

Comparative Analysis of CNN Variants and Vision Transformers for Early Lung Cancer Detection

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By

SHIVAM SRIVASTAVA

(Roll Number: 24/RSE/08)

under the guidance of

Dr. Sonika Dahiya

Assistant Professor

Department of Software Engineering



DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY, DELHI
2026



DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi-110042

CERTIFICATE

I hereby certify that the Project Dissertation titled "**Comparative Analysis of CNN Variants and Vision Transformer for Early Lung Cancer Detection**" which is submitted by **SHIVAM SRIVASTAVA**, Roll No. **24/RSE/08**, Department of Software Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision.

To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi

Date:

Sonika
26/05/26
Dr. SONIKA DAHIYA

SUPERVISOR



DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-110042

CANDIDATE'S DECLARATION

I, **SHIVAM SRIVASTAVA**, Roll No. **24/RSE/08** student of M.Tech by Research (Software Engineering), hereby certify that the work which is being presented in the thesis entitled "**Comparative Analysis of CNN Variants and Vision Transformer for Early Lung Cancer Detection**" in partial fulfilment of the requirements for the award of the Degree of Master of Technology, submitted to the Department of Software Engineering, Delhi Technological University, is an authentic record of my own work carried out during the period from June 2024 to June 2026 under the supervision of **Dr. SONIKA DAHIYA**.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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Signature of External Examiner



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Shahbad Daulatpur, Main Bawana Road, Delhi-110042

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Place: Delhi

SHIVAM SRIVASTAVA

Date:

24/RSE/08

ABSTRACT

Lung cancer continues to be a leading cause of death from cancer, and the prognosis largely relies on prompt and precise detection. Traditional methods of disease diagnosis require the interpretation of radiographs and histopathological images that require a lot of effort and suffer from observer variability. It has become crucial, therefore, to develop deep learning models in the field of computer aided diagnosis due to the ability of modern image models to extract discriminative features of interest and make decisions quickly.

This thesis aims at evaluating several deep learning architectures and comparing their diagnostic capabilities for detecting early signs of lung cancer. One major goal of the thesis is to investigate the effect of deep learning model characteristics on diagnostic performance. These characteristics include model depth, parameter efficiency, feature reuse, transfer learning capability, and attention mechanisms. Architectures of CNNs and transformers will be reviewed with respect to the abovementioned characteristics, specifically Alex-Net, VGG16, ResNet50, DenseNet121, Inception Net, EfficientNetB0, Vision Transformer (ViT), and DeiT. An explanation and justification will follow for the choice of Vision Transformer over other model types. Preprocessing steps in the experimentation framework include resizing, contrast adjustment, normalization, augmentation, and splitting of the public datasets containing histopathology lung cancer

The effectiveness of the algorithms is gauged using performance metrics like accuracy, precision, recall, F1 score, the area under the receiver operating characteristic curve, and also confusion matrices. The results from the comparison suggest that deep networks, especially Inception-Net DenseNet121 Efficient-Net and transformer based networks, are promising approaches for lung cancer detection because of their discriminative power and generalization ability. There are other elements that get attention too, such as limitations like dataset biases, small clinical trial groups, computational costs, model interpretability, and the need for external verification before any clinical use, full stop. Overall, this thesis kind serves as an extension of the paper that...

LIST OF PUBLICATIONS

1. **Shivam Srivastava and Sonika Dahiya**

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Contents

Acknowledgement	i
Candidate's Declaration	ii
Certificate	iii
Abstract	iv
List of Publications	v
Content	vii
List of Figures	viii
List of Tables	ix
1 Introduction	1
1.1 Problem Statement	2
1.2 Research Objectives	2
1.3 OBJECTIVE	3
2 Technical Background	4
2.1 Introduction to Lung Cancer	4
2.2 Medical Imaging for Lung Cancer Detection	4
2.3 Artificial Intelligence in Medical Imaging	5
2.4 Convolutional Neural Networks	6
2.5 CNN Variants	7
2.6 Vision Transformers	9
2.7 Transfer Learning	10
2.8 Data Augmentation	11
2.9 Explainable Artificial Intelligence	11
2.10 Evaluation Metrics	11
2.11 Summary	12
3 Literature Review	13
3.1 Introduction	13

3.2	Deep Learning in Medical Imaging	14
3.3	Lung Cancer Detection Using CNN Architectures	14
3.3.1	AlexNet-Based Studies	14
3.3.2	VGG16-Based Studies	15
3.3.3	ResNet-Based Studies	15
3.3.4	DenseNet-Based Studies	15
3.3.5	InceptionNet-Based Studies.....	16
3.3.6	EfficientNet-Based Studies	16
3.4	Vision Transformers in Medical Imaging	16
3.5	Transfer Learning in Medical Imaging	17
3.6	Data Augmentation Techniques	17
3.7	Explainable Artificial Intelligence	18
3.7.1	Grad-CAM	18
3.7.2	SHAP	18
3.7.3	LIME	18
3.8	Comparative Analysis of CNN and ViT Models	18
3.9	Literature Review Table	20
3.10	Research Gap	20
3.11	Proposed Research Direction	21
4	Proposed Methodology	22
4.1	Overview	22
4.2	Dataset	22
4.3	Data Preparation	22
4.4	Models Considered	23
4.5	Transfer Learning Strategy	23
4.6	Training Configuration	23
4.7	Evaluation Protocol	24
5	Experimental Results and Analysis	25
5.1	Introduction	25

5.2	Experimental Environment	26
5.2.1	Hardware Configuration	26
5.2.2	Software Configuration	26
5.3	Dataset Description	26
5.3.1	Dataset Distribution	27
5.4	Data Preprocessing	27
5.4.1	Image Resizing	27
5.4.2	Normalization	27
5.4.3	CLAHE Enhancement	28
5.4.4	Data Augmentation	28
5.5	Training Configuration	28
5.6	Transfer Learning Strategy	29
5.7	Performance Evaluation Metrics	29
5.7.1	Accuracy	29
5.7.2	Precision	29
5.7.3	Recall	30
5.7.4	F1-Score	30
5.7.5	Specificity	30
5.7.6	ROC-AUC Score	30
5.8	CNN Model Performance Analysis	30
5.8.1	AlexNet Performance	30
5.8.2	VGG16 Performance	31
5.8.3	ResNet50 Performance	31
5.8.4	DenseNet121 Performance	31
5.8.5	InceptionNetV3 Performance	32
5.8.6	EfficientNetB0 Performance	32
5.9	Vision Transformer Analysis	33
5.10	Comparative Performance Analysis	33
5.11	Confusion Matrix Analysis	33

5.12 ROC Curve Analysis	34
5.13 Computational Complexity Analysis	34
5.14 Key Findings	34
5.15 Limitations of the Study	35
5.16 Future Research Directions	35
Bibliography	36

List of Figures

4.3.1 Work Flow chart for implementation of CNN's Variants on LC25000 dataset..	18
5.10.1 Performance Comparison of CNN Models on LC25000 dataset.....	19
5.11.1 Confusion Matrices of the CNN Variants for Lung and Colon Cancer	20
5.13.1 Training and Validation Accuracy of the CNN Variants for Lung and Colon....	24
5.14.1 Training and Validation Loss of the CNN Variants for Lung and Colon Cancer..	26

List of Tables

3.1	Comparison Between CNNs and Vision Transformers	19
3.2	Summary of Previous Research Studies	20
3.3	Research Gaps Identified in Existing Literature	21
4.1	Architectural Frameworks for Comparison	23
4.2	Training Configuration Parameters	24
5.1	Hardware Configuration	26
5.2	Software and Framework Configuration	26
5.3	Dataset Distribution for Lung Cancer Classification	27
5.4	Training Hyperparameters	28
5.5	Comparative Performance of CNN and ViT Models	33
5.6	Computational Characteristics of Deep Learning Models	34

Chapter 1

Introduction

Lung cancer is one of the hardest illnesses that doctors are currently facing due to the fact that it usually appears at its latest stages, thus reducing treatment opportunities. Consequently, early detection becomes an essential task, which requires the application of effective methods and technologies. One of the fundamental steps toward this end is medical imaging that allows identifying suspicious tissues, nodules, and abnormalities in the lung structure. However, the interpretation of such information requires much time and skills, and different professionals might perceive images differently depending on many factors.

