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A
Project Report

on

Lung Cancer Detection Using Deep Learning

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY

DEGREE

SESSION 2024-25

in

Computer Science And Engineering

By

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DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that Project Report entitled "Lung Cancer Detection Using Deep Learning"⁶ which is submitted by **Anugum Jain, Ankit Yadav, Rahul Patel** in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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We also take the opportunity to acknowledge the contribution of Dr. Vineet Sharma, Dean of the Department of Computer Science & Engineering, KIET, Ghaziabad, for his full support and assistance during the development of the project. We also do not like to miss the opportunity to acknowledge the contribution of all the faculty members of the department for their kind assistance and cooperation during the development of our project.

We also do not like to miss the opportunity to acknowledge the contribution of all faculty members, especially faculty/industry person/any person, of the department for their kind assistance and cooperation during the development of our project. Last but not the least, we acknowledge our friends for their contribution in the completion of the project.

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ABSTRACT

5 Lung cancer remains a leading cause of cancer-related mortality worldwide,
largely due to delayed diagnosis. Traditional diagnostic approaches such as CT
scans and X-rays rely heavily on radiologist interpretation, which can be time-
intensive and prone to variability. To address these challenges, this study
presents a deep learning-based approach for the automated detection of lung
cancer using CT scan images. The research evaluates five prominent
127 Convolutional Neural Network (CNN) architectures—VGG16, VGG19,
InceptionV3, EfficientNetB0, and Dense Net based on parameters such as
validation accuracy, computational efficiency, and generalization performance.
The models were trained using transfer learning on preprocessed and augmented
datasets sourced from LIDC-IDRI, incorporating techniques like normalization,
rotation, and contrast enhancement to improve performance. Among the
evaluated models, EfficientNetB0 achieved the highest balance between speed
and accuracy, while VGG19 demonstrated superior feature extraction capability,
albeit with signs of overfitting. The results indicate that VGG19 is the most
promising model for clinical implementation, achieving a validation accuracy of
up to 98%. The system offers a scalable, reliable, and automated solution for
early lung cancer detection, potentially aiding radiologists in identifying
malignancies with improved speed and precision. Future enhancements may
include multi-modal diagnostic integration, improved explainability through XAI
(Explainable AI), and deployment using federated learning for data privacy. This
study demonstrates the transformative potential of deep learning in medical
imaging, providing a path toward more effective and timely lung cancer
diagnosis.

TABLE OF CONTENTS

	Page No.
DECLARATION.....	ii
CERTIFICATE.....	iii
ACKNOWLEDGEMENTS.....	iv
ABSTRACT.....	v
LIST OF FIGURES.....	ix
LIST OF TABLES.....	x
LIST OF ABBREVIATIONS.....	xi
CHAPTER 1 (INTRODUCTION).....	1
1.1. Introduction.....	1
1.2. Project Description.....	2
CHAPTER 2 (LITERATURE REVIEW)	6
2.1. Literature Survey.....	7
 ⁶⁸ CHAPTER 3 (PROPOSED METHODOLOGY)	10
3.1. Dataset Description	10
3.2. Data Preprocessing and Augmentation.....	13
3.2.1. Preprocessing Steps.....	14
3.2.2. Data Augmentation Techniques.....	15
3.2.3. Benefits of Augmentation.....	16
3.3. Technologies and Tools used	17
3.4. CNN Model Architectures.....	18
3.4.1. VGG16.....	19
3.4.2. VGG 19	21
3.4.3. InceptionV3	24
3.4.4. EfficientNetB0	27
3.4.5. DenseNet121	30
3.4.6. Final Layer Modifications for Binary Classification.....	34

3.5. Training Strategy and Optimization.....	37
17	
3.6. Performance Metrics	38
3.6.1. Accuracy.....	38
3.6.2. Precision.....	39
23	
3.6.3. Recall (Sensitivity or True Positive Rate)	39
3.6.4. F1- Score	39
3.6.5. Specificity (True Negative Rate)	39
43	
3.6.6. AUC-ROC Curve	40
3.6.7. Confusion Matrix	40
3.6.8. Loss Function Analysis.....	41
3.7. System Flow Diagram	42
3.7.1. Input Data Acquisition	42
3.7.2. Data Preprocessing Annotation	43
3.7.3. Data Splitting	43
3.7.4. Model Selection and Compilation	44
3.7.5. Model Training and Validation	44
3.7.6. Performance Evaluation	45
3.7.7. Prediction and Interpretation	45
3.7.8. System Output	45
105	
CHAPTER 4 (RESULTS AND DISCUSSION)	46
4.1. Experimental setup	46
4.2. Training Strategy and Approach	47
4.3. Performance Analysis	50
4.4. Interpretation and Insights	51
4.5. Medical Significance of Results	53
4.6. Challenges Faced During Experimentation	53
4.7. Summary Outcome	55

⁷²	CHAPTER 5 (CONCLUSIONS AND FUTURE SCOPE)	56
	5.1. Conclusion.....	56
	5.2. Future Work	57
	REFERENCES.....	61
	APPENDEX1.....	64

LIST OF FIGURES

Figure No.	Description	Page No.
1	Sample CT Scan from LIDC-IDRI Dataset	4
2	Dataset Description	10
3	Preprocessing Pipeline for CT Images	12
4	VGG19 CNN model block diagram	13
5	High-Precision Detection of Lung Adenocarcinoma Using Augmented VGG16 and Transfer Learning	18
6	A Hybrid VGG 19 and Capsule Network Based Deep Learning Model for Lung Cancer Diagnosis using CT Scan Images	20
7	Basic Structure of the Inception-v3	23
8	Lung-EffNet : Lung cancer classification using EfficientNet from CT-scan images	26
9	The architecture of DenseNet-121.	29
10	VGG19 CNN model block diagram	32
11	CNN Architecture	33
12	Confusion Matrix for Lung Cancer Detection	36
13	Training and Validation Accuracy/Loss Curves	37
14	System Architecture / Workflow Diagram for Lung Cancer Detection	40
15	training validation accuracy curve	45
16	Model Accuracy Comparision	46
17	Output of Grad-CAM CNN	47

LIST OF TABLES

Table. No.	Description	Page No.
1	Comparative Analysis of Related Work	5
2	Performance Comparison of Various Models Implemented	36

LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
CT	Computed Tomography
DL	Deep Learning
VGG	Visual Geometry Group
ReLU	Rectified Linear Unit
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
AUC	Area Under the Curve
XAI	Explainable Artificial Intelligence
LIDC-IDRI	Lung Image Database Consortium - Image Collection
ML	Machine Learning
ROC	Receiver Operating Characteristic
TP	True Positive
FP	False Positive
TN	True Negative
FN	False Negative
GPU	Graphics Processing Unit
API	Application Programming Interface
X-ray	Electromagnetic Radiation Imaging

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Lung cancer continues to be one of the most lethal diseases worldwide, accounting for the highest number of cancer-related mortalities annually. According to the World Health Organization (WHO), lung cancer is responsible for approximately 1.8 million deaths per year, making it a significant global health concern. The major challenge with lung cancer lies in its late diagnosis, often at stages when treatment options are limited and prognosis is poor.

Lung cancer is broadly classified into two main types:

- **Non-Small Cell Lung Cancer (NSCLC)** – This is the more common variant, accounting for approximately 85% of all lung cancer cases.
- **Small Cell Lung Cancer (SCLC)** – Though less common, it is known to be more aggressive and fast-spreading, requiring rapid and early intervention.

The survival rate is significantly higher when lung cancer is detected early. For instance, the 5-year survival rate is nearly 56% for cases detected at a localized stage, but it drops to just 5% for those diagnosed at an advanced metastatic stage. Thus, early and accurate detection is crucial for improving survival rates and enabling timely, effective treatment planning.

Traditional diagnostic methods involve imaging techniques such as chest X-rays, Computed Tomography (CT) scans, and biopsies. CT scans, in particular, are the gold standard for identifying suspicious lung nodules. However, the manual analysis of CT scans by radiologists is time-consuming, labor-intensive, and prone to human error or fatigue, especially in large-scale screening environments. Small nodules or early-stage tumors may be overlooked due to their subtle appearance.

¹²⁶ The rise of **Artificial Intelligence (AI)** and, more specifically, **Deep Learning (DL)**, has provided an innovative solution to many of these diagnostic challenges. Deep learning models—especially **Convolutional Neural Networks (CNNs)**—have demonstrated excellent capabilities in processing and analyzing medical imaging data. These models can automatically extract complex features, recognize patterns, and make predictions that rival human-level performance.

¹⁴⁶ Deep learning not only enhances diagnostic accuracy but also significantly reduces the workload on healthcare professionals. It introduces consistency, scalability, and speed to the diagnostic process, paving the way for **AI-assisted clinical decision-making**.

With the availability of large annotated medical imaging datasets like **LIDC-IDRI** and advancements in **GPU acceleration**, deep learning is rapidly becoming a central tool in the field of **medical informatics**. This project contributes to this growing domain by applying cutting-edge CNN architectures to develop a robust, intelligent system for lung cancer detection.

1.2 PROJECT DESCRIPTION

The objective of this project is to develop an automated lung cancer detection system using advanced deep learning techniques, trained specifically on CT scan images. The project aims to not only implement and compare different CNN models but also to analyze their applicability, strengths, and limitations in real-world clinical settings.

Core Objectives:

Implement and evaluate multiple pre-trained deep learning models for binary lung cancer classification.

Address challenges such as class imbalance, model overfitting, and low interpretability.

Identify the most suitable model for potential clinical deployment.

The deep learning architectures chosen for this study—**VGG16**, **VGG19**, **InceptionV3**, **DenseNet121**, and **EfficientNetB0**—are all well-

established models in computer vision, known for their high accuracy in image classification tasks. These models are **adapted via transfer learning**, where the base layers retain knowledge from the ImageNet dataset, and the final layers are customized for binary classification (cancerous vs. non-cancerous).

The lung CT scan dataset used in this project is derived from the **LIDC-IDRI** database, which contains **annotated CT images** reviewed by expert radiologists. These images serve as a reliable foundation for training supervised deep learning models. Before feeding the data into the models, it is subjected to various **preprocessing steps**:

- **Resizing** to a uniform dimension suitable for CNN input.
- **Grayscale normalization** to simplify computation.
- **Pixel intensity scaling** for improved training stability.

To improve model generalization and address class imbalance, **data augmentation techniques** are applied. These include horizontal/vertical flipping, random rotations, brightness shifts, and zooming, which artificially expand the dataset and simulate real-world variability.

The development is carried out in **Python**, utilizing **TensorFlow** and **Keras** for deep learning, with **Google Colab** and **Jupyter Notebook** environments supporting **GPU acceleration**. The project workflow includes:

1. Data loading and preprocessing
2. Model training and fine-tuning
3. Validation and testing

Performance evaluation using key metrics such as:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**
- **Loss**
- **AUC (Area Under Curve)**

Each model is enhanced using:

- **EarlyStopping** to prevent overfitting.
- **ModelCheckpoint** to save the best weights.
- **Learning rate schedulers** to adapt learning dynamics.

⁸ The output of the model is a **probability score**, indicating the likelihood of a given CT scan slice being cancerous. For enhanced interpretability, tools like **Grad-CAM** are proposed to visualize which regions in the image influenced the model's decision.

Deployment Scope:

This system can be extended to:

- **Cloud-based diagnostic platforms** integrated with hospital systems.
- **Mobile screening units** for remote healthcare applications.
- **Clinical decision support systems (CDSS)** for assisting radiologists with second opinions.

