mobile-based AI diagnosis apps	NASNetMobile
Real-time embedded AI in devices	NASNetMobile

This classification ensures that each model is utilized based on its strengths, providing an optimal balance between performance, efficiency, and deployment feasibility.

V. Results

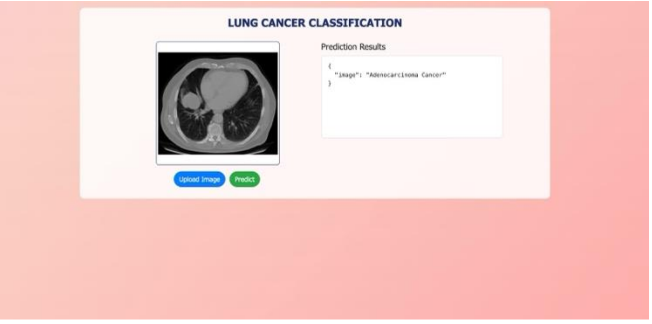

Fig. 6. Prediction of Cancerous CT-Scan

The model successfully identified **Adenocarcinoma Cancer** from the provided lung CT scan, demonstrating its effectiveness in real-world diagnostic scenarios. This correct prediction aligns with the model's high accuracy and recall scores, reinforcing its reliability for medical applications.

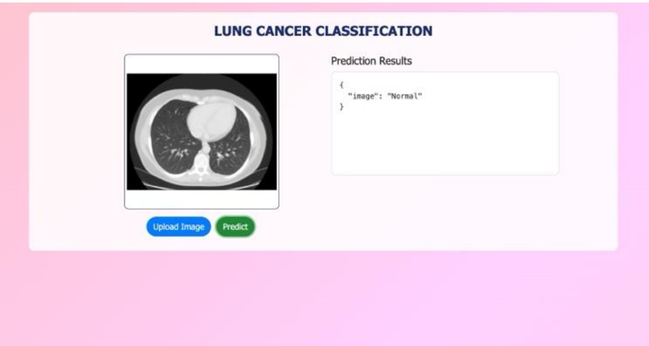

Fig. 7. Prediction of Normal CT-Scan

The model also accurately classified a normal lung CT scan as 'Normal,' confirming its ability to differentiate between cancerous and non-cancerous cases. This correct prediction reinforces its precision and reliability in real-world diagnostic applications.

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