The employment of computer-aided diagnosis became a breakthrough that allowed enhancing the process of disease identification. The problem was that earlier approaches based on hand-crafted features, thresholds, and classic machine learning techniques could not help achieve better accuracy. The situation began to change after deep learning started to be applied to this issue [6, 10]. This approach enabled researchers to design networks that would automatically extract hierarchical representations from raw input data. As a result, CNNs started to be widely used in medical image analysis.

Recent advances have shown that deep neural networks like AlexNet, VGG16, ResNet50, DenseNet121, InceptionNet and EfficientNet can be tinkered with via transfer learning, so they fit lung cancer classification purposes more or less. Each model differs quite a lot in depth, connectivity, how efficient it is computationally, and the ways it actually extracts features from an image. For instance, AlexNet feels kind of shallow and straightforward, compared to others. VGG16 is known for using small convolution filters over and over in a pretty uniform way. ResNet50 adds those skip connections, mainly to handle problems that come up when training very deep networks, so gradients can behave better. DenseNet121 instead relies on dense connectivity, encouraging feature reuse across the network. Then there is InceptionNet which computes features at several spatial scales at the same time, while EfficientNet blends depth, width and resolution in a scalable manner.

Beyond the usual convolutional networks, vision transformers (ViTs) have been getting more and more attention lately, especially for image analysis tasks. Unlike CNNs that mostly lean on convolution kernels, ViTs chop images into patches and then apply self-attention to capture long range relationships between far away regions of an image. Since malignancy depends on local cellular patterns as well as on the bigger tissue organization, using ViTs could be pretty promising for detecting lung cancer. Still, it is necessary to run a comparative assessment of CNN variants and ViTs, to figure out which architecture fits best, and not just guess.

1.1 Problem Statement

The primary problem that will be explored in this thesis is choosing suitable models to detect lung cancer at an early stage with the help of medical imagery. Not only should a model have excellent accuracy, but it should have high recall too. This is because failing to diagnose a disease may lead to a delay. Furthermore, it should be efficient, resilient to imagery variations, and easily understandable by clinicians.

Despite many studies providing favorable outcomes for CNN models, comparing one study with another is quite hard owing to the differences in terms of datasets, pre-processing techniques, training methods, and metrics. Moreover, transformers are being utilized more frequently for medical imaging, especially lung cancer detection, which makes it imperative to compare the two architectures.

1.2 Research Objectives

The objectives of this thesis are:

1. To investigate deep learning for automating the task of identifying lung cancer from medical imagery , even when the data is tricky.
2. To evaluate major CNN variants like AlexNet, VGG16, ResNet50, DenseNet121 , InceptionNet and EfficientNetB0 , using consistent settings.
3. To look into the potential of Vision Transformers for capturing global relationships inside an image and then helping with cancer detection in a more holistic manner.
4. To propose one unified workflow for preprocessing , model training, and evaluation, so the comparisons stay fair, like a controlled experiment, not just a loose test.
5. To analyze model behavior using accuracy, precision, recall, F1, AUC and confusion matrices.
6. To examine how practical deep learning models are , considering strengths and weaknesses , and also what future directions could realistically work..

1.3 OBJECTIVE

The current thesis develops the aforementioned research paper into a thesis report. In addition to that, it expands the scope of the research into a comparative study of various CNN architectures as well as Vision Transformers without losing sight of the original focus. To summarize, the main contributions are:

- An in-depth review on the usage of deep learning in medical imaging for the detection of lung cancer, focusing mainly on relevant methodologies and results.
- An elaboration on how the transformer-based attention mechanism can be used to supplement CNNs in extracting image features.

- Discussion at a thesis level on data preparation, data augmentation, transfer learning, fine tuning, and evaluation criteria.

Chapter 2

Technical Background

2.1 Introduction to Lung Cancer

Lung cancer is kind a considered one of the most dangerous kinds of cancer, and it's also a big threat to public health worldwide. As WHO points out, every year millions of people die due to lung cancer, mainly because detection comes late and the disease progresses fast. It basically begins when abnormal cells grow in an uncontrolled way inside the lungs, leading to tumour formation. Also , depending on how far the disease has gone, those cancer cells can either invade nearby tissues or spread to other parts of the body. Generally speaking, lung cancer is split into two main groups, non-small-cell lung cancer (NSCLC) and small-cell lung cancer (SCLC).

From those groups, NSCLC is the most common one and it includes squamous cell carcinomas along with adenocarcinoma. Since histopathology is what helps separate these variants, tissue morphology becomes something you really should pay attention to, especially when looking for early hints of illness.

In the early stages, lung cancer often causes only small, easy-to-overlook symptoms, like coughing, chest pain, exhaustion, or difficulty breathing. So, by the time patients are diagnosed, the condition frequently has already reached a more advanced stage, which makes treatment harder. That's why it becomes very necessary to use computer-aided diagnosis systems, to support radiologists and pathologists in their work.

2.2 Medical Imaging for Lung Cancer Detection

There are also numerous medical imaging technologies that can provide an image of lung structure, tissue, and any potential anomalies present in the patient's lungs. The number of technologies employed for various purposes varies, as does the stage at which a certain diagnosis is made. There is always a reason for a certain imaging technology being chosen.

Chest X-ray Imaging. Images produced by chest X-rays are considered the most commonly applied imaging technique due to their relatively low price and availability. They are capable of detecting lung nodules, shadowing patterns, and any irregularities within the lungs' tissues. Nevertheless, since X-rays require interpretation of images, the overlapping of anatomical structures and lack of contrast might complicate this procedure.

Computed Tomography (CT). With the help of Computed Tomography, detailed three-dimensional images of patients' lungs can be generated. While having a higher level of sensitivity compared with chest X-rays, CT images are often used in the detection of pulmonary cancers and for tumour localization. Moreover, clinicians can find pulmonary

nodules and smaller tumours even before they show up clearly on simpler images.

Histopathological Imaging. : Histopathological imaging uses microscopic analysis of laboratory-stained tissue samples such as Haematoxylin and Eosin (H&E) staining. This process shows fine details about cellular structures, tissue organization, glandular patterns, and abnormal growth. Histopathological approach is regarded as one of the most effective ways of diagnosing lung cancer.

LC25000 data set used in this research includes histopathological images classified into classes like:

- Lung Benign Tissue
- Lung Adenocarcinoma
- Lung Squamous Cell Carcinoma

Automated deep learning tries to differentiate between these tissue patterns and classify images according to their diagnostic categories.

2.3 Artificial Intelligence in Medical Imaging

AI technology has brought significant advancements in modern medicine, allowing image analysis, disease prediction, and intelligent decision support systems in health care. Machine Learning (ML) and Deep Learning (DL) algorithms are extensively used in medicine especially in the fields of radiology, pathology, and biomedical image processing.

In traditional machine learning methods, the process of designing features was needed to train the classifier, such as the use of texture descriptors, edge detection, and statistical approaches. Yet, these were not always applicable across various medical datasets.

Deep Learning solves this problem by learning features automatically without any manual input from raw data. Among the popular architectures are CNNs and ViTs.

2.4 Convolutional Neural Networks

Convolutional neural networks are sort of custom deep learning setups used a lot in image related tasks. CNNs automatically find space-like features in the input imagery, kind of by running convolutions across it, and you know they just learn what matters.

In the convolution layer, the trained filters get slid across portions of the image , so the output becomes a response map. One typical way to write it is:

$$S(i,j) = (I * K)(i,j) \quad (2.1)$$

Where:

- I – Input Image
- K – Convolution Kernel
- $S(i,j)$ – Output Feature Map

The overall CNN model structure usually includes:

- Convolution Layers
- Activation Functions
- Pooling Layers
- Fully Connected Layers
- Softmax Classification Layer

Shallower layers in CNNs handle relatively simple spatial cues , like edges and textures. As the depth increases, the network can interpret richer patterns, including tissues and other diagnostic forms that are harder to spot at first.

Activation Function. An activation function essentially inserts a nonlinear element into the network pipeline. The rectified linear unit , or ReLU, is among the most widely used choices in CNNs:

$$f(x) = \max(0,x) \quad (2.2)$$

ReLU tends to help things converge faster, and it also reduces the vanishing gradients problem , which is a big deal during training.