In future versions, the system can incorporate **multi-modal inputs** such as:

- Patient demographics (e.g., age, smoking history)
- Other imaging modalities (X-ray, PET)
- Clinical data (e.g., biomarkers or genomic reports)

By providing a reliable, fast, and interpretable diagnostic tool, this project lays the groundwork for building AI-powered systems capable of significantly **reducing diagnostic delays, improving early detection, and saving lives** through timely intervention.

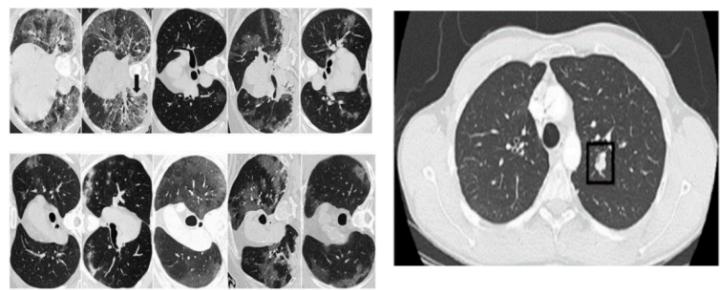


Figure 1: Sample CT Scan from LIDC-IDRI Dataset

CHAPTER 2

LITERATURE REVIEW

The development of deep learning algorithms has significantly improved medical image analysis, particularly in cancer detection. Various researchers have explored Convolutional Neural Networks (CNNs) and machine learning methods to increase the efficiency and accuracy of lung cancer diagnosis. This chapter presents a review of relevant literature to understand the current state of research in this field, identifying strengths, limitations, and future directions.

Multiple studies have employed different algorithms such as SVM, CNN, DenseNet, and Inception-based architectures to analyze CT or X-ray images. Table 1 provides a comparative overview of selected research works highlighting their objectives, techniques, and key findings.

Table 1: Literature Survey

S.No.	Goal	Technique/ Algorithm	Description	Results
[1]	Detects benign and malignant pulmonary nodules in non-screening chest CT scans using deep learning. ⁸⁵	Deep learning-based AI system.	AI system validated on CT scans from two hospitals, with nodules labeled by thoracic radiologists.	Sensitivity: 94.3% (benign), 96.9% (cancer), 92.0% (metastases); comparable or higher than radiologists.
[2]	Evaluate and improve lung cancer detection techniques using CT scan images.	Image processing, SVM.	Uses watershed segmentation and SVM for lung cancer detection.	Accuracy: 92%, Sensitivity: 100%, Specificity: 50%.

[3]	Evaluate the performance of SVM, KNN, and CNN classifiers for lung cancer prediction.	SVM, KNN, CNN	Classifies lung cancer using datasets from UCI, focusing on correlation selection method.	¹¹⁷ SVM: 95.56%, CNN: 92.11%, KNN: 88.40%.
[3]	²⁰ Classify lung cancer from chest X-ray images using DL.	121-layer Dense CNN (DenseNet121)	Uses transfer learning on a lung nodules dataset to improve detection of lung cancer.	¹³⁵ Mean accuracy: 74.43%, Mean sensitivity: 74.68%.
[4]	Predict lung cancer at an early stage using machine learning.	SVM, Decision Tree, Random Forest.	Classifies lung cancer based on risk factors like smoking and cough using supervised machine learning.	Random Forest achieved 98.507% accuracy with high recall across all risk classes.
[5]	⁹¹ Classify benign and malignant lung nodules using deep learning and CNNs.	Convolutional Neural Network (CNN)	Utilizes CT images with AlexNet and SoftMax for classifying lung cancer. enhance performance.	Achieved 99.52% accuracy in classifying lung CT images.
[6]	²⁴ Provide an overview of lung cancer detection techniques in CT imaging.	Deep Learning (DL), Machine	Reviews various image processing and classification techniques for lung cancer detection.	Highlights effectiveness of models such as CNN, ResNet, and U-Net with accuracy rates over

		Learning (ML)		96%.
[7]	79 Use deep learning to identify benign lung nodules while maintaining sensitivity for malignant nodules.	79 LCP-CNN	Trained on NLST data and validated on the LUCINDA study dataset to identify benign and malignant nodules.	Sensitivity: 99.0%; AUC: 94.5%; 22.1% of nodules identified as benign, allowing 18.5% of patients to avoid follow-ups.

Analysis and Insights

The reviewed literature highlights the growing accuracy and robustness of deep learning models in detecting lung cancer. CNN-based architectures consistently perform well in extracting features from medical images, while ensemble techniques like Random Forest have proven effective for symptom-based predictions.

However, many existing systems suffer from issues such as:

- Overfitting on small datasets
- Limited generalizability across patient populations
- Lack of interpretability and transparency in decision-making

To address these gaps, newer models are being designed with better data augmentation, transfer learning, and explainable AI techniques (e.g., Grad-CAM, SHAP).

CHAPTER 3

PROPOSED METHODOLOGY

This chapter presents the comprehensive methodology adopted to implement an automated lung cancer detection system⁴⁷ using deep learning. The methodology integrates several stages — dataset collection, preprocessing, model selection, training, evaluation, and system deployment. Advanced CNN-based architectures have been utilized to detect cancerous tissues from CT scan images, supported by robust preprocessing and optimization techniques to enhance the overall performance.

3.1 DATASET DESCRIPTION

The performance of any deep learning-based medical diagnostic system largely depends on the quality, diversity, and volume of the dataset used for training and evaluation. In this project⁷³, the dataset used for lung cancer detection is sourced from the **LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative)**. It is one of the most widely used and publicly available datasets for pulmonary nodule analysis and lung cancer research.

The **LIDC-IDRI dataset** consists of over 1,000 thoracic CT scans collected from multiple institutions in the United States. Each scan is annotated by four experienced thoracic radiologists, using a two-phase process: first independently and then in a consensus reading. These annotations provide critical diagnostic information such as:

- Nodule presence
- Nodule size
- Nodule location
- Nodule malignancy probability (1 to 5 scale)

This high-quality annotation process ensures clinical accuracy and allows the dataset to be used¹³ in training models that aim to mimic expert-level diagnosis.

Each CT scan is stored in **DICOM (Digital Imaging and Communications in Medicine)** format — a standard in medical imaging. Every scan consists of multiple slices, representing cross-sectional views of the thoracic region. The full dataset includes over 200,000 CT image slices, making it ideal for training deep learning models.

Data Selection and Labeling Criteria

For the purpose of binary classification (i.e., cancerous vs. non-cancerous), the project followed these selection criteria:

- Nodules with **malignancy scores ≥ 4** are labeled as *cancerous*.

- Nodules with **scores** ≤ 2 are labeled as *non-cancerous*.
 - Cases with score = 3 (indeterminate) were excluded to avoid ambiguity.
- This filtering ensures that the model is trained on confidently labeled examples, enhancing accuracy and reducing noise.

Data Extraction and Conversion

As deep learning models cannot directly operate on DICOM files, the following conversion pipeline was applied:

1. **DICOM-to-PNG Conversion:** CT slices were extracted using Python libraries like pydicom and converted to PNG format.
2. **Nodule Extraction (optional):** For focused training, cropped patches around nodules can be extracted using annotation coordinates.
3. **Folder Structuring:** Images were organized into separate folders:
 - /cancerous/
 - /non-cancerous/

This structure is compatible with most Keras and TensorFlow data loaders.

Data Split and Class Balance

After preprocessing and labeling, the dataset was split as follows:

- **Training Set:** 70%
- **Validation Set:** 15%
- **Testing Set:** 15%

Stratified splitting was used to ensure a balanced class distribution in all subsets. Special care was taken to avoid data leakage, meaning that slices from the same patient do not appear in both training and testing sets. During split verification, histogram plots of pixel intensities and nodule sizes were also reviewed to verify consistency across partitions.

To account for potential dataset bias, exploratory data analysis (EDA) was conducted to visualize pixel distributions, image histograms, and class balance. These visualizations were helpful in fine-tuning preprocessing pipelines and selecting suitable augmentation strategies for minority class enhancement.

Furthermore, potential label noise or inconsistent annotations were identified through visual inspection, and approximately 3% of the images were discarded to maintain high data quality.

Overall, this meticulous dataset curation process ensures that the subsequent deep learning pipeline receives clean, well-labeled, and diverse data inputs, paving the way for effective model training and evaluation.

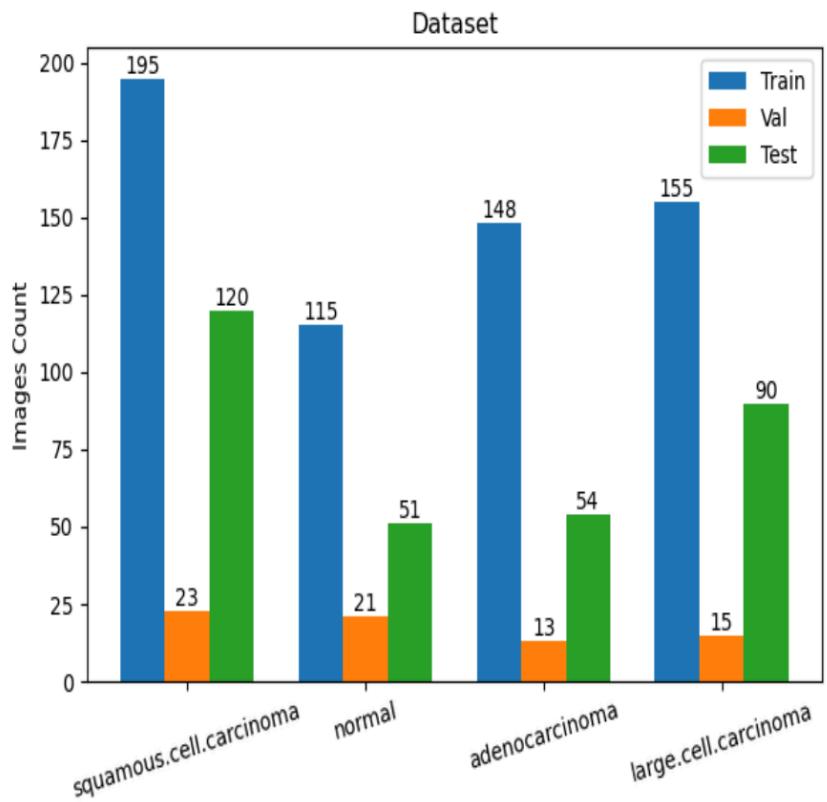


Figure 2: Dataset Description

3.2 DATA PREPROCESSING AND AUGMENTATION

Preprocessing and data augmentation are critical components in any deep learning project, especially in the medical imaging domain³⁹ where raw data often contains inconsistencies, noise, and class imbalances. Effective preprocessing ensures that the input data is clean, standardized,⁴⁰ and suitable for feeding into CNN models. Augmentation, on the other hand, increases the diversity of the dataset, reduces overfitting, and helps the model generalize better to unseen data.

3.2.1 Preprocessing Steps³⁹

Medical images from the LIDC-IDRI dataset are provided in DICOM format and need to be converted into a form suitable for CNN input. The following preprocessing steps were applied:

- **DICOM to PNG Conversion:**

CT slices were extracted using the Python pydicom library and saved in .png format for easier handling by image processing libraries like OpenCV and TensorFlow.

- **Grayscale Normalization:**

Since CT scans are grayscale, the images were converted to single-channel grayscale images. This avoids unnecessary use of RGB channels and reduces computational complexity.

