

# **Disease Prediction: The Role of Explainable Machine Learning for Lungs Cancer**

**By**

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## **FINAL YEAR DESIGN PROJECT REPORT**

**This Report Presented in Partial Fulfillment of the Requirements for  
the Degree of Bachelor of Science in Computer Science and  
Engineering**

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**January 12, 2025**

## APPROVAL

This Project titled “**Disease Prediction: The Role of Explainable Machine Learning for Lungs Cancer**”, submitted by Md. Shakhawat Hossain, ID No: 203-15-14513 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 12 January, 2025.

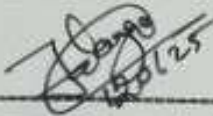
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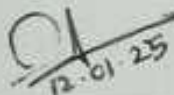
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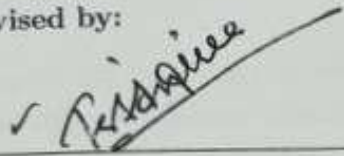
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# DECLARATION

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I hereby declare that this project has been done by me under the supervision of **Mr. Narayan Ranjan Chakraborty**, Associate Professor and Associate Head, Department of Computer Science and Engineering, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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# ABSTRACT

Lung cancer remains the leading cause of cancer-related deaths worldwide, highlighting the urgent need for improved diagnostic and prognostic tools. The identification and prognosis of lung cancer may be improved by recent developments in machine learning. The lack of interpretability in classic machine learning models, however, prevents them from being widely used in clinical settings. Explainable AI (XAI) tools, which provide insights into the decision-making processes of models, overcome this problem. This paper explores the application of explainable machine learning approaches to improve the detection and prediction of lung cancer. Our results demonstrate how explainable models can provide physicians with valuable information while increasing diagnosis accuracy. A potent tool for enhancing the identification and prognosis of lung cancer is machine learning. The analysis of histopathological images for precise cancer classification has shown significant promise thanks to recent developments in deep learning algorithms. Convolutional neural networks (CNNs) have been shown in studies to have the ability to identify between benign and cancerous lung tissue with high accuracy. For example, a research that used CNNs to diagnose lung cancer on digital pathology images had accuracy rates of over 97%. Traditional machine learning models, however, frequently lack interpretability, which makes it challenging for physicians to comprehend the logic behind the predictions despite their remarkable success. This restriction has made it more difficult for AI to be widely used in healthcare contexts. Researchers have resorted to explainable AI (XAI) methods in order to tackle this problem. XAI techniques seek to increase the transparency of AI models by offering insights into their decision-making processes.

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# Chapter 1

## Introduction

### 1.1 Introduction

Lung cancer remains one of the most prevalent and deadly forms of cancer worldwide, accounting for approximately 18% of all cancer-related deaths globally. Improving patient outcomes and raising survival rates need early detection and precise diagnosis. On the other hand, conventional diagnostic techniques might not be sensitive enough to identify lung cancer in its early stages and frequently depend on invasive procedures. Machine learning (ML) has become a potent tool in medical diagnostics in recent years, especially for risk assessment and illness prediction. Large amounts of data, such as clinical details, imaging findings, and molecular profiles, can be analyzed by these methods in order to find trends that can point to the existence of lung cancer.

In the realm of medical diagnostics, explainable machine learning (XAI), a branch of machine learning that focuses on offering insights into how models produce predictions, has attracted a lot of interest. XAI seeks to close the knowledge gap between sophisticated AI systems and humans, enabling medical professionals to accept and comprehend the judgments made by these models. Lastly, research hopes to improve patient outcomes and quality of life by making a substantial contribution to the diagnosis and treatment of lung cancer. We think that the use of XAI methods to medical diagnostics might completely change how medical practitioners approach illness management and prediction, resulting in more precise diagnosis, individualized care plans, and enhanced patient outcomes.