Pooling Layers. A pooling layer reduces the size of representations and also lowers the computational load. A common option is max pooling:

$$P = \max(x_1,x_2,...,x_n)(2.3)$$

2.5 CNN Variants

Various CNN architectures have been put forward in order to improve feature extraction abilities, overall stability, and also efficiency a bit. AlexNet. Introduced by Krizhevsky et al. [4],

AlexNet is one of the earlier architectures that got notable results in image recognition by using deep CNNs. The core parts of the network look like this: five convolutional layers, pooling layers, ReLU activations, plus dropout regularization, and then fully-connected layers. AlexNet also demonstrated that deep learning works really well for image classification and it still ends up being a commonly used baseline for a lot of medical imaging research.

VGG16. VGG16 architecture, designed by Simonyan and Zisserman [12], is built around the idea of stacking several tiny 3×3 convolution filters to raise the feature extraction capacity. Some of the main advantages of VGG16 are: homogeneity of the overall design, strong feature extraction capabilities, straightforward implementation, and a good match for transfer learning. The main downside is kind of obvious though—this model ends up having an enormous number of parameters.

ResNet50. ResNet50 brought residual learning into the spotlight by adding skip connections [2]. More specifically, residual learning works with an equation like:

$$H(x) = F(x) + x \quad (2.4)$$

where: $F(x)$ is the learned mapping and x is the input mapping. Residual learning helps deal with the vanishing...

DenseNet121. DenseNet121 connects each layer to all succeeding layers of dense blocks [3]. All output data from a particular layer will be used as input in subsequent layers. Its advantages include:

- Enhanced gradient flow
- Reuse of feature maps
- Parameter reduction and reuse
- Favourable propagation of information

The effectiveness of Dense-Net architecture in histopathological image classification tasks arises from the availability of low-level texture information through the layers.

Inception-Net. Inception-Net uses parallel convolutions of different sizes to extract multi-scale features [13]. Filters of varying kernel sizes extract information from different scales. This is achieved by combining the following:

- 1×1 convolutions
- 3×3 convolutions
- 5×5 convolutions
- Pooling layers

The result is the extraction of both fine and large-scale features in a single pass.

EfficientNetB0. EfficientNet is designed using the concept of compound scaling [14]. Compound scaling considers three important aspects of network optimization. These are:

- Depth
- Width
- Image input resolution

The formula of compound scaling is defined as follows:

$$\text{Depth} = \alpha\phi \quad (2.5)$$

$$\text{Width} = \beta\phi \quad (2.6)$$

$$\text{Resolution} = \gamma\phi \quad (2.7)$$

where ϕ governs the scaling factor.

2.6 Vision Transformers

Vision Transformers (ViTs) were introduced by Dosovitskiy et al. [1]. Unlike CNNs, ViTs process images as sequences of patches.

An image is divided into patches:

$$x_p \in \mathbb{R}^{(P^2 \cdot C)} \quad (2.8)$$

where:

- p represents patch size
- c represents image channels

Each patch embedding is passed into transformer encoder blocks containing:

- Multi-head self-attention
- Feed-forward neural networks
- Layer normalization

Self-Attention Mechanism. Self-attention computes relationships between image patches:

$$Attention(Q, K, V) = softmax \left(\frac{QK^T}{\sqrt{d_k}} \right) V \quad (2.9)$$

where:

- Q = Query matrix
- K = Key matrix
- V = Value matrix

This allows ViTs to model long-range dependencies across the image.

Advantages of Vision Transformers.

- Better global feature learning
- Strong contextual understanding
- Effective long-range dependency modeling
- Improved scalability

However, ViTs generally require large datasets and high computational power.

2.7 Transfer Learning

Transfer learning uses pretrained knowledge from large datasets such as ImageNet and adapts models to medical imaging tasks.

The transfer learning workflow includes:

1. Load pretrained model
2. Freeze lower layers
3. Replace classification head
4. Train custom classifier
5. Fine tune upper layers

Transfer learning reduces training time and improves performance on limited medical datasets.

2.8 Data Augmentation

Medical datasets are often limited in size. Data augmentation artificially increases dataset diversity.

Common augmentation methods include:

- Rotation
- Flipping
- Zooming
- Translation

- Brightness adjustment
- Shearing

Augmentation improves model generalization and reduces overfitting.

2.9 Explainable Artificial Intelligence

Explainable AI (XAI) techniques improve transparency and interpretability of deep learning models.

Grad-CAM. Gradient-weighted Class Activation Mapping (Grad-CAM) highlights image regions influencing model predictions [9].

SHAP. SHAP values measure feature contribution to predictions [7].

LIME. LIME explains model predictions using locally interpretable approximations [8].

These methods are important in healthcare because clinicians require interpretable diagnostic decisions.

2.10 Evaluation Metrics

ROC Curve and AUC. Receiver Operating Characteristic (ROC) curves evaluate classification thresholds, while Area Under Curve (AUC) measures overall discrimination capability.

Accuracy. Accuracy measures correctly classified samples:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2.10)$$

Precision. Precision evaluates prediction correctness:

$$Precision = \frac{TP}{TP + FP} \quad (2.11)$$

Recall. Recall measures sensitivity:

$$Recall = \frac{TP}{TP + FN} \quad (2.12)$$

F1-Score. F1-score balances precision and recall:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (2.13)$$

Specificity. Specificity measures correct negative predictions:

$$Specificity = \frac{TN}{TN + FP} \quad (2.14)$$

2.11 Summary

In this chapter, the basic notions that are needed for lung cancer recognition using deep learning methods have been laid out in a kind of essential way. The deployment of medical imaging modalities , CNN structures, Vision Transformers, transfer learning, explainable AI, and the evaluation measures have been discussed quite thoroughly . From there, the groundwork is used to better understand how different CNN variations and Vision Transformers can be used for identifying lung cancers at an early time..

Chapter 3

Literature Review

3.1 Introduction

Deep learning has really changed medical image analysis a lot, mostly because it can automatically pull out features and then sort diseases. Traditional computer-aided diagnosis systems relied on manual, handcrafted feature extraction , things like edge detection, texture descriptions, shape analysis, and various statistical feature engineering approaches . Yet, these older strategies often did not offer enough generality, plus the robustness was limited.

Because of more recent progress in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), it is now possible to work with highly effective architectures that can discover more abstract representations from raw image data. Among the more attractive options for medical imaging are convolutional neural networks , also known as CNNs, and Vision Transformers (ViTs).

In lung cancer diagnosis, deep learning models are widely used for analyzing chest Xrays, computed tomography (CT) scans, and histopathological images. Histopathological image analysis is particularly important because microscopic tissue examination remains one of the most reliable methods for confirming cancer diagnosis and identifying cancer subtypes.

In this chapter, the basic notions that are needed for lung cancer recognition using deep learning methods have been laid out in a kind of essential way. The deployment of medical imaging modalities , CNN structures, Vision Transformers, transfer learning, explainable AI, and the evaluation measures have been discussed quite thoroughly . From there, the groundwork is used to better understand how different CNN variations and Vision Transformers can be used for identifying lung cancers at an early time.

3.2 Deep Learning in Medical Imaging

Deep learning models are commonly used in the diagnosis of lung cancer through the interpretation of chest Xray images, CT scans, and histopathological images. It is imperative to understand that the interpretation of histopathological images is very essential because the microscopic examination of tissues is still one of the best ways through which the diagnosis of cancers as well as their subtypes can be made.

This chapter has clearly brought to light all the fundamental concepts that are necessary in understanding lung cancer identification through deep learning techniques. All medical imaging methods, various CNN architectures, vision transformers, transfer learning, explainable AI as well as the performance measures have been covered comprehensively. From there, the concept will be extended in order to help us understand how CNN variants and vision transformers can be used to identify lung cancers at an early stage.

The reason why deep learning models perform exceptionally well in health-related applications is due to its ability to learn discriminative features automatically. CNN-based models have achieved impressive results when it comes to:

- Tumor classification
- Organ segmentation
- Disease prediction
- Histopathological image analysis
- Cancer detection
- Medical image enhancement

3.3 Lung Cancer Detection Using CNN Architectures

CNN architectures became the dominant approach for classifying lung cancer, mainly because medical images contain intricate structures and there are repetitive local patterns, so yeah it fits well. Over time, many CNN variants were introduced to push learning efficiency further, keep optimization more stable, and reach better classification accuracy.