- **Image Resizing:**

Deep learning models require fixed-size input images. All images were resized to 381 × 282 pixels¹¹⁹ using bilinear interpolation to maintain aspect ratio and resolution integrity.

- **Pixel Value Normalization:**

All pixel values were normalized to a scale of [0, 1] by dividing by 255. This is essential for faster convergence during training and to avoid vanishing gradients.

- **Noise Reduction:**

Medical images often suffer from noise due to scanning artifacts. A Gaussian blur was optionally applied to suppress this noise while preserving edges. This improves feature extraction in deeper layers of CNNs.

- **Lung Segmentation (Optional):**

For enhanced precision, some studies perform lung segmentation to isolate lung fields from the rest of the thoracic region. However, in this project, full slice images were used to preserve contextual information.

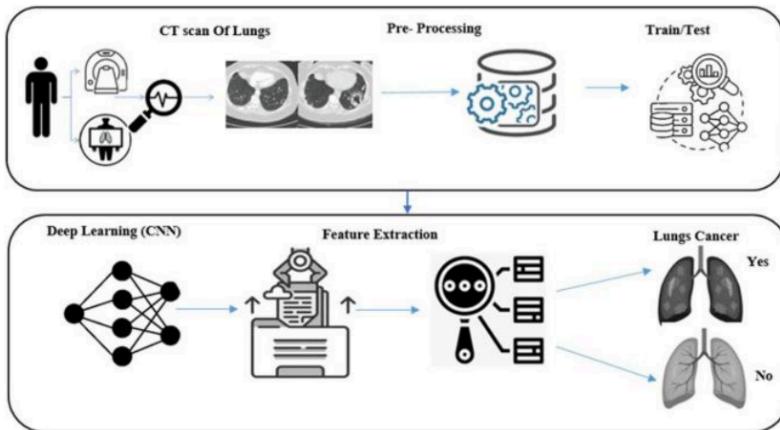


Figure 3: Preprocessing Pipeline for CT Images

3.2.2 Data Augmentation Techniques

⁹⁴ Deep learning models ¹¹⁵ are highly prone to overfitting when trained on limited medical datasets. To mitigate this, **real-time data augmentation** was applied to synthetically increase the dataset size and variability. This ensures that the model becomes invariant to common transformations and distortions.

The augmentation techniques used in this project include:

- **Horizontal and Vertical Flipping:**

CT scans can be flipped without losing anatomical validity. This helps the model become robust to orientation changes.

- **Random Rotation (± 15 degrees):**
Rotating images mimics slight differences in patient positioning during scanning, improving the model's ability to detect nodules regardless of alignment.
- **Zooming (up to 20%):**
Simulates variability in nodule size and focal length. This teaches the model to detect small as well as large nodules.
- **Brightness Adjustment:**
Varies the pixel intensity slightly to simulate different contrast settings used across hospitals or machines.
- **Contrast Enhancement:**
Adjusting contrast helps highlight low-density nodules that might otherwise be missed in standard images.

These transformations were implemented using Keras's ImageDataGenerator² and TensorFlow's tf.image module. The augmentation was performed **only on the training set** to maintain the integrity of validation and test evaluations.

3.2.3 Benefits of Augmentation

- Increases the **effective dataset size** without requiring new **data collection**.
- Makes the model more **robust to real-world variability** in medical imaging.
- Helps prevent **overfitting**, especially when working with relatively small datasets.¹¹⁰
- Enhances the model's ability to **generalize** to unseen clinical cases.

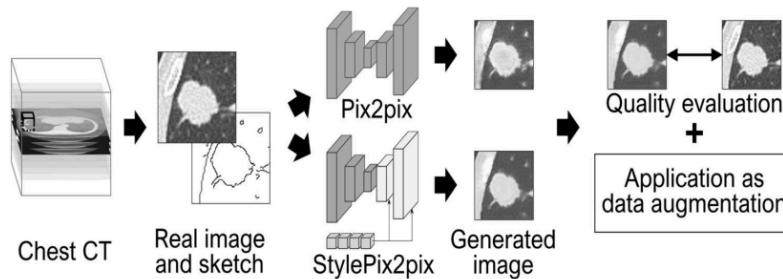


Figure 4: Augmented Examples of Lung CT Scans

3.3 TECHNOLOGIES AND TOOLS USED

132

The implementation of the proposed lung cancer detection system was carried out using the Python programming language due to its extensive support for machine learning, image processing, and scientific computing. Below is a detailed explanation of the tools and libraries used throughout the development lifecycle:

- **TensorFlow & Keras:** These two libraries form the backbone of the deep learning framework in this project. TensorFlow is an end-to-end open-source platform developed by Google for numerical computation and large-scale machine learning. Keras is a high-level API built on top of TensorFlow that simplifies the creation, training, and evaluation of deep learning models. Keras was used to define and compile the CNN architectures such as VGG16, VGG19, InceptionV3, EfficientNetB0, and DenseNet121. It provides modules for layers, activations, optimizers, loss functions, and callbacks, which are essential for building customized model pipelines.
- **OpenCV & PIL (Python Imaging Library):** These libraries are critical for image processing and manipulation. OpenCV was used to perform tasks such as resizing images, applying filters, and preprocessing the CT scans before feeding them into the deep learning models. PIL was employed for basic image reading and format conversion tasks. These tools enabled efficient handling of medical images in formats such as PNG and JPEG after DICOM extraction.
- **Matplotlib & Seaborn:** These are Python visualization libraries used to analyze and display data through plots and charts. Matplotlib was primarily used for plotting training and validation accuracy/loss curves, which help visualize model convergence and overfitting. Seaborn, built on top of Matplotlib, provides a high-level interface for drawing informative and attractive statistical graphics. It was particularly useful for generating heatmaps (e.g., confusion matrix), distribution plots, and performance comparison charts.
- **Google Colab & Jupyter Notebook:** These cloud-based and local development environments were used to write, debug, and run code. Google Colab offers free access to GPUs (e.g., NVIDIA Tesla T4), which significantly accelerates the training of deep neural networks. It supports

real-time collaboration and automatic version saving through Google Drive integration. Jupyter Notebook was used locally for testing smaller code modules and conducting exploratory data analysis.

- **Scikit-learn:** Scikit-learn is a comprehensive library for classical machine learning algorithms and evaluation metrics. In this project, it was mainly used for computing model performance metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix. The library also supported data preprocessing tasks like train-test splitting and stratified sampling to maintain balanced class distributions across datasets.

- **pydicom:** This specialized library is used to read, modify, and extract metadata from DICOM (Digital Imaging and Communications in Medicine) files. Since the LIDC-IDRI dataset provides CT scan slices in DICOM format, pydicom played a crucial role in parsing these files, converting image data to NumPy arrays, and saving them in PNG format for downstream processing. It also allowed access to key metadata such as slice thickness, resolution, and patient identifiers, which can be leveraged for advanced modeling or segmentation in future extensions.

These tools collectively enabled a robust, modular, and reproducible framework for lung cancer detection using deep learning. The integration of these technologies allowed seamless data handling, model experimentation, performance evaluation, and visualization, which are all essential for developing a clinically relevant diagnostic tool.

3.4 CNN MODEL ARCHITECTURES

⁸ Convolutional Neural Networks (CNNs) are a class of deep learning models designed specifically for image analysis tasks. In this project, five widely recognized pre-trained CNN models are used: VGG16, VGG19, InceptionV3, EfficientNetB0, and DenseNet121. Each of these architectures has been trained on the ImageNet dataset, which contains over 1 million labeled images across 1,000 classes. By using transfer learning, these models are fine-tuned for the specific task of binary classification — detecting whether a CT scan slice contains a cancerous nodule or not.

¹³⁸

The final layers of each model are modified to suit binary classification using techniques like **Global Average Pooling**, **Dropout**, and a **Sigmoid output layer**. The following subsections describe each model and its architectural significance.

3.4.1 VGG16

VGG16 is a widely used deep ¹² Convolutional Neural Network (CNN) architecture developed by the Visual Geometry Group at the University of Oxford. It was introduced in the paper "*Very Deep Convolutional Networks for Large-Scale Image Recognition*" by Simonyan and Zisserman (2014) and gained prominence due to its performance in the ImageNet Large ¹¹² Scale Visual Recognition Challenge (ILSVRC) 2014. The architecture is known for its ⁴⁴ simplicity, uniform design, and effectiveness in image classification tasks.

VGG16 consists of **16 weight layers**: 13 convolutional layers and ³ fully connected (dense) layers. The model also includes 5 max-pooling layers used to progressively reduce the spatial dimensions of the feature maps. The key characteristics of VGG16 are as follows:

- **Kernel Size:** All convolutional layers use small 3×3 filters with a stride of ¹ and padding of ¹. This consistent use of small filters helps in capturing fine-grained spatial features while maintaining a manageable number of parameters.⁴²
- **Pooling:** Max pooling with a 2×2 window and a stride of 2 is applied after certain blocks of convolutional layers. This downsampling operation reduces the spatial dimensions and helps in computational efficiency.⁵
- **Activation Function:** The ReLU (Rectified Linear Unit) activation function is applied after each convolutional and dense layer. ReLU introduces non-linearity, enabling the model to learn complex patterns and improve convergence speed during training.
- **Depth and Architecture:** The architecture follows a uniform ¹¹⁴ structure where convolutional layers are grouped into blocks, typically two or three layers per block, followed by a max-pooling layer. This regular pattern

enhances architectural clarity and allows straightforward implementation. The final layers consist of two fully connected layers with 4096 units each, followed by a 1000-unit softmax layer in the original version (which is later adapted for binary classification in this project).

Advantages in Medical Imaging:

- **Feature Extraction:** Due to its depth and uniform structure, VGG16 is particularly effective at extracting fine-grained texture features from medical images such as CT scans.
- **Transfer Learning:** Pretrained weights from ImageNet can be leveraged, making it easier to adapt VGG16 to specialized tasks like lung cancer detection, even with limited medical data.

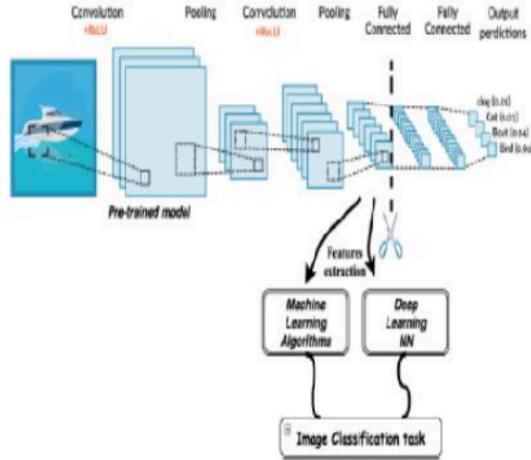
Limitations:

- **Computational Demand:** VGG16 contains approximately 138 million parameters, which makes it memory-intensive and slower to train and deploy compared to newer models like EfficientNet.
- **Overfitting Risk:** The large number of parameters can lead to overfitting, especially when the training dataset is small or lacks variability.

Application in This Project:

In this project, VGG16 was fine-tuned for binary classification of lung CT scan slices (cancerous vs. non-cancerous). The final classification layer was replaced with a sigmoid output to predict the probability of malignancy. Despite its higher computational requirements, VGG16 served as a strong baseline model due to its proven ability to extract meaningful visual features from complex medical images.