### 1.2 Motivation

Despite their effectiveness, traditional diagnostic techniques frequently struggle with accuracy, rapidity, and interpretability. When working with medical imaging data like CT scans, machine learning—in particular, deep learning algorithms like Convolutional Neural Networks (CNN), ResNet, InceptionNet and DenseNet—has shown great promise in increasing the accuracy of disease prediction. Although machine learning is a promising approach to improving the prediction of lung cancer, the intrinsic intricacy of these models

may prevent their widespread use in clinical settings. The goal of this research is to close the gap between high predicted accuracy and model interpretability by incorporating explainable AI approaches like SHAP (SHapley Additive exPlanations). In order to enable clinicians to make well-informed decisions that ultimately improve patient outcomes and promote confidence in AI-driven healthcare technologies, the objective is to give medical professionals tools that not only provide accurate predictions of lung cancer but also provide an explanation of the reasoning behind these predictions. Additionally, by using XLM, we can create more accurate and dependable lung cancer prediction models, which will improve patient care by enabling earlier detection and better treatment choices.

### 1.3 Objectives

Lung cancer is a silent killer and a significant worldwide health issue. Improving patient outcomes and survival rates requires early diagnosis and detection. Despite their effectiveness, conventional imaging methods such as CT scans have limits when it comes to detecting lung cancer in its early stages. This restriction has a detrimental effect on patients. To improve the sensitivity, specificity and accuracy of lung cancer diagnosis, researchers are investigating deep learning and sophisticated imaging methods. By lowering needless follow-up tests and treatments, these strategies hope to enhance early-stage detection while also perhaps raising survival rates. Healthcare practitioners aim to increase patient survival rates and create more potent instruments for early lung cancer detection by utilizing deep learning and sophisticated imaging.

### 1.4 Methodology

A number of crucial processes are involved in the process of creating an explainable machine learning model for the prediction of lung cancer. Large databases of clinical characteristics, imaging data and genetic information pertaining to patients with lung cancer would first be gathered and preprocessed. To assess the performance of the model, this data would thereafter be divided into training and testing sets. We would use a variety of machine learning algorithms that can produce interpretable feature importance scores including CNN. Explainability might be improved by assigning importance ratings to specific attributes and producing local explanations for forecasts using methods such as SHAP (SHapley Additive exPlanations) values. In order to direct feature selection and model interpretation, we would also take into account domain expertise from medical specialists.

### 1.5 Project Outcome

In this work, explainable machine learning (XLM) initiative has produced important results that improve our comprehension and diagnostic skills. In comparison to conventional machine learning models, the system has shown increased accuracy in forecasting the risk

of lung cancer by utilizing XLM approaches. The creation of a strong XLM model that offers interpretable insights into its decision-making process is one of the project's main results, allowing doctors to comprehend the elements influencing high-risk forecasts. More informed treatment decisions have been made possible by this transparency, which has also increased confidence in AI-driven diagnosis. Furthermore, it has been demonstrated that the system can detect new risk factors and biomarkers linked to lung cancer, which could result in the creation of new screening procedures.

## 1.6 Organization of the Report

- In Chapter 1, There is the portion of Introduction which makes the intro of the project, then comes motivation and objectives which is important to understand why this project. And lastly, Methodology and Project outcome shows us the further go of this work.
- In Chapter 2, There comes with background portion started with introduction and then it's literature review which makes the comparison between existed Work. And it's have Related research, Similar applications, Gap Analysis.
- In Chapter 3, Which started with research methodology and it's overview. There is a;so Proposed Methodolgy, Functional and Nonfunctional Requirements, Context Diagram, Data Flow Diagram Level 1 and UI design. Then it goes through detailed Methodology and Design, Project Plan and Task Allocation.
- In Chapter 4, Here it goes through Environment setup, Testing and Performance which shows the upcoming output. And finally, there comes the result by using different model. And there is also derivation of them.
- In Chapter 5, Now it's have Engineering Standards and Design Challenges Where we have discussion of Software standards, Hardware standards, Communication standards. In another section , there we have Impact on life, Impact on Society & Environment, Ethical aspects, Sustainability Plan. Over this, it's have two most important things which is Project Management and Financial Analysis, Complex Engineering Problems.
- In Chapter 6, It's the ending and first it's have he whole summary of the project. Then it shows the limitation and future work.

# Chapter 2

## Background

### 2.1 Introduction

In today's healthcare system, disease prediction is crucial, especially for catastrophic illnesses like lung cancer. More than 2 million new cases of lung cancer are identified each year, making it one of the most prevalent and deadliest types of cancer in the world. By facilitating earlier detection and more specialized treatment strategies, accurate lung cancer risk and outcome prediction may save thousands of lives annually. Traditional statistical models for disease prediction, however, frequently lack interpretability and are unable to capture intricate relationships between several variables. Explainable machine learning (XAI) approaches are useful in this situation. In order for clinicians to trust and successfully use predictive models in clinical practice, XAI approaches seek to make AI/ML models more transparent and intelligible.