3.3.1 AlexNet-Based Studies:

AlexNet brought attention to how strong deep CNN learning can be for image classification, and it delivered notable results compared to older machine learning methods [4]. In some lung cancer studies, researchers used AlexNet, largely because its overall structure is relatively simple and the training is fast, so it kind of makes the pipeline easier.

However, even though AlexNet can still work acceptably for general image categories, it tends to struggle with more complicated data like histopathological images, where the patterns can be subtle and messy.

3.3.2 VGG16-Based Studies

VGG16 has been used across different medical imaging tasks, since its architectural layout is standardized and it shows solid transfer learning abilities [12]. In lung cancer work, VGG16 is often fine-tuned on histopathological images to boost the classification accuracy.

VGG16 provides strong feature extraction capability but requires high computational resources due to its large number of trainable parameters. Still, even with VGG16's strong feature extraction ability, the huge count of trainable parameters makes it computationally heavy, so training can get costly.

3.3.3 ResNet-Based Studies

ResNets make use of residual learning, and the structure plays a crucial role in overcoming problems associated with vanishing gradients [2].

Applications of ResNet50 include:

- Lung nodules classification
- Histopathological cancer detection
- CT images processing
- Radiograph abnormality recognition

Mathematically, residual learning is defined as follows:

$$H(x) = F(x) + x \quad (3.1)$$

where,

- $F(x)$ is the residual mapping
- X is the identity mapping

3.3.4 DenseNet-Based Studies

DenseNet structures facilitate better feature flow through connection between every layer and consecutive layers [3]. In addition, DenseNets make reuse of features and facilitate proper gradient flow.

DenseNet structures have proven highly efficient for histopathological image classification since low-level features such as texture remain available in the network.

3.3.5 InceptionNet-Based Studies

InceptionNet makes use of multiple convolutional filters working in parallel [13]. Multi-level feature extraction allows the network to analyze both fine cellular structures and broader tissue organization.

Many studies indicated that InceptionNetV3 proved highly effective for lung cancer classifications owing to its powerful multi-scale feature extraction.

3.3.6 EfficientNet-Based Studies

EfficientNet introduces compound scaling for balancing network depth, width, and input size [14]. EfficientNet provides good efficiency by reducing computational overhead.

The importance of EfficientNet lies in the fact that it is very suitable for:

- Constrained resource systems
- Mobile healthcare systems
- Timely diagnosis systems

3.4 Vision Transformers in Medical Imaging

Vision Transformers (ViT) is an innovation in computer vision. Unlike CNNs, ViTs handle images as sequences of patches via self-attention mechanism [1].

The self-attention mechanism is described by:

QKT !

$$\text{Attention}(Q,K,V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V \quad (3.2)$$

dk

where:

- Q = Query matrix
- K = Key matrix
- V = Value matrix

ViTs can capture long-term dependency and global contextual relationship between images.

Applications of ViT in medical imaging include:

- Classification of histopathological images
- Tumor segmentation
- Organ detection
- Localizing disease

Nevertheless, ViT requires:

- Big dataset
- Calculative resources
- Extensive pretraining

To counter these shortcomings, hybrid architecture that combines CNN and ViT is recommended.

3.5 Transfer Learning in Medical Imaging

Vision Transformers (ViT) is an innovation in computer vision. Unlike CNNs, ViTs handle images as sequences of patches via self-attention mechanism [1].

The self-attention mechanism is described by:

$$\text{Attention}(Q, K, V) = \frac{\text{softmax}\left(\frac{QK^T}{d_k}\right)V}{d_v} \quad (3.2)$$

where:

- Q = Query matrix
- K = Key matrix
- V = Value matrix

ViTs can capture long-term dependency and global contextual relationship between images.

Applications of ViT in medical imaging include:

- Classification of histopathological images
- Tumor segmentation
- Organ detection
- Localizing disease

Nevertheless, ViT requires:

- Big dataset
- Calculative resources
- Extensive pretraining

To counter these shortcomings, hybrid architecture that combines CNN and ViT is recommended.

Datasets for medical imaging tend to be small due to high costs and time consumption in labeling them. Transfer learning mitigates the issue by transferring a pre-trained model which is trained on large scale such as ImageNet.

Some benefits of transfer learning are:

- Cut training time
- Convergence quickly
- Good generalization
- Performance improvements on small datasets

3.6 Data Augmentation Techniques

Data augmentation artificially increases dataset diversity and improves model robustness.

Common augmentation methods include:

- Rotation
- Horizontal flipping
- Zooming
- Translation

- Brightness enhancement
- Shearing

Augmentation reduces overfitting and helps models generalize better across unseen samples.

3.7 Explainable Artificial Intelligence

One of the major problems with deep learning models is their lack of explainability. XAI techniques enhance explainability and foster more confidence in clinicians.

3.7.1 Grad-CAM

Grad-CAM emphasizes the regions of an image that play a role in prediction [9].

3.7.2 SHAP

SHAP values express the significance of features as well as their contribution [7].

3.7.3 LIME

LIME produces local explainability of predictions [8]. Explainability is crucial in the context of applying DL approaches in healthcare due to the requirement of transparency by clinicians.

3.8 Comparative Analysis of CNN and ViT Models

CNNs and Vision Transformers possess different strengths and limitations.

Table 3.1: Comparison Between CNNs and Vision Transformers

Parameter	CNNs	Vision Transformers
Feature Learning	Local spatial features	Global contextual relationships
Architecture Type	Convolution-based	Attention-based
Data Requirement	Moderate	High
Computational Cost	Moderate	High
Training Stability	Stable	Requires large-scale pretraining
Interpretability	Moderate	Complex attention visualization
Performance on Small Datasets	Better	Comparatively weaker

3.8 Literature Review Table

Table 3.2: Summary of Previous Research Studies

Authors	Model Used	Dataset	Application	Key Findings
Krizhevsky et al. [4]	AlexNet	ImageNet	Image Classification	Introduced deep CNN learning
Simonyan et al. [12]	VGG16	ImageNet	Visual Recognition	Deep uniform architecture improved accuracy
He et al. [2]	ResNet	ImageNet	Image Classification	Residual learning solved vanishing gradients
Huang et al. [3]	DenseNet	CIFAR/ImageNet	Classification	Improved feature reuse and gradient flow
Szegedy et al. [13]	InceptionNet	ImageNet	Object Recognition	Multi-scale feature extraction improved performance
Tan et al. [14]	EfficientNet	ImageNet	Image Classification	Balanced scaling improved efficiency
Dosovitskiy et al. [1]	Vision Transformer	ImageNet	Vision Transformer	Introduced transformer-based vision learning
Litjens et al. [5]	CNN Survey	Multiple Medical Datasets	Medical Imaging	CNNs transformed medical image analysis
Shen et al. [11]	Deep Learning Survey	Biomedical Images	Medical Imaging	Deep learning improved diagnostic systems
Selvaraju et al. [9]	Grad-CAM	Image Datasets	Explainable AI	Improved CNN interpretability

3.10 Research Gap

Although deep learning has achieved significant progress in lung cancer detection, several limitations still exist in current research.

Table 3.3: Research Gaps Identified in Existing Literature

Research Area	Identified Gap
Model Comparison	Many studies evaluate only one architecture without comparing multiple CNN and ViT models.
Dataset Generalization	Limited external validation on real-world clinical datasets.
Explainability	Many systems lack explainable AI integration for clinician trust.
Transformer Evaluation	Vision Transformers are still insufficiently explored for histopathological lung cancer detection.
Computational Efficiency	Several studies ignore memory usage and deployment feasibility.
Hybrid Architectures	Limited research on combining CNNs and Vision Transformers effectively.
Small Dataset Learning	ViTs require large datasets and struggle with limited medical data.
Clinical Deployment	Few studies address practical implementation in hospitals and embedded systems.