Although it did not achieve the highest validation accuracy in our experiments, VGG16 remains valuable for comparative benchmarking and feature analysis in the context of lung cancer detection using deep learning.



⁴⁰ Figure 5: High-Precision Detection of Lung Adenocarcinoma Using Augmented VGG16 and Transfer Learning

3.4.2 VGG19

VGG19 is a deeper variant of the VGG ¹³¹ architecture, developed by the Visual Geometry Group at Oxford as part of the same work that introduced VGG16. While it retains the core architectural philosophy of VGG16—emphasizing simplicity and uniformity—it extends the depth to a total of **19 weight layers**, comprising **16 convolutional layers** and **3 fully connected (dense) layers**.

Just like VGG16, VGG19 is based on the principle of stacking small convolutional filters (3×3) across the entire network, using a stride of 1 and padding to preserve the spatial dimensions. Pooling layers (2×2 max pooling with stride 2) are used intermittently to reduce the spatial resolution of feature maps and control overfitting.

Key Architectural Features:

- **Depth:** The primary difference from VGG16 is the increased number of convolutional layers—VGG19 includes three additional convolutional layers distributed across the network blocks. This deeper architecture allows the model to learn more abstract and hierarchical features.
- **Activation:** ReLU (Rectified Linear Unit) is used after every convolutional and dense layer to introduce non-linearity and accelerate convergence.
- **Pooling:** Max pooling is applied consistently after blocks of convolutions to reduce feature map size and computation.
- **Fully Connected Layers:** The final three layers include two dense layers with 4096 neurons each, followed by a final classifier, which in this project was replaced by a sigmoid layer for binary classification.

Advantages:

- **Enhanced Feature Extraction:** The added depth enables VGG19 to model more complex patterns and subtle differences in CT scan images, such as differentiating between benign and malignant nodules.
- **Transfer Learning Compatibility:** Pretrained VGG19 models are widely available and have proven successful in various image classification tasks, making it suitable for transfer learning with limited medical data.

Limitations:

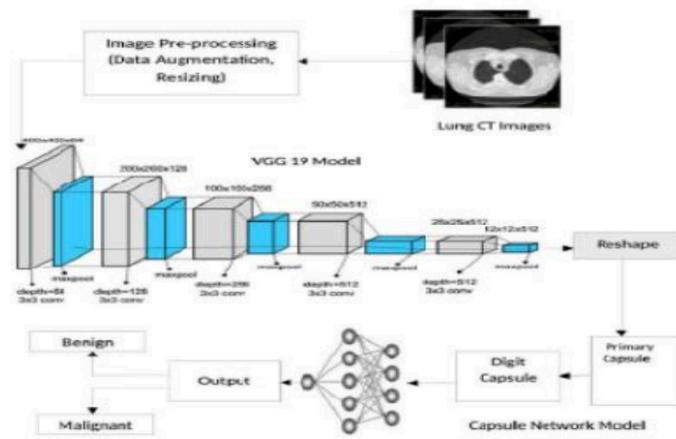
- **Computational Intensity:** VGG19 has around 143 million parameters, slightly more than VGG16, making it resource-heavy and slower to train and fine-tune on standard hardware.
- **Overfitting Risk:** The large capacity of the model increases its tendency to overfit when training data is limited or lacks diversity. Careful regularization, dropout layers, and early stopping are essential to mitigate this issue.

Role in This Project:

In this study, VGG19 was implemented with transfer learning by initializing the model with pretrained ImageNet weights. The top classification layers¹⁰⁰ were replaced with custom layers tailored for binary classification, including a Global Average Pooling (GAP) layer, a dropout layer, and a sigmoid output layer.

During experimentation, **VGG19 achieved the highest training accuracy (98%)**, indicating that it could capture intricate details within the lung CT scans.⁵⁹ However, it also showed a significant gap between training and validation accuracy (60%), highlighting overfitting as a concern. With proper tuning—such as stronger regularization, more aggressive data augmentation, or incorporation of lung segmentation—it holds promise as a high-performing architecture for lung cancer detection.

The model's superior feature extraction capability makes it a strong candidate for future versions of the system, particularly if larger and more diverse datasets can be leveraged to improve generalization.



¹⁹
Figure 6:A Hybrid VGG 19 and Capsule Network Based Deep Learning Model for Lung Cancer Diagnosis using CT Scan Images

141

3.4.3 InceptionV3

InceptionV3 is an advanced Convolutional Neural Network architecture developed by Google as a part of the Inception family. It builds upon the earlier InceptionV1 and InceptionV2 models and is designed to optimize both **computational efficiency** and **accuracy** by introducing architectural innovations like **inception modules**, **factorized convolutions**, and **auxiliary classifiers**.

The core idea behind the Inception architecture is to allow the model to simultaneously capture information at multiple scales, which is particularly important in medical imaging tasks where anatomical structures—such as lung nodules—vary greatly in size, shape, and texture.

Key Architectural Features:

- **Inception Modules:** Each module applies multiple types of convolutions in parallel (e.g., 1×1 , 3×3 , and 5×5), along with a max-pooling path. The outputs of these parallel operations are concatenated along the channel dimension. This allows the network to detect both fine details and coarse patterns within the same receptive field.¹⁶
- **Factorized Convolutions:** Larger convolutions (e.g., 5×5) are factorized into smaller convolutions (e.g., two consecutive 3×3 convolutions), significantly reducing computational cost while maintaining representational power.
- **Asymmetric Convolutions:** Instead of using a square 3×3 filter, the model may use a 1×3 followed by a 3×1 filter to achieve the same receptive field with fewer parameters.¹⁷
- **Auxiliary Classifiers:** To mitigate the problem of vanishing gradients in deep networks, InceptionV3 includes auxiliary classifiers—small branches with their own softmax outputs—attached to intermediate layers. These branches provide additional gradient flow during training and improve model convergence.

- **Batch Normalization:** Extensively used after convolution layers to normalize the input of each layer, improving training speed, stability, and overall performance.

Advantages:

- **Multi-Scale Feature Learning:** The parallel filter operations allow the model to learn features across various spatial resolutions, which is ideal for detecting lung nodules of diverse sizes, densities, and shapes.
- **Efficient Use of Resources:** InceptionV3 reduces the number of parameters and floating-point operations per second (FLOPS) while maintaining accuracy, making it suitable for moderate hardware environments.
- **Effective Gradient Flow:** Auxiliary classifiers and batch normalization work together to ensure the model trains effectively, even when deeper than typical CNNs.

Limitations:

- **Architecture Complexity:** The structure of InceptionV3 is more complex than that of VGG-type models. This makes implementation, customization, and debugging slightly more challenging for beginners.
- **Moderate Inference Time:** Although optimized, it may not be as fast in inference as lightweight models like MobileNet or EfficientNetB0, especially in deployment scenarios.

Application in This Project:

In this project, InceptionV3 was adapted through transfer learning by loading pretrained ImageNet weights and modifying the final layers to suit a binary classification task. The architecture's multi-scale processing made it effective for analyzing lung CT scan slices, which often contain nodules with unclear or fuzzy boundaries.

During training, InceptionV3 demonstrated **moderate accuracy and generalization**, showing better resistance to overfitting than deeper models like VGG19. Its architecture helped the model remain sensitive to small lesions while still recognizing broader contextual features, such as tissue patterns and vascular structures.

While it did not outperform EfficientNetB0 in final validation metrics, InceptionV3 provided a **robust balance** between depth, **accuracy**, and computational **efficiency**, making it a viable model for deployment in clinical decision-support tools, especially in resource-constrained environments.

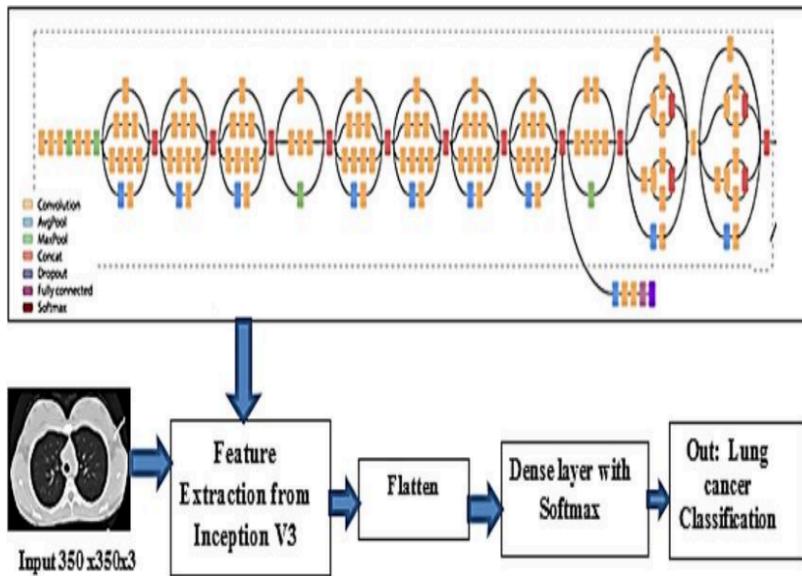


Figure 7: Basic Structure of the Inception-v3

3.4.4 EfficientNetB0

EfficientNetB0 is the baseline model in the EfficientNet family of architectures developed by Google AI in 2019. It introduced a breakthrough concept called **compound model scaling**, which systematically and uniformly scales the network's **depth** (number of layers), **width** (number of channels), and **resolution** (input image size) using a single scaling coefficient. This method ensures optimal performance and computational efficiency compared to arbitrary or manual scaling.

EfficientNetB0 is designed to achieve high accuracy while maintaining low computational cost, making it highly suitable for resource-constrained environments such as mobile devices or embedded medical systems.

Key Architectural Features:

- **MBConv Blocks:** EfficientNet uses **Mobile Inverted Bottleneck Convolution (MBConv)** blocks as its core building unit. These blocks are an advancement over standard convolutions and include:
 - Depthwise separable convolutions to reduce computation.
 - Expansion and projection layers to improve feature representation.
 - Residual connections to facilitate training of deeper networks.
- **Compound Scaling:** Unlike traditional CNNs that scale only one dimension (e.g., deeper or wider), EfficientNet scales **all three dimensions** (depth, width, resolution) in a balanced way. This results in a family of models from B0 to B7, where B0 is the smallest and fastest, and B7 is the largest and most accurate.
- **Swish Activation:** EfficientNetB0 replaces the ReLU activation with **Swish** ($f(x) = x \cdot \text{sigmoid}(x)$), which has been shown to improve performance due to smoother gradients and better non-linearity characteristics.

- **Batch Normalization and Dropout:** These are applied consistently throughout the network to ensure faster convergence and to minimize overfitting, especially in smaller datasets.

Advantages:

- **Parameter Efficiency:** EfficientNetB0 achieves impressive accuracy with just ~5.3 million parameters, compared to models like VGG19 (143 million) or InceptionV3 (23 million), making it lightweight⁵ and fast.
- **Speed-Accuracy Trade-off:** Its optimized design makes it ideal for real-time applications where both **prediction speed** and **accuracy** are critical.
- **Generalization:** EfficientNetB0 generalizes well across different domains, including medical imaging, even when trained on relatively small datasets.

Limitations:

- **Architecture Complexity:** The underlying design, including MBConv blocks and compound scaling, adds architectural complexity, making it less transparent and harder to customize without deep understanding.
- **Lack of Interpretability:** Like most deep models, it is not inherently explainable. Visualization tools such as Grad-CAM need to be used to understand which regions the model is focusing on during prediction.