### 2.2 Literature Review

Table 2.1: Summary of Literature Review.

Author(s)	Year	Title	Methodology	Key Findings
I. Ahmad et al.	2024	Early cancer detection using deep learning and medical imaging: A survey [1]	Survey paper review in between 2020 to 2024	Deep learning can improve cancer detection accuracy and efficiency, but requires large datasets, data augmentation, and interpretable models.

Author(s)	Year	Title	Methodology	Key Findings
A. Chen et al.	2024	Development of Lung Cancer Risk Prediction Machine Learning Models for Equitable Learning Health System: Retrospective Study[2]	Electronic health records (EHR)	Lung cancer risk and demonstrated transportability to different EHR and claims data.
Constance Margerie-Mellona et al.	2023	Artificial intelligence: A critical review of applications for lung nodule and lung cancer [3]	Deep Convolutional Neural Network (DCNN), Optimal Deep Neural Network (ODNN)	Gained 96.40% accuracy by using the model to predict accuracy.
A. Ali Shah et al.	2023	Deep learning ensemble 2D CNN approach towards the detection of lung cancer[4]	Ensemble Deep Learning with Convolutional Neural Networks (CNN)	Gained 95% accuracy by using the model to predict accuracy.
Colton Ladbury et al.	2023	Integration of artificial intelligence in lung cancer: Rise of the machine [5]	Lung cancer research using artificial intelligence (AI) and its relevance to the interdisciplinary	AI can personalize lung cancer treatment based on available data..
Hesamoddin Hosseini et al.	2023	Deep Learning Applications for Lung Cancer Diagnosis: A systematic review [6]	Deep Convolutional Neural Network (DCNN), Optimal Deep Neural Network (ODNN)	SMS with SLR findings on lung cancer that use deep learning with varying degrees of sensitivity and accuracy.
Bas H.M. van der Velden et al.	2021	Explainable artificial intelligence (XAI) in deep learning-based medical image analysis [7]	Artificial intelligence (XAI) techniques in deep learning-based medical image analysis	the importance of XAI strategies in improving the transparency and reliability of deep learning algorithms used to analyze medical images.

Author(s)	Year	Title	Methodology	Key Findings
Mohammad A Thanoon et al.	2021	A Review of Deep Learning Techniques for Lung Cancer Screening and Diagnosis Based on CT Images [8]	CT scans for the diagnosis and screening of lung cancer. It emphasizes two primary approaches: segmentation and classification.	Can improve lung cancer screening and diagnosis accuracy using CT images when we have large scale data.
P. Mohamed Shakeel et al.	2019	Lung cancer detection from CT image using improved profuse clustering and deep learning instantaneously trained neural networks [9]	CT images that combines improved profuse clustering (IPC) and deep learning with instantaneously trained neural networks (DLITNN)	Obtained a sensitivity of 94.2% and a specificity of 95.6% in the detection and classification of lung nodules, indicating great accuracy. The study illustrates how well IPC and DLITNN work together.
Wafaa Alakwaa et al.	2017	Lung Cancer Detection and Classification with 3D Convolutional Neural Network (3D-CNN) [10]	CNN	Obtained a 86% in the detection and classification of lung cancer.
Hiram Madero Orozco et al.	2015	Automated system for lung nodules classification based on wavelet feature descriptor and support vector machine [11]	Support Vector Machine(SVM)	Got 82% accuracy on the dependency of the model.

### 2.2.1 Similar Applications

Here is some applications of explainable machine learning in medical diagnostics include:

1. Breast cancer diagnosis: Using methods such as LIME and SHAP values, machine learning models that predict breast cancer from clinical data and mammography pictures are interpreted. [12]
2. Risk assessment for cardiovascular disease: Explainable AI is used to clarify how models use clinical variables such as blood pressure and cholesterol levels to forecast the likelihood of a heart attack.
3. Mental health disorder diagnosis: Using methods such as feature significance, interpretable models are developed to diagnose anxiety and depression from electronic health information.
4. Predicting readmissions: Explainable machine learning is used to determine the main clinical factors that influence hospital readmission risk for patients with heart failure and other illnesses. [13]
5. Medical imaging analysis: Deep learning models are interpreted using methods like CAM and Grad-CAM to identify anomalies in ultrasounds, CT scans.