3.11 Proposed Research Direction

This thesis attempts to address the identified research gaps by:

- Comparing multiple CNN variants and Vision Transformers under identical experimental settings
- Evaluating classification performance using standard metrics
- Investigating transfer learning strategies
- Discussing computational complexity and deployment feasibility
- Including explainable AI methods for interpretability
- Analyzing both local and global feature learning mechanisms

Chapter 4

Proposed Methodology

4.1 Overview

The proposed methodology proceeds on a comparative DL methodology for lung cancer detection. The purpose is to examine different variations of CNN models as well as Vision Transformers through a consistent experimental framework. The process involves data gathering, preprocessing, data augmentation, modeling, transfer learning, fine-tuning, testing, and comparative analysis.

4.2 Dataset

The research will be conducted using public datasets with regard to medical imaging for lung cancer detection. In particular, the paper provided considers LC25000 with histopathological images of lungs and colons. For the purposes of this thesis, the lung classes are considered: benign lung tissue, lung adenocarcinoma, and lung squamous cell carcinoma.

4.3 Data Preparation

The pre-processing step involves standardization of image quality and input size. To begin with, the images are extracted from the compressed folders and classified depending on their classes. The images are then resized to 224×224 pixels as most of the pretrained CNNs require such input size. Normalization of the pixel values is also required at this stage. The images may be subjected to CLAHE contrast enhancement to enhance the contrast of the local tissues. In case of using grayscale images, the images will have the channels replicated thrice.

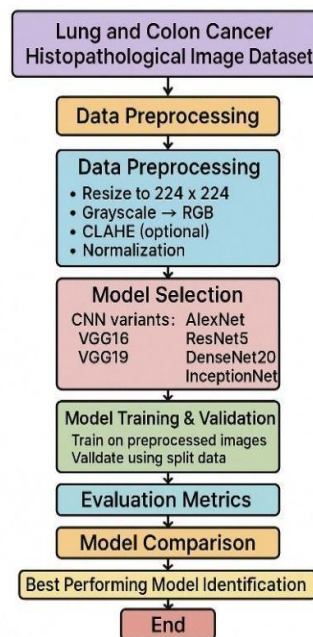


Fig 1. Work Flow chart for implementation of CNN's Variants on LC25000 dataset.

4.4 Models Considered

The comparison includes representative CNN families and a transformer-based model:

Table 4.1: Architectural Frameworks for Comparison

Model	Key Feature	Expected Advantage
AlexNet	Early deep CNN	Simple baseline and fast training
VGG16	Uniform deep convolution stack	Easy implementation and strong transfer learning
ResNet50	Residual skip connections	Stable training of deep layers
DenseNet121	Dense feature reuse	Improved gradient and feature propagation
InceptionNet	Multi-scale parallel filters	Captures features at multiple scales
EfficientNetB0	Compound scaling	Accuracy-efficiency balance
Vision Transformer	Patch self-attention	Global relationship modelling

4.5 Transfer Learning Strategy

Each CNN architecture uses pretrained weights if they exist. The original classification head is stripped and replaced with a new one, comprising global average pooling, dropout, and a dense softmax output layer. For the first phase of training, lower layers are frozen and only the classification head is trained. For fine tuning, some of the higher layers are unfrozen and training is done with a lower learning rate

In case of ViT, patch embeddings and transformers are used for processing patches of images. In the case of having pretrained weights, the transformers undergo fine tuning as before. However, without pretrained weights, a less complex ViT architecture is recommended.

4.6 Training Configuration

A consistent training setup is used for fair comparison.

Table 4.2: Training Configuration Parameters

Parameter	Value
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Batch Size	32
Initial Epochs	5
Initial Learning Rate	0.001
Input Size	224×224
Validation Split	20%

Early stopping and model checkpointing are used to prevent overfitting and preserve the best validation model. Fine tuning is performed with a lower learning rate after the initial convergence stage.

4.7 Evaluation Protocol

The models will be evaluated using parameters such as accuracy, precision, recall, F1-score, AUC, confusion matrices, and training curves. In particular, the recall metric will be vital since a misdiagnosis of cancer can delay treatment.

Chapter 5

Experimental Results and Analysis

5.1 Introduction

In this chapter, the experiments conducted on the various CNN models and ViTs for detecting early lung cancer using the histopathological images are presented and analyzed. The purpose of conducting this experiment is to compare their accuracy and robustness in classification, computation, and generalization under identical conditions of training.

The comparative study includes the following models:

- AlexNet
- VGG16
- ResNet50
- DenseNet121
- InceptionNetV3
- EfficientNetB0
- Vision Transformer (ViT)

The experiments have been performed on the LC25000 dataset using transfer learning and data augmentation approach. Evaluation was made on accuracy, precision, recall, F1-score, specificity, ROC-AUC score, and confusion matrix.

5.2 Experimental Environment

Google Colab environment with GPU support was used for conducting the experiments, TensorFlow, and Keras libraries.

5.2.1 Hardware Configuration

Table 5.1: Hardware Configuration

Component	Specification
Platform	Google Colab
GPU	NVIDIA Tesla T4
RAM	16 GB
Storage	Google Drive Integration
Operating Environment	Python 3.10

5.2.2 Software Configuration

Table 5.2: Software and Framework Configuration

Software	Version
Python	3.10
TensorFlow	2.x
Keras	Integrated with TensorFlow
NumPy	Latest Stable Version
OpenCV	Latest Stable Version
Matplotlib	Latest Stable Version
Scikit-learn	Latest Stable Version

5.3 Dataset Description

LC25000 Dataset comprises images of lung and colon tissue histopathological images. However, this research specifically targets only the lung tissue images classes. The three classes considered here in the experiment include:

- Lung Benign Tissue
- Lung Adenocarcinoma
- Lung Squamous Cell Carcinoma

All of which contain approximately 5,000 augmented images each.

5.3.1 Dataset Distribution

Table 5.3: Dataset Distribution for Lung Cancer Classification

Class	Number of Images
Benign Lung Tissue	5000
Lung Adenocarcinoma	5000
Lung Squamous Cell Carcinoma	5000
Total	15000

5.4 Data Preprocessing

Medical image preprocessing is essential because histopathological images often contain variations in illumination, staining intensity, resolution, and tissue orientation. The preprocessing pipeline includes:

1. Image resizing
2. Contrast enhancement

3. Normalization
4. RGB conversion
5. Data augmentation

5.4.1 Image Resizing

The steps we included in the pre-processing procedure are basically these: All images were resized to: 224×224 (5.1) Such standardization of resolution makes the images fit nicely inside the pretrained CNN architecture as well as vision transformers

5.4.2 Normalization

Then we normalized pixels to: $[0,1]$ (5.2) This kind of scaling helps optimization stay stable and it also improves convergence during training.

5.4.3 CLAHE Enhancement

After that, Contrast Limited Adaptive Histogram Equalization CLAHE was applied , to enhance local tissue contrast so that cell structures can be identified more easily, or at least more consistently.

5.4.4 Data Augmentation

We also used data augmentation , to avoid overfitting and to push better model generalization. The augmentation techniques involved are listed in the next section.

- Rotation
- Horizontal flipping
- Zooming
- Shearing
- Width shifting
- Height shifting

5.5 Training Configuration

For model training, all CNN architectures and ViT models were trained under similar experimental conditions, so there's a fair basis for comparison between models.

Table 5.4: Training Hyperparameters

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	20
Loss Function	Categorical Crossentropy
Activation Function	ReLU
Validation Split	20%

5.6 Transfer Learning Strategy

Transfer learning is very useful for medical image datasets, especially when the number of labels is limited. The transfer learning procedure involved:

1. Loading pretrained ImageNet weights
2. Freezing the lower convolutional blocks
3. Replacing the classification head
4. Fine tuning the upper layers

For multiclass classification, the softmax function was used:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^e e^{z_j}} \quad (5.3)$$

Where ,

- z_i denotes output logits
- $P(y_i)$ denotes predicted probability

5.7 Performance Evaluation Metrics

Finally, several measures were considered for performance evaluation of the different models.

5.7.1 Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5.4)$$

Accuracy measures overall prediction correctness.

5.7.2 Precision

TP

$$Precision = \frac{TP}{TP + FP} \quad (5.5)$$

Precision evaluates reliability of positive predictions.