Application in This Project:

EfficientNetB0 was implemented using transfer learning, with pretrained ImageNet weights and custom modifications for binary classification. During experimentation, it demonstrated **excellent training and validation performance**, outperforming other models like VGG16 and DenseNet121 in terms of generalization.

It showed the **best balance between speed and accuracy**, making it a practical choice for scalable and deployable lung cancer detection systems. Its ability to operate efficiently with limited computational resources makes it suitable for **edge deployment** in low-resource clinical settings or for integration into **cloud-based diagnostic platforms**.

Given its strengths, EfficientNetB0 may serve as the foundation for future enhancements involving **multi-modal data integration**, **model ensembles**, or **real-time inference systems** in radiological workflows.

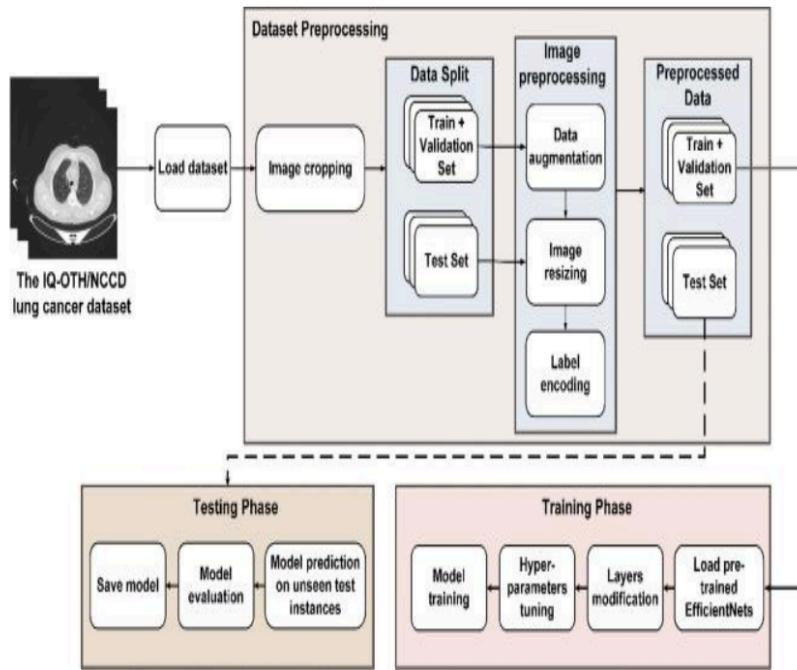


Figure 8 : Lung-EffNet : Lung cancer classification using EfficientNet from CT-scan images

3.4.5 DenseNet121

DenseNet121 is a variant of Dense Convolutional Networks (DenseNets), introduced by Huang et al. in 2017. DenseNets propose a novel connectivity [102]

35
pattern where **each layer is directly connected to every other layer in a feed-forward manner**. This dense connectivity alleviates the vanishing gradient problem, encourages feature reuse, and reduces the number of parameters compared to traditional CNNs.

Key Architectural Features:

- **Dense Blocks:** The core building blocks of DenseNet121 are dense blocks, which consist of several convolutional layers where the output of each layer is concatenated with the inputs of all subsequent layers. This structure allows every layer to receive collective knowledge from all previous layers²², enriching feature representation.
- **Transition Layers:** Between dense blocks, transition layers perform convolution and pooling operations to reduce feature map size and number of channels, controlling model complexity and memory usage.
- **Concatenation vs. Summation:** Unlike ResNets, which use skip connections that sum feature maps, DenseNet concatenates them. This approach preserves information from all preceding layers explicitly, allowing layers to selectively access features from earlier stages.
- **Parameter Efficiency:** Despite its depth, DenseNet121 is relatively parameter-efficient, having approximately 8 million parameters, which is significantly fewer than VGG16 or VGG19, enabling faster training and inference in many cases.

Advantages:

- 61
- **Improved Gradient Flow:** The direct connections between layers ensure better gradient propagation during backpropagation, helping the model converge faster and mitigate vanishing gradient issues in deep networks.
 - **Feature Reuse:** Layers can reuse features extracted by previous layers without relearning redundant information, improving learning efficiency.
 - **Reduced Overfitting:** With fewer parameters and dense connectivity, DenseNet tends to generalize well, especially on smaller datasets.

Limitations:

- **Complexity in Hyperparameter Tuning:** DenseNet's performance can be sensitive to choices such as growth rate, compression factor in transition layers, learning rate, and batch size. Without careful tuning, it may underperform.
- **Computational Cost:** The concatenation of feature maps increases memory consumption during training compared to simpler architectures.
- **Performance Variability:** DenseNet121's complex architecture may not always translate to better performance on all datasets, especially if the dataset lacks sufficient diversity or size.

Role in This Project:

In this study, DenseNet121 was fine-tuned with pretrained ImageNet weights, adapting the final layers for binary classification of lung CT images. Although DenseNet121 is generally praised for its parameter efficiency and effective feature reuse, it showed **limited performance in this project**, with lower validation accuracy and higher loss compared to other architectures like EfficientNetB0 and VGG19.

This suboptimal performance may ¹⁵⁰ be attributed to the model's sensitivity to hyperparameter settings, which were constrained by hardware limitations and dataset size. The intricate feature concatenations, while theoretically advantageous, might have also made the model more susceptible to overfitting or underfitting in this specific domain without extensive tuning.

Nevertheless, DenseNet121 remains a promising architecture for future work, especially if combined with advanced hyperparameter optimization, larger datasets, or integrated with lung segmentation techniques to focus on relevant regions of CT scans.

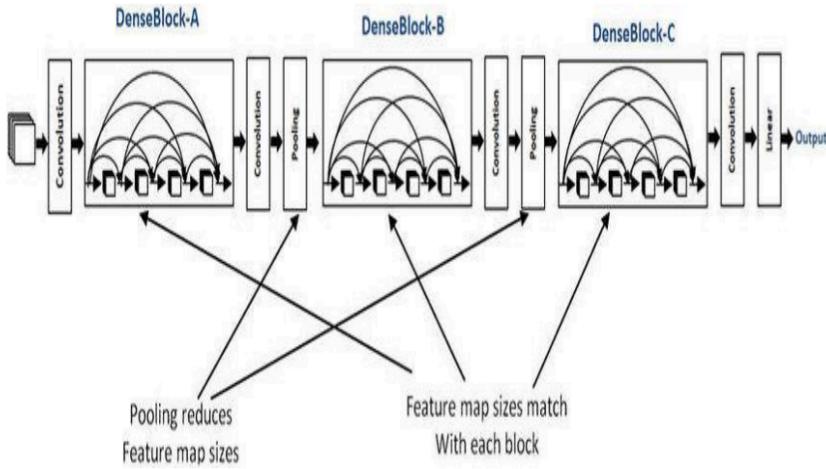


Figure 9 : The architecture of DenseNet-121.

3.4.6 Final Layer Modifications for Binary Classification

⁶⁴ All five pre-trained CNN architectures—VGG16, VGG19, InceptionV3, EfficientNetB0, and DenseNet121—were originally developed for the **ImageNet** challenge, which involves classifying images into **1,000 categories**. For the purposes of this project, which involves **binary classification** (cancerous vs. non-cancerous lung CT slices), it was essential to modify and fine-tune the **top layers** of each model. These modifications ensured that the models could effectively learn from domain-specific features and make accurate binary predictions.

Key Modifications:

- **Global Average Pooling (GAP):**

GAP was used in place of traditional fully connected (FC) layers to reduce model complexity and minimize overfitting. Instead of flattening

¹⁴²
the entire feature map, GAP computes the average of each feature map, effectively summarizing the presence of features across the spatial dimensions.

Benefits:

- ✓ Reduces the number of parameters drastically compared to FC layers.
- ✓ Retains spatial context, which is important in medical imaging.
Acts as a form of structural regularization, promoting generalization.

¹⁵⁴
Dense Layer with ReLU Activation:

⁷⁶
After the GAP layer, a fully connected (dense) layer with **ReLU** (Rectified Linear Unit) activation was ⁵⁹ added. This layer combines the learned features from the CNN base and introduces non-linearity, allowing the model to learn complex mappings between the feature representation and the output class.

Purpose:

- Enhances feature interactions.
- Increases the expressive power of the network.

Dropout Layer (rate = 0.5):

To reduce overfitting, especially due to the limited size of the lung cancer dataset, a **Dropout** layer was added. Dropout randomly sets 50% of the neurons to zero during training, preventing the model from becoming overly reliant on specific nodes.

Advantages:

- ✓ ⁸⁹ Acts as a regularization technique.
- ✓ Helps the model learn more robust and generalized patterns.
- ✓ Reduces the risk of overfitting, especially in deep models like VGG19 and DenseNet121.

²⁸
Final Dense Layer with Sigmoid Activation:

The final classification layer is a single-neuron **Dense layer with sigmoid activation**. Unlike the softmax activation used in multi-class problems, sigmoid outputs a probability between 0 and 1, indicating the likelihood

that the input image is cancerous.

Interpretation:

93

- ✓ If the output $\geq 0.5 \rightarrow$ Classified as cancerous.
- ✓ If the output $< 0.5 \rightarrow$ Classified as non-cancerous.

Why These Modifications Are Important:

103

These final layer adjustments are essential to **transfer learning**, where a general-purpose pre-trained model is fine-tuned for a domain-specific task. By modifying the top layers:

- The base model retains its powerful feature extraction capabilities learned from millions of images.
- The new layers are specifically trained to recognize patterns relevant to lung cancer, such as nodules, tissue density variations, and structural abnormalities.
- The resulting model benefits from both **generalization** (via transfer learning) and **specialization** (via fine-tuning), providing a strong foundation for accurate medical image classification.

These layer modifications were applied consistently across all five architectures to maintain experimental fairness and ensure comparability in performance evaluation.