These applications aim to improve model trustworthiness by providing insights into how AI systems make predictions and decisions in healthcare settings.

### 2.2.2 Related Research

From the first, Ahmad et al. reviewed the application of deep learning in early cancer detection using medical imaging, highlighting its potential to improve accuracy and efficiency while emphasizing the need for large datasets, data augmentation, and interpretable models. Constance de Margerie-Mellona et al. explored the use of deep convolutional neural networks and optimal deep neural networks for lung cancer detection and have a better accuracy. Similarly, A. Ali Shah et al. proposed an ensemble deep learning approach using convolutional neural networks for lung cancer detection with a good accuracy. Colton Ladbury et al. discussed AI integration in lung cancer research, emphasizing personalized treatment based on patient-specific data. Hesamoddin Hosseini et al. conducted a systematic review on deep learning applications for lung cancer diagnosis, analyzing studies using DCNNs and ODNNs, noting varying degrees of sensitivity and accuracy. Bas H.M. van der Velden et al. explored the role of explainable AI techniques in deep learning-based medical image analysis, stressing the importance of transparent and reliable models for better clinical decision-making. Mohammad A Thanoon et al. reviewed deep learning techniques for lung cancer screening using CT images, focusing on segmentation and classification approaches, which could be enhanced by large-scale datasets. P. Mohamed Shakeel et al. proposed a combination of improved profuse clustering and deep learning

with instantaneously trained neural networks for lung cancer detection from CT images, achieving high sensitivity and specificity. Lastly, Wafaa Alakwaa et al. explored the use of 3D convolutional neural networks for lung cancer detection by achieving a better accuracy.

## 2.3 Gap Analysis

Here we have focused on gap analysis from different work-

- Absence of uniform assessment criteria for XAI approaches, which makes comparing the effectiveness of various models and approaches challenging.[14]
- Although XAI techniques can shed light on model projections, attention must be paid to how applicable these insights are in clinical settings.
- Pay attention to model accuracy. The creation of reliable and understandable XAI methods that can offer significant insights into model choices should be the top priority of future research.[15]
- This study, which mostly concentrated on conventional ML models, obtained good accuracy.[12]

## 2.4 Summary

From this part, there is over 2 million new cases of lung cancer are reported worldwide each year, making it a serious public health concern. Survival rates can be considerably raised with precise early detection and targeted treatment plans. Explainable machine learning (XAI) techniques are useful in this situation because traditional statistical models are difficult to grasp and cannot adequately capture intricate correlations between variables. In order for physicians to trust and successfully use predictive models in clinical practice, XAI techniques seek to make AI/ML models more transparent and understandable. A literature review reveals various studies employing deep learning models for lung cancer detection, including works by Ahmad et al., Constance de Margerie-Mellona et al., A. Ali Shah et al., Colton Ladbury et al., Hesamoddin Hosseini et al., Bas H.M. van der Velden et al., Mohammad A Thanoon et al., P. Mohamed Shakeel et al., and Wafaa Alakwaa et al. These studies demonstrate the effectiveness of models like ResNet50, EfficientNetB7, VGG16, InceptionV3, MobileNetV2, and DenseNet121 in lung cancer prediction. The study also emphasizes how crucial XAI methods like SHAP are to model interpretability. Notwithstanding the encouraging outcomes of these models, there are still unmet needs in the field, such as the requirement for consistent evaluation standards for XAI methodologies and additional study into developing trustworthy and intelligible XAI techniques

that provide important insights into model choices. Depending on the model and technique, the studies show varied degrees of accuracy, ranging from 86% to 96.40%. All things considered, these results show how deep learning and XAI methods can enhance lung cancer detection and diagnosis while pointing out areas that require more study and advancement.

# Chapter 3

## Research Methodology

### 3.1 Methodology

#### 3.1.1 Overview

In order to improve lung cancer prediction models, we have concentrated on convolutional neural network (CNN) architectures in this research project, such as VGG16, ResNet50, ResNet101, ResNet152, InceptionNetV3, DenseNet121 and DenseNet169. The goal of these deep learning methods is to improve the precision and comprehensibility of systems for diagnosing lung cancer. Furthermore, these models incorporate explainable AI methods like SHAP (SHapley Additive exPlanations) to