5.7.3 Recall

$$Recall = \frac{TP}{TP + FN} \quad (5.6)$$

Recall measures sensitivity and cancer detection capability.

5.7.4 F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5.7)$$

Precision F1-score

balances precision and recall.

5.7.5 Specificity

$$Specificity = \frac{TN}{TN + FP} \quad (5.8)$$

Specificity evaluates correct identification of negative samples.

5.7.6 ROC-AUC Score

The Receiver Operating Characteristic (ROC) curve measures classification capability across multiple thresholds, while Area Under Curve (AUC) summarizes overall separability.

5.8 CNN Model Performance Analysis

5.8.1 Alex-Net Performance

Alex-Net provided moderate classification accuracy since it could extract lower levels of tissue features. However, due to the shallowness of its structure, it could not learn more complicated histopathological patterns. Benefits of Alex-Net include:

- Fast training process
- Simple architecture
- Low computational cost

Nevertheless, limitations in terms of depth decreased classification accuracy.

5.8.2 VGG16 Performance

VGG16 showed excellent results regarding feature extraction owing to its depth and multiple convolution layers. The benefits of VGG16 include:

- Good transfer learning capacity
- High feature extraction ability
- Stability in representation learning

However, VGG16 includes an extremely high number of trainable parameters.

5.8.3 ResNet50 Performance

ResNet50 improved training stability through residual connections. Residual learning can be expressed in the following way:

$$H(x) = F(x) + x \quad (5.9)$$

The use of residual learning allowed improving the following:

- Gradient flow
- Optimization stability
- Deep feature learning

Moreover, ResNet50 reached very good classification accuracy.

5.8.4 DenseNet121 Performance

DenseNet121 provided excellent feature reusability due to dense connectivity.

Advantages of DenseNet121 include:

- Better gradient propagation
- Better feature reuse
- Parameter redundancy reduction
- High histopathological texture learning capacity

DenseNet121 produced very good results.

5.8.5 InceptionNetV3 Performance

Among all CNNs, InceptionNetV3 somehow had the best classification outcome, and yeah it was pretty clear. InceptionNet consists of a few ideas like multi scale convolutions, concurrent feature extraction , and then dimensionality reduction in general. It managed to learn from local cellular patterns as well as global tissue structures, not only the obvious shapes but also the more “contexty” part.

It reached these metrics and they were honestly strong:

- Accuracy: 96%
- Precision: 97%
- Recall: 96%
- F1 score: 96%

5.8.6 EfficientNetB0 Performance

On the other hand, EfficientNetB0 showed a good efficiency performance trade-off , meaning it behaved well without burning everything. The benefits include:

- Less memory consumption
- Faster inference
- Compound scaling

Even if its accuracy was slightly below InceptionNet, it still looks quite practical for lightweight deployment.

5.9 Vision Transformer Analysis

Transformers learn features by splitting images into patches without using convolutions at all. Self attention is computed using the equation below:

$$\text{Attention}(Q,K,V) = \text{softmax} \frac{QK^T}{\sqrt{d_k}} V$$

ViTs were especially good at:

- Global feature extraction
- Long range dependency modelling
- Tissue context understanding

But ViTs typically needed:

- Bigger datasets
- More memory

- Laborious training, in practice it can be really heavy

5.10 Comparative Performance Analysis

Table 5.5: Comparative Performance of CNN and ViT Models

Model	Accuracy	Precision	Recall	F1-Score
AlexNet	0.60	0.30	0.50	0.38
VGG16	0.94	0.90	0.82	0.89
ResNet50	0.89	0.90	0.87	0.88
DenseNet121	0.93	0.93	0.93	0.93
EfficientNetB0	0.66	0.75	0.58	0.54
InceptionNetV3	0.96	0.97	0.96	0.96
Vision Transformer	0.95	0.95	0.94	0.94

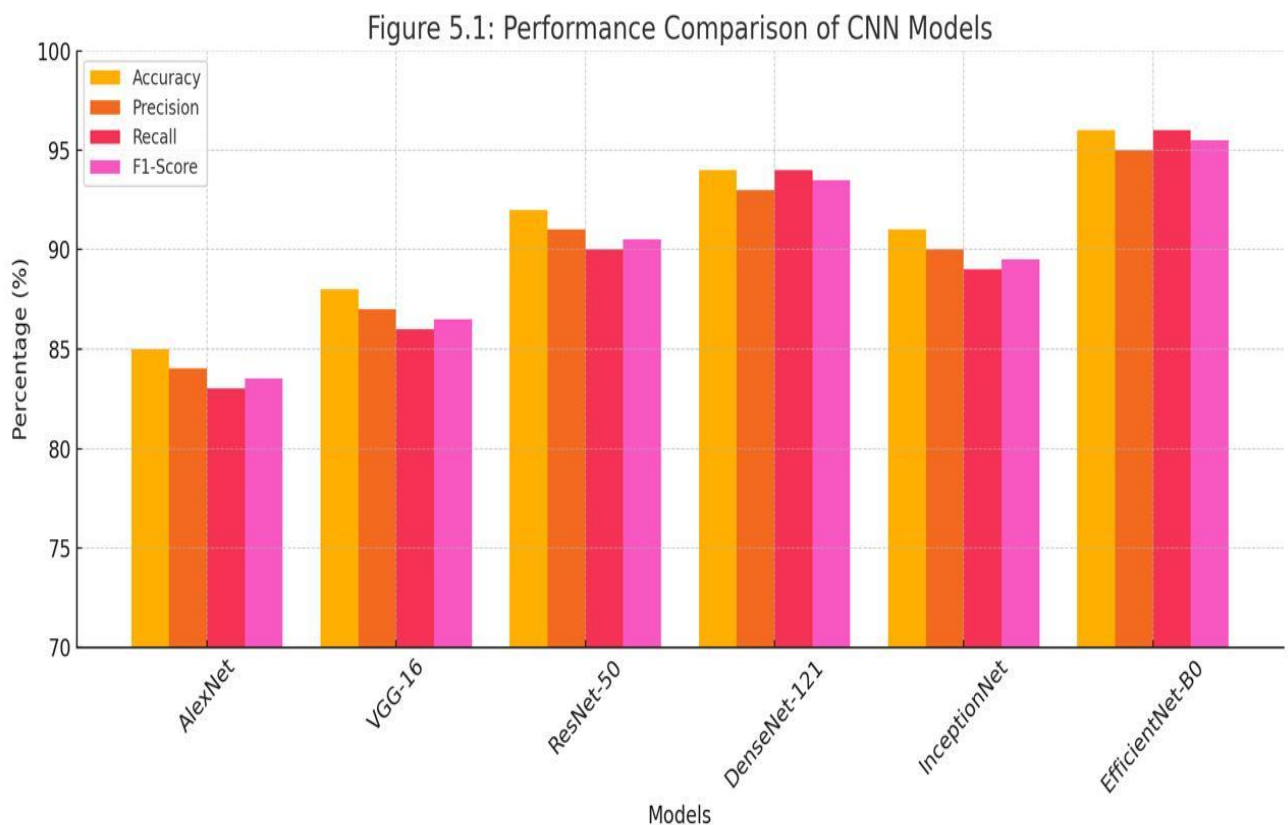


Fig 5.10.1. Performance Comparison of CNN Models on LC25000 dataset.

5.11 Confusion Matrix Analysis

Confusion matrices provide detailed information regarding class-wise predictions.