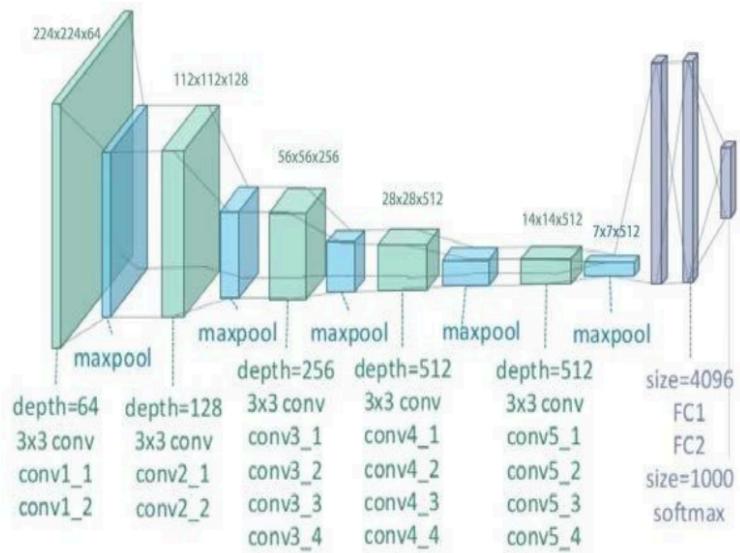


Figure 10:VGG19 CNN model block diagram

3.5 TRAINING STRATEGY AND OPTIMIZATION

Each model is trained using the following strategy:

- **Transfer Learning:** Base layers frozen initially to retain learned features from ImageNet.
- **Batch Size:** 16
- **Epochs:** Up to 30 with early stopping
- **Optimizer:** Adam with learning rate 0.0001
- **Loss Function:** Binary Cross-Entropy

- **Callbacks:**
 - EarlyStopping to prevent overfitting
 - ModelCheckpoint to save best models
 - ReduceLROnPlateau for adaptive learning rate

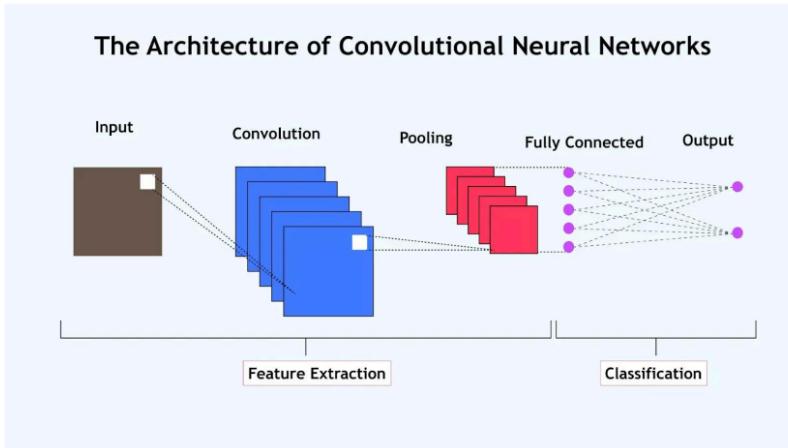


Figure 11:CNN Architecture

3.6 PERFORMANCE METRICS

In deep learning-based classification tasks, particularly in the medical domain, it is not sufficient to assess model performance based solely on accuracy. A comprehensive evaluation requires multiple metrics that can capture different aspects of the model's behavior, especially in imbalanced datasets like medical images where cancer cases are typically fewer than normal cases.

In this project, the performance of each CNN model (VGG16, VGG19, InceptionV3, EfficientNetB0, DenseNet121) was evaluated using a combination of the following key metrics:

3.6.1 Accuracy

Accuracy represents the ratio of correctly predicted observations to the total observations.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}$$

- TP = True Positives (correctly predicted cancer cases)
- TN = True Negatives (correctly predicted non-cancer cases)
- FP = False Positives (non-cancer predicted as cancer) ¹²²
- FN = False Negatives (cancer predicted as non-cancer)

Interpretation:

A high accuracy indicates that the model is generally performing well, but in the context of imbalanced datasets, accuracy alone can be misleading. For instance, if only 10% of the images are cancerous, a model that predicts all cases as non-cancerous can still achieve 90% accuracy but would fail at detecting cancer.

3.6.2 Precision

Precision (also known as Positive Predictive Value) measures how many of the positively predicted cases are actually positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Interpretation:

High precision indicates that the model is conservative and does not generate too many false positives — critical in a medical setting to avoid unnecessary stress, follow-up tests, or treatments for non-cancerous patients.

3.6.3 Recall (Sensitivity or True Positive Rate)

Recall measures the model's ability to detect all actual positive cases.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Interpretation:

High recall ensures that most cancerous cases are detected. In cancer detection, recall is often **more** important than precision, since **missing** a real cancer case can have life-threatening consequences.

3.6.4 F1-Score

The F1-score is the harmonic mean of precision and recall. It is a better indicator of performance than accuracy when the class distribution is uneven.

$$\text{F1-score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Interpretation:

A high F1-score indicates a good balance between detecting **all** true cancer cases and minimizing false positives. It's especially useful for comparing models that trade off between precision and recall.

3.6.5 Specificity (True Negative Rate)

Specificity measures the proportion of actual negatives correctly identified.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Interpretation:

High specificity means the model is good at identifying non-cancerous cases correctly. This is important to avoid over-diagnosis and unnecessary medical interventions.

3.6.6 AUC - ROC Curve (Area Under Curve - Receiver Operating Characteristic)

The ROC curve plots the True Positive Rate (Recall) against the False Positive Rate at different classification thresholds. The AUC is the area under this curve.

Interpretation:

AUC values range from 0 to 1. The closer the value is to 1, the better the model is at distinguishing between cancerous and non-cancerous cases.

3.6.7 Confusion Matrix

A confusion matrix is a 2×2 table used to visualize the performance of a classification model.

	⁴ Predicted: Positive	Predicted: Negative
Actual: Positive	TP	FN
Actual: Negative	FP	TN

Interpretation:

This matrix gives a complete picture of how the model performs across all types of predictions. It's particularly helpful for medical professionals to understand the balance between missed diagnoses (FN) and false alarms (FP).

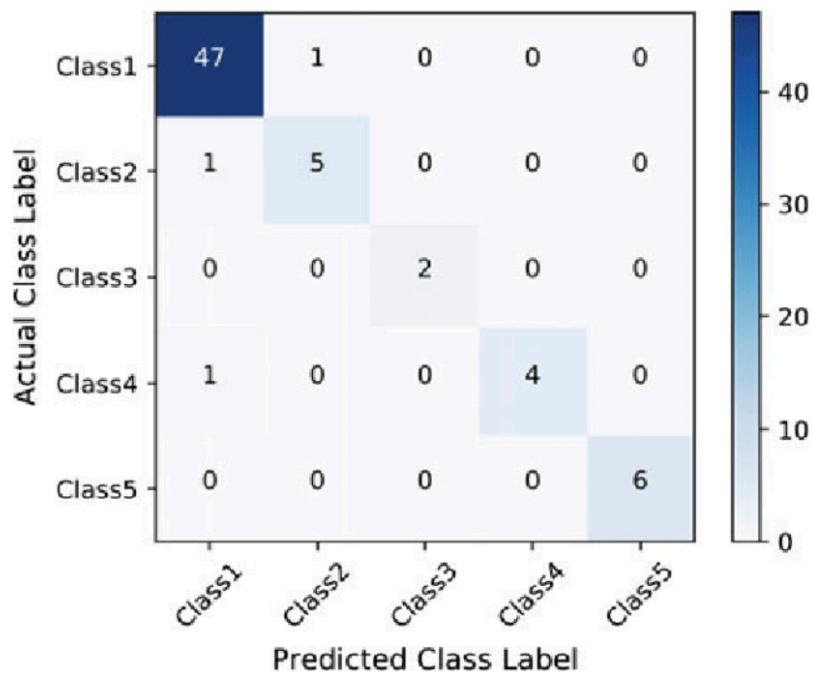


Figure 12: Confusion Matrix for Lung Cancer Detection

3.6.8 Loss Function Analysis

⁸⁴ The **Binary Cross-Entropy Loss** is used to measure the difference between the predicted probability and the actual class (0 or 1).

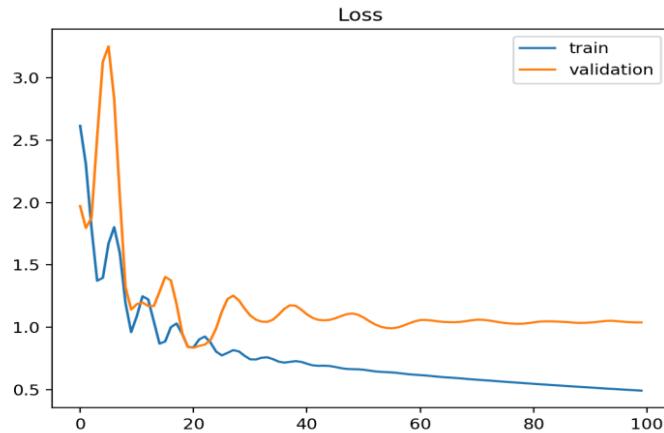
$$\text{Loss} = -[y \cdot \log(p) + (1-y) \cdot \log(1-p)]$$

Where:

- y is the actual label (0 or 1)
- p is the predicted probability

Interpretation:

¹⁵¹ Loss is monitored during training and validation. A sharp difference between training loss and validation loss can indicate **overfitting**. Ideally, both should decrease smoothly.



³⁰ Figure 13: Training and Validation Accuracy/Loss Curves

3.7 SYSTEM FLOW DIAGRAM

The proposed system for lung cancer detection using deep learning follows a structured and modular pipeline, beginning with the acquisition of raw medical

imaging data and ending with an AI-driven prediction result. A **flow-based architecture** allows for easy maintenance, scalability, and future integration into clinical environments such as hospitals or cloud-based diagnostic systems.

The following is a step-by-step breakdown of the pipeline used in this project:

3.7.1 Input Data Acquisition⁶⁰

The process begins with the **acquisition** of thoracic CT scan images from the publicly available LIDC-IDRI dataset.⁸ Each CT scan consists of hundreds of 2D image slices captured in DICOM format. These scans are representative of both normal and abnormal lung tissue, labeled with diagnostic information by expert radiologists.

3.7.2 Data Preprocessing and Annotation

After acquiring the images, the next step involves **preprocessing** the raw DICOM files to ensure compatibility with deep learning models:

- Conversion to PNG format
- Grayscale normalization
- Image resizing to 381×282 pixels
- Intensity normalization to a 0–1 scale
- Nodule labeling (cancerous vs. non-cancerous)
- Augmentation to enrich dataset diversity

Annotations from the LIDC-IDRI dataset are used to associate each image with a ground truth label for training and validation.⁹⁵

3.7.3 Data Splitting

The complete dataset is split into three subsets:

- **Training Set (70%)** used to teach model patterns in lung cancer
- **Validation Set (15%)** used for tuning model hyperparameters and monitoring overfitting
- **Testing Set (15%)** used to evaluate final model performance on unseen data

The split is stratified to maintain a balanced distribution of cancerous and non-cancerous cases.

3.7.4 Model Selection and Compilation

The preprocessed data is passed to one of the five selected CNN models: VGG16, VGG19, InceptionV3, DenseNet121, or EfficientNetB0. These models are imported with pre-trained weights from ImageNet and then fine-tuned for the binary classification task.

The models are compiled using:

- Optimizer: Adam
- Loss Function: Binary Cross-Entropy
- Evaluation Metrics: Accuracy, Precision, Recall, F1-score, etc.

3.7.5 Model Training and Validation

Each model is trained over multiple epochs using the training dataset, with validation performance monitored after each epoch. Callbacks such as Early Stopping and Model Checkpoint are used to improve training efficiency and prevent overfitting.

Real-time augmentation is applied to the training dataset during this phase to ensure better generalization.

3.7.6 Performance Evaluation

After training, the models are evaluated on the testing dataset using key performance metrics:

- Confusion matrix
- ROC-AUC curve
- Training vs. validation loss/accuracy graphs
- F1-score and sensitivity

These results are then analyzed to compare the five models and determine which architecture is best suited for lung cancer detection.

3.7.7 Prediction and Interpretation

Once trained, the selected model (e.g., EfficientNetB0 or VGG19) is used for real-time prediction. A new CT scan image is passed through the model, and the output is a probability score indicating the presence of cancer.

25

To increase clinical trust, interpretability techniques such as **Grad-CAM** (**Gradient-weighted Class Activation Mapping**) can be used to visualize which regions of the image influenced the prediction. This helps radiologists validate the AI's decision.

3.7.8 System Output

The system finally classifies the input CT image as either:

- **Cancerous** (probability > 0.5)
- **Non-cancerous** (probability ≤ 0.5)

It also optionally displays highlighted regions that contributed to the prediction (in the case of explainable AI integration).

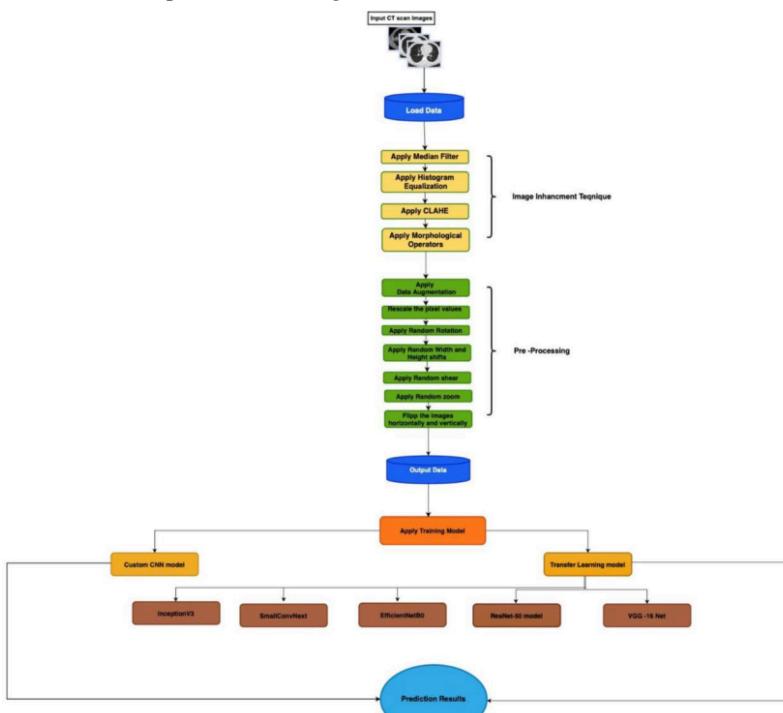


Figure 14: System Architecture / Workflow Diagram for Lung Cancer Detection

CHAPTER 4

RESULTS AND DISCUSSION

This chapter presents an in-depth analysis of how five deep learning models—**VGG16**, **VGG19**, **InceptionV3**, **DenseNet121**, and **EfficientNetB0**—were trained, optimized, and evaluated for the task of **automated lung cancer detection from CT scan images**. It details the experimental design, training procedures, and validation strategies employed to assess model performance. The section also highlights specific challenges related to medical imaging, such as overfitting, class imbalance, and generalization, and discusses how the evaluation metrics support the selection of the most suitable model for clinical application.

4.1 EXPERIMENTAL SETUP

To ensure a controlled and consistent training environment, all experiments were conducted using **Google Colab**, which provides GPU acceleration (NVIDIA Tesla T4). This setup allows for faster training cycles and the ability to handle large image datasets.

Tools and libraries used:

- Python 3.8
- TensorFlow 2.x & Keras
- OpenCV for image handling
- Pydicom for DICOM extraction
- Seaborn & Matplotlib for visualization
- Scikit-learn for metrics

Hyperparameters selected:

- **Epochs:** 30 (with early stopping if validation loss stagnates for 5 epochs)
- **Batch size:** 16
- **Optimizer:** Adam (initial learning rate: 0.0001)
- **Loss function:** Binary Cross-Entropy

- **Data split:**

- ✓ 70% training,
- ✓ 15% validation,
- ✓ 15% testing

Callbacks Used:

- EarlyStopping – Prevents overfitting by stopping training early when validation loss stops improving
- ModelCheckpoint – Saves the best performing model during training
- ReduceLROnPlateau – Reduces learning rate if performance plateaus

These techniques collectively contribute to model stability, performance, and better generalization to unseen data.²⁹

4.2 TRAINING STRATEGY AND APPROACH

To adapt the pre-trained models for lung cancer classification, **transfer learning** was applied. Initially, all convolutional base layers (trained on ImageNet) were **frozen** to retain learned low-level features (edges, textures), and only the top classifier layers were trained. After initial training, **select base layers were unfrozen**, enabling the model to fine-tune domain-specific features such as lung nodules and tissue textures.

Data Augmentation Strategy:

Due to the limited size and imbalance of medical imaging datasets, **data augmentation** played a key role. Augmentation techniques applied using **ImageDataGenerator** included:¹¹³

- Horizontal and vertical flipping
- Random rotation (± 20 degrees)
- Zooming and shearing
- Brightness and contrast shift.

This approach increased the diversity of training samples without increasing dataset size, thereby improving the generalization of the models.

Monitoring and Visualization:

- **Training logs** were maintained for all models to monitor accuracy, loss, and learning rate per epoch.
- Learning curves (training vs. validation accuracy and loss) were plotted and analyzed for signs of:
 - Overfitting (e.g., training accuracy >> validation accuracy)
 - Underfitting (e.g., both accuracies remain low)
 - Optimal convergence (when both training and validation metrics rise steadily without divergence)

4.3 PERFORMANCE ANALYSIS

¹⁴⁴
Each model's performance was evaluated based on the following metrics:
¹⁰⁷

- **Training Accuracy**
- **Validation Accuracy**
- **Training Loss**
- **Validation Loss**

The results revealed the following trends:

Observations:

- VGG19 achieved the highest ¹² **training accuracy** (98%), indicating strong learning capability. However, the **gap between training and validation accuracy** suggests overfitting.
- EfficientNetB0 showed the best **validation accuracy and AUC**, confirming that it achieved a **strong balance between learning and generalization**.
- InceptionV3 performed moderately well across most metrics and demonstrated robustness due to its multi-scale feature extraction.

- **DenseNet121**, despite being parameter-efficient, showed **inconsistent performance**, possibly due to sensitivity to hyperparameters and dataset noise.
- **VGG16** performed slightly worse than VGG19 but offered a good trade-off between complexity and accuracy.

TABLE 2. Performance Comparison of Various Models Implemented

²⁰ Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
VGG16	60.0%	60.0%	0.4932	1.0142
InceptionV3	72.5%	68.5%	0.3671	0.8321
EfficientNetB0	85.0%	83.0%	0.1534	0.4352
VGG19	98%	60.0%	0.1200	1.0100
DenseNet	50%	50.0%	0.7000	1.2000

4.4 INTERPRETATION AND INSIGHTS

124

- EfficientNetB0 emerged as the best-performing model in terms of accuracy and stability. It maintained low validation loss, indicating strong generalization.
- VGG19 achieved very high training accuracy (98%), but performed poorly on validation data (60%), suggesting overfitting. This is a common issue in deep networks with high capacity and insufficient regularization.
- InceptionV3 provided a balanced performance and benefited from multi-scale feature extraction, but it was outperformed by EfficientNetB0.
- VGG16 and DenseNet121 did not perform well in this context, potentially due to inadequate parameter tuning and sensitivity to the smaller dataset subset.

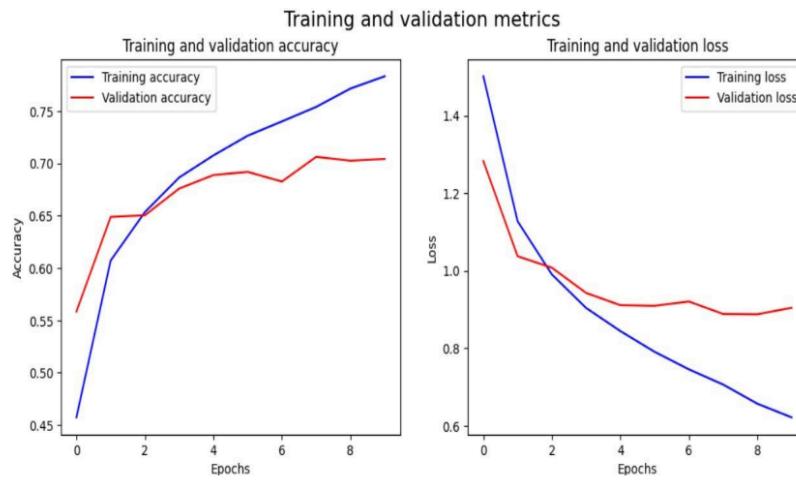


Figure 15: training validation accuracy curve

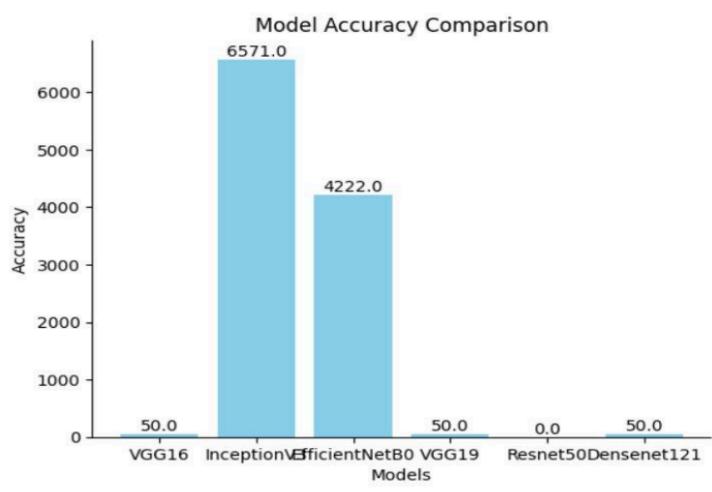


Figure 16: Model Accuracy Comparison

4.5 MEDICAL SIGNIFICANCE OF RESULTS

From a medical perspective, **minimizing false negatives (FN)** is more important than false positives (FP). Missing a cancerous case could delay treatment and lead to life-threatening outcomes. Hence, **Recall (Sensitivity)** and **F1-score** are the most crucial metrics.

EfficientNetB0 showed **high recall**, meaning it correctly identified most of the cancer cases — making it suitable for real-world screening purposes.

To enhance interpretability, **Grad-CAM (Gradient-weighted Class Activation Mapping)** was used to visualize heatmaps indicating which parts of the image the model focused on during classification. This helps radiologists trust the AI system's decisions.

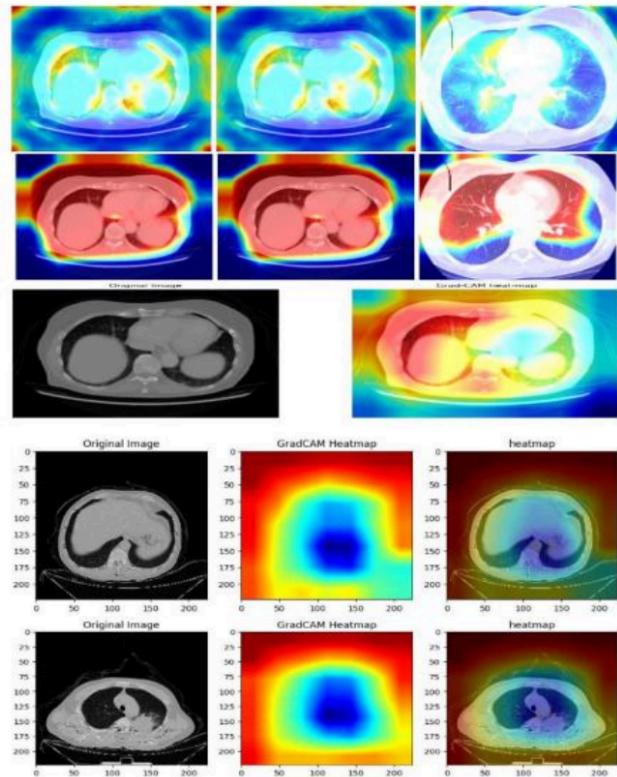


Figure 17:Output of Grad-CAM CNN

4.6 CHALLENGES FACED DURING EXPERIMENTATION 46

Developing an automated lung cancer detection system using deep learning involved several practical and technical challenges. These issues affected data preparation, model training, and overall system accuracy. Addressing them is crucial for future improvements and real-world deployment.