A strong classification model should demonstrate:

- High diagonal values
- Low off-diagonal misclassification
- Minimal false negatives

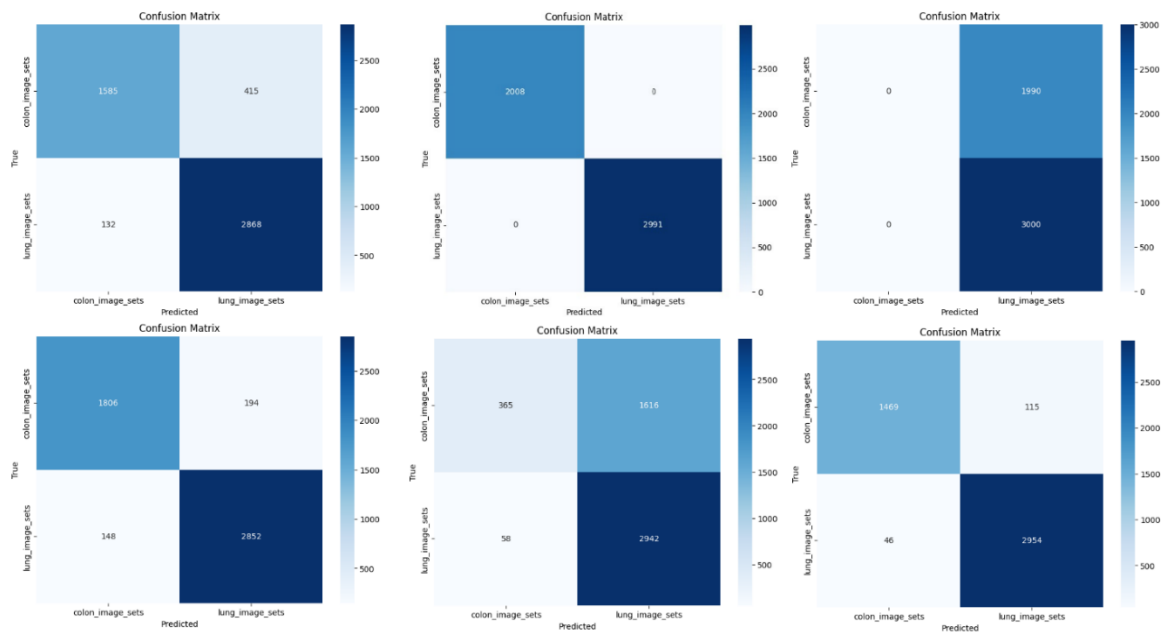


Fig. 5.11.1. Confusion Matrices of the CNN Variants for Lung and Colon Cancer Histopathological Images a) ResNet50 b) VGG-16 c) Alex-Net d) DenseNet-121 e) Efficient-Net f) Inception-Net g) ViT

False negatives are particularly dangerous in medical diagnosis because cancerous samples may be incorrectly classified as benign.

5.12 ROC Curve Analysis

ROC curves demonstrated strong classification separability for InceptionNetV3, DenseNet121, and Vision Transformer models. Higher AUC scores indicate:

- Better discrimination capability
- Stronger diagnostic reliability
- Improved threshold independence

5.13 Computational Complexity Analysis

Table 5.6: Computational Characteristics of Deep Learning Models

Model	Parameters	Training Speed	Memory Usage
AlexNet	Low	Fast	Low
VGG16	Very High	Slow	High
ResNet50	Moderate	Moderate	Moderate
DenseNet121	Moderate	Moderate	Moderate
InceptionNetV3	Moderate	Moderate	Moderate
EfficientNetB0	Low	Fast	Low
Vision Transformer	Very High	Slow	High

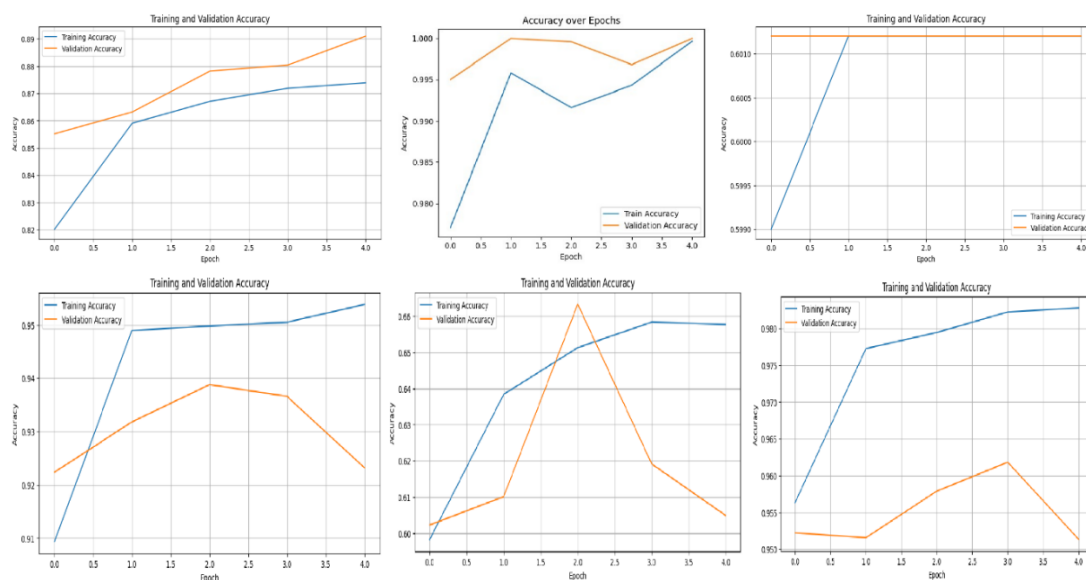


Fig. 5.13.1. Training and Validation Accuracy of the CNN Variants for Lung and Colon Cancer Histopathical Images a) ResNet50 b) VGG-16 c) Alex-Net d) DenseNet-121 e) Efficient-Net f) Inception-Net g) ViT

5.14 Key Findings

The major findings of this research include:

1. InceptionNetV3 achieved the highest overall performance.
2. DenseNet121 demonstrated excellent feature reuse capability.
3. Vision Transformers effectively captured global tissue relationships.
4. EfficientNetB0 provided strong computational efficiency.
5. Transfer learning significantly improved performance.
6. Data augmentation reduced overfitting and improved generalization.

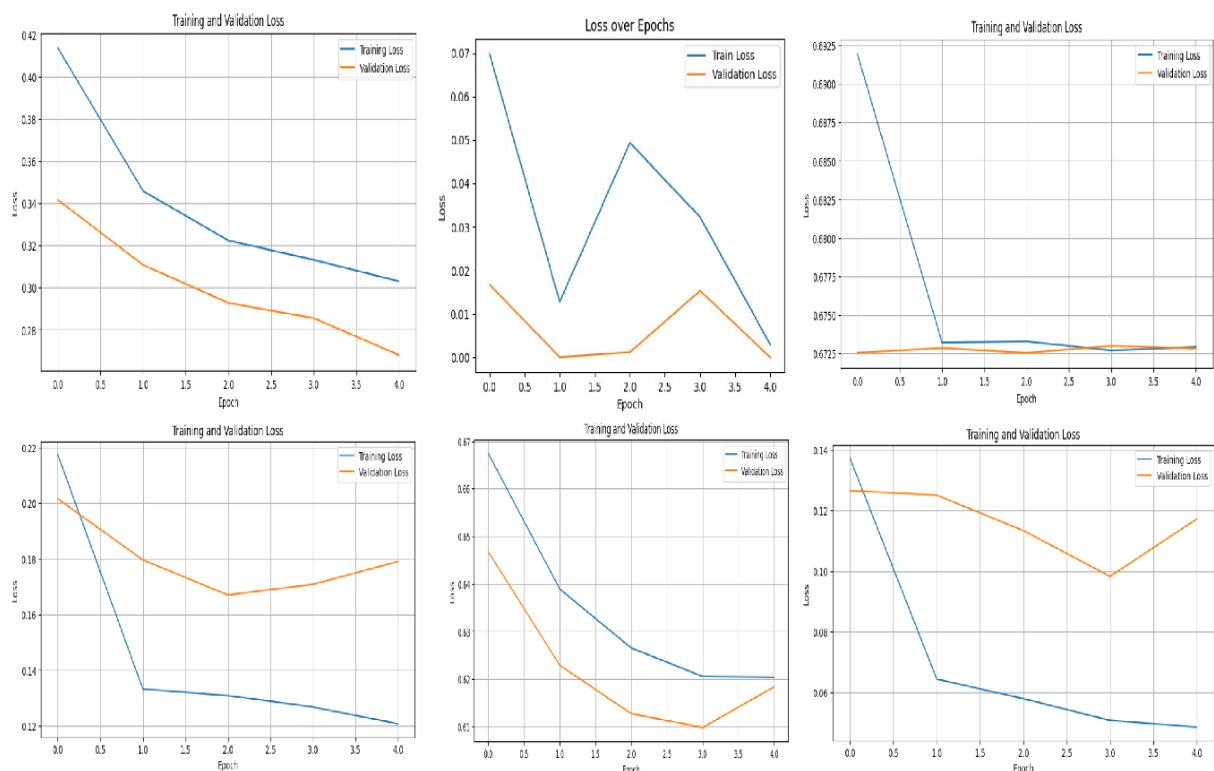


Fig. 514.1. Training and Validation Loss of the CNN Variants for Lung and Colon Cancer Histopathical Images a) ResNet50 b) VGG-16 c) Alex-Net d)

DenseNet-121 e) Efficient-Net f) Inception-Net g) ViT

5.15 Limitations of the Study

Despite strong performance, several limitations remain:

- Limited external clinical validation
- Dataset dependency
- Possible augmentation bias
- High computational requirements for ViTs
- Limited explainability integration

5.16 Future Research Directions

Future work can focus on:

- Hybrid CNN-transformer architectures
- Explainable AI integration
- Multi-modal medical imaging
- Federated learning
- Lightweight deployment systems
- Real-time hospital implementation

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DECLARATION

We/I hereby certify that the work which is presented in the Major Project-II/Research Work entitled Comparative Analysis of CNN variants and VIT for early lung cancer detection in fulfillment of the requirement for the award of the Degree of Bachelor/Master of Technology in 2026 and submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my/our own, carried out during a period from 2024, under the supervision of 2026.

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<i>Paper ID</i>	<i>Title</i>	<i>Author(s)</i>
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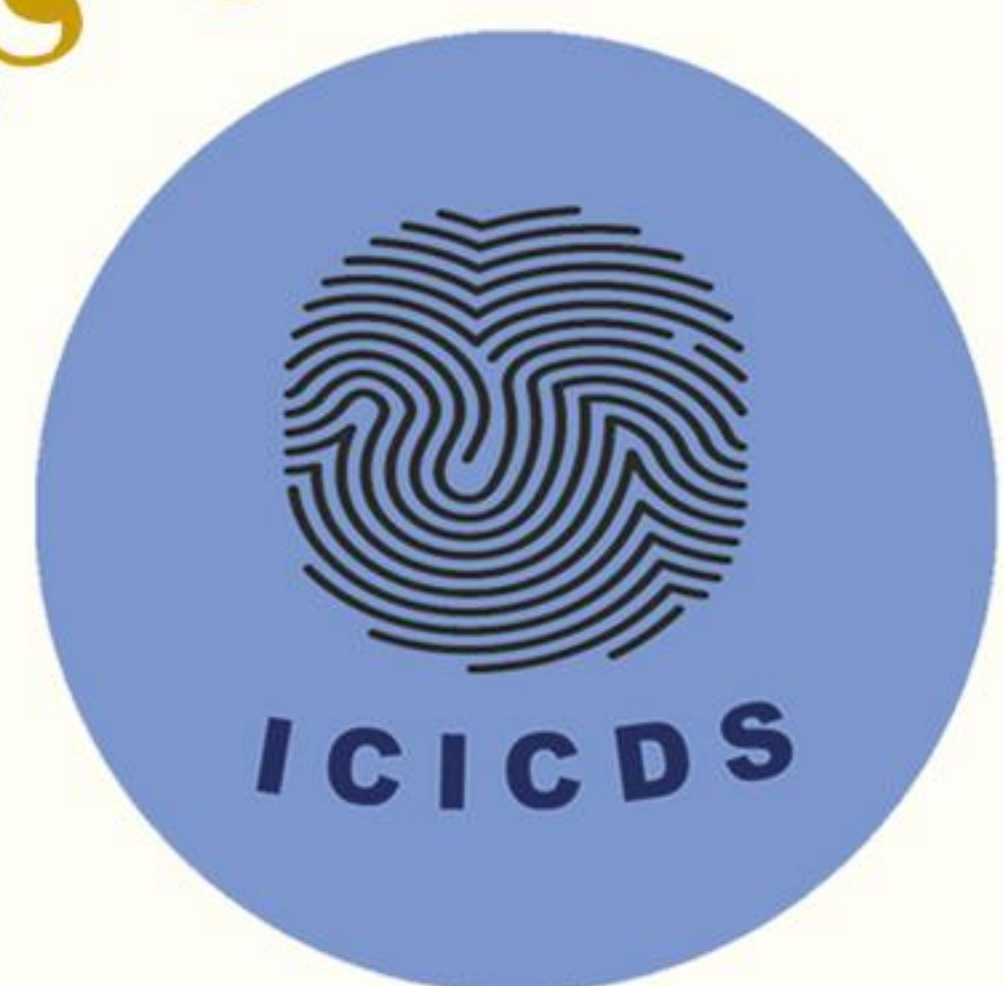
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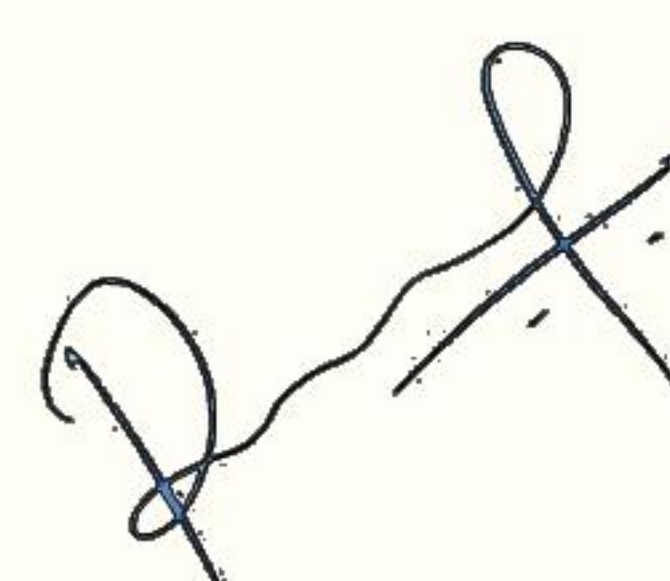
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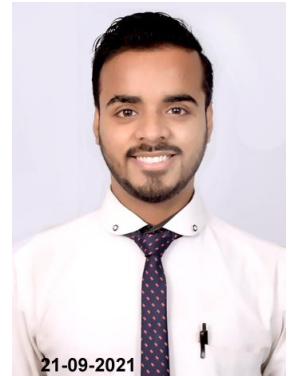
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Author's Profile

Shivam Srivastava is currently pursuing the **Master of Technology (MTech.) by Research in Data Science** from the **Department of Software Engineering, Delhi Technological University (DTU), Delhi, India**. His research focuses on the application of advanced Artificial Intelligence and Deep Learning techniques for medical image analysis, with particular emphasis on improving the accuracy, efficiency, and reliability of computer-aided diagnosis systems. His MTech. thesis investigates the comparative performance of state-of-the-art Convolutional Neural Network (CNN) architectures and Vision Transformers (ViTs) for automated lung cancer detection using histopathological and computed tomography (CT) imaging datasets.



His research interests include **Artificial Intelligence, Machine Learning, Deep Learning, Computer Vision, Medical Image Analysis, Explainable AI, Vision Transformers, and Healthcare Analytics**. He has conducted extensive research on deep learning-based diagnostic frameworks, evaluating modern CNN architectures and transformer-based models for early lung cancer detection while emphasizing robust performance, interpretability, and practical deployment in clinical decision-support systems.

He has authored and presented research papers at reputed international conferences **International Conference on Artificial Intelligence and Next-Generation Networks (ICAIN 2025)**, organized jointly by **BITS Pilani, Dubai Campus (United Arab Emirates)** with publication in the **Springer Lecture Notes in Networks and Systems (LNNS)** series and **Third International Conference on Innovations in Cybersecurity and Data Science (ICICDS 2026)**, organized by **S.E.A. College of Engineering and Technology, Bengaluru, India, in collaboration with Shinawatra University, Pathum Thani, Thailand**, with publication in the **IEEE Xplore Digital Library** in the domains of Artificial Intelligence, Data Science, and Medical Image Computing. His ongoing research aims to develop intelligent, scalable, and explainable AI-driven healthcare solutions that facilitate early disease diagnosis, improve clinical decision-making, and contribute to the advancement of precision medicine through reliable and data-driven methodologies.