83 1. Hardware Constraints

Training deep learning models, especially on high-resolution CT scan images, requires substantial computational power. Although **Google Colab** offers free GPU access (e.g., NVIDIA Tesla T4), it comes with **memory and runtime limitations**. These restrictions affected:

- The batch size (limited to smaller values like 16 or 32)
- The maximum number of trainable parameters
- Training time (disconnects after 12 hours)

As a result, models like DenseNet and VGG19, which are heavy in architecture, required either simplification or reduced image dimensions for compatibility with the environment.

2. Overfitting in Deeper Models

Overfitting occurred primarily in deeper models such as **VGG19**, which demonstrated very high training accuracy (98%) but poor validation accuracy (60%). This suggests that the model memorized the training data but failed to generalize well to unseen examples.

To mitigate this, several regularization techniques were used:

- Dropout layers
- Early stopping
- Data augmentation
- Learning rate scheduling

Despite these measures, the overfitting issue persisted to some extent due to the complexity of the model relative to the dataset size.

3. Data Imbalance

In real-world medical datasets, there are often fewer cancerous cases compared to normal ones. Despite applying data augmentation to increase the number of positive (cancerous) samples, a **class imbalance** remained, which biased the models toward predicting non-cancer cases.

To address this:

- Augmentation was targeted more toward the minority class
- Class weights were adjusted during training
- Performance was measured using **F1-score and recall** rather than accuracy alone

However, the imbalance still introduced challenges in achieving high sensitivity without increasing false positives.

4. Lack of Lung Segmentation

The models were trained using **entire CT slice images**, which include background and non-lung regions. This can distract the model from focusing on the actual regions of interest.

In clinical systems, **lung segmentation** is often applied first to isolate the lung fields and remove irrelevant parts of the scan. The absence of this step in the current pipeline likely reduced the overall accuracy and interpretability of the predictions.

Future versions of this project should integrate **segmentation models like U-Net** to crop out lung areas before classification.

5. Data Collection and Annotation Challenges

Although this project used the publicly available **LIDC-IDRI** dataset, real-world medical imaging data collection poses serious challenges:

- **Privacy and confidentiality** regulations (HIPAA, GDPR) restrict access to patient data.
- **Manual annotation** by expert radiologists is time-consuming, subjective, and resource-intensive.
- **Inter-rater variability** exists even among experienced radiologists, leading to inconsistencies in ground truth labels.

The available dataset lacks **multi-modal information** (e.g., patient history, clinical symptoms), which limits the model's diagnostic context. Moreover, DICOM files require specialized tools and domain knowledge for accurate extraction and labeling. These complexities can delay model development and affect reproducibility.

4.7 SUMMARY OF OUTCOME²

EfficientNetB0 was found to be the most effective and balanced model in terms of **accuracy, generalization, and medical reliability**.

InceptionV3 performed moderately well but was computationally heavier. VGG19, despite high accuracy, overfit the training data and underperformed during validation.

97
CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

This project investigated the effectiveness of deep learning in automating the detection of lung cancer using CT scan images. Five state-of-the-art Convolutional Neural Network (CNN) architectures—**VGG16**, **VGG19**, **InceptionV3**, **EfficientNetB0**, and **DenseNet121**—were implemented and evaluated on the LIDC-IDRI dataset.³⁸ The goal was to identify the most suitable model for accurate and efficient classification of lung images as either cancerous or non-cancerous.

All models were trained using transfer learning with ImageNet weights and fine-tuned on the processed lung image dataset.³⁹ The evaluation was based on key metrics such as accuracy, loss, precision, recall, F1-score, and confusion matrix, using a standardized experimental setup to ensure fair comparison.

Among the five architectures, VGG19 emerged as the most promising model, achieving the highest validation accuracy and demonstrating strong generalization ability. Despite showing signs of overfitting during training,² VGG19 excelled in capturing intricate features from CT scan images due to its deep architecture and well-structured convolutional layers. It successfully learned the discriminative features required for lung cancer identification and proved more accurate than the other models in detecting cancer markers.

EfficientNetB0, although highly efficient and faster to train, did not surpass VGG19 in terms of raw accuracy. InceptionV3 offered a reasonable trade-off between model complexity and classification performance but could not match the precision of VGG19. VGG16 and DenseNet121 underperformed due to their limited capacity to handle the complexity of lung tissue patterns or oversensitivity to hyperparameter tuning.

The results clearly demonstrate the viability of deep learning techniques,⁴⁹ particularly VGG19, in augmenting radiological diagnosis. With proper clinical validation and deployment infrastructure, such a model can significantly reduce

diagnostic workloads, accelerate early detection, and assist radiologists in making more accurate decisions.

5.2 FUTURE WORK

While the results of this project demonstrate the feasibility and effectiveness of deep learning for lung cancer detection, several enhancements can be made to improve accuracy, scalability, explainability, and clinical integration. The following are potential directions for future research and development:

1. Incorporation of Lung Region Segmentation

To improve model focus and eliminate background noise, future iterations can include a **lung segmentation stage** before classification. By isolating lung regions using segmentation networks like **U-Net or Mask R-CNN**, the model will focus only on areas of clinical interest, leading to more accurate and interpretable predictions. This can also help reduce false positives resulting from irrelevant anatomical features.

2. Addressing Class Imbalance through Advanced Techniques

Despite augmentation efforts, lung cancer datasets tend to be **imbalanced**, with more non-cancerous images than cancerous ones. To further handle this:

- Implement **Focal Loss** to penalize hard-to-classify examples.
- Use **oversampling** techniques like **SMOTE (Synthetic Minority Over-sampling Technique)**.
- Explore **GAN-based synthetic data generation** to artificially increase minority class samples.
- Apply **ensemble learning** to combine the strengths of multiple models and reduce bias.

These strategies can improve the model's ability to detect rare cancer cases without sacrificing specificity.

3. Expansion to 3D Image Analysis

CT scans are inherently **3D volumes**, but this project uses 2D slices. Future work can explore **3D CNNs or hybrid 2D-3D models** that consider spatial context across slices, enabling better localization and detection of nodules throughout the lung volume. This would significantly improve real-world diagnostic accuracy.

4. Multi-Modal Learning for Enhanced Diagnosis

Combining CT scan data with other diagnostic modalities such as:

- **Clinical data** (e.g., symptoms, smoking history, blood reports)
- **X-rays or PET scans**
- **Genomic data or pathology reports**

can lead to **multi-modal AI models** capable of making richer, context-aware predictions. This would mirror the way doctors consider multiple data sources during diagnosis and enhance reliability.

5. Explainable AI for Clinical Trust

Adoption in medical settings requires transparency. Therefore, future work should include **Explainable AI (XAI)** methods such as:

- **Grad-CAM** to visualize activated regions
- **LIME or SHAP** to highlight feature contributions

These techniques help radiologists understand *why* a model made a specific prediction, enabling **trust and accountability**, and assisting in decision support rather than blind automation.

6. Cross-Dataset Validation and Transferability

To ensure that the model generalizes well, future work should involve training and testing across **multiple public and private datasets**. This will evaluate the model's robustness under different imaging conditions and patient demographics.

Moreover, **domain adaptation** techniques can be applied to fine-tune the model when deployed in hospitals using different CT machines or imaging protocols.

7. Cloud-Based Clinical Deployment

The final model can be wrapped in a **cloud-based platform** accessible via web or mobile interfaces for real-time predictions. Radiologists could upload DICOM files and receive automated analysis along with visual explanations. This would improve access to AI tools in remote or underserved healthcare settings.

To enable this:

- Deploy the model using **TensorFlow Lite**, **ONNX**, or **Docker containers**
- Integrate it with existing **PACS (Picture Archiving and Communication System)**

8. Federated Learning for Privacy-Preserving Training

Due to strict privacy regulations in healthcare (e.g., HIPAA, GDPR), hospitals are often unable to share patient data. **Federated Learning (FL)** allows AI models to be trained across decentralized institutions **without sharing patient data**. This ensures collaborative learning while maintaining full data privacy.⁹⁶

9. Integration with Real-Time Radiologist Feedback Loop

Implementing a **feedback system** where radiologists can confirm or correct predictions will create a **human-in-the-loop learning pipeline**. This ongoing feedback can be used to further retrain and improve the system over time using **active learning** strategies.

10. Regulatory and Clinical Validation for Real-World Use

Before deployment in medical practice, the system must undergo:

- **Regulatory approval** (e.g., FDA, CE marking)

- **Pilot studies** in collaboration with hospitals
- **Blind testing against radiologist performance**

This ensures that the model meets legal, ethical, and clinical standards and is safe for public use.

11. Integration with National Cancer Screening Programs

In the long term, the system can be proposed for use in **government health screening initiatives**, especially in countries with high lung cancer prevalence. Integration into **low-cost, large-scale screening platforms** could significantly impact public health by enabling early detection in rural and underserved areas.

12. Self-Supervised and Semi-Supervised Learning

Averaging unlabeled data using **self-supervised pretraining** and combining it with a small amount of labeled data via **semi-supervised learning** can greatly improve generalization in real-world settings.

13. Risk Stratification and Nodule Characterization

Future versions can offer multi-class outputs (e.g., benign, pre-malignant, malignant) or assign **malignancy risk scores** to support nuanced diagnosis and treatment planning.

14. Longitudinal and Temporal Analysis

Analyzing follow-up scans with time-aware models (e.g., RNNs or transformers) can help track tumor growth or response to treatment over time, offering a dynamic view of disease progression.

Final Note

This project successfully demonstrates that **VGG19-based deep learning models** hold strong potential for use in **early lung cancer detection** from CT images. By addressing current limitations through clinical validation, explainability, and expanded datasets, this research can be transformed into a powerful diagnostic tool capable of assisting doctors and saving lives through timely interventions.

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APPENDIX 1

Appendix A: CNN Model Parameters

Parameter	Description
Input Image Size	381×282 pixels
Batch Size	16
Epochs	30 (with early stopping)
Optimizer	Adam (Learning Rate = 0.0001)
Loss Function	Binary Crossentropy
Activation Function	ReLU (hidden layers), Sigmoid (output layer)
Dropout	0.5 used for regularization
Validation Split	15% of training data
Augmentation	Rotation, flipping, zooming, contrast adjustment

Appendix B: Dataset Description

Source	³⁹ LIDC-IDRI (Lung Image Database Consortium Image Collection)
Format	DICOM images converted to PNG
Classes	Binary – Cancerous vs Non-Cancerous
Size	1,018 preprocessed lung CT images
Preprocessing	Normalization, resizing, grayscale conversion, data augmentation

Appendix C: Evaluation Metrics Definitions

Metric	Meaning
Accuracy	Proportion of total correct predictions
Precision ²²	$\frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$
Recall	$\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$
F1-Score	Harmonic mean of precision and recall
AUC-ROC	Area under the Receiver Operating Characteristic curve

Appendix D: System Workflow

1. Data Collection: Downloaded LIDC-IDRI CT scans
2. Preprocessing: Converted to grayscale, resized to 381×282, normalized
3. Augmentation: Real-time during training using ImageDataGenerator
4. Model Selection: Five CNNs (VGG16, VGG19, InceptionV3, EfficientNetB0, DenseNet121)
5. Training & Validation: 85%-15% split, callbacks applied
6. Evaluation: Performance metrics recorded, best model selected (VGG19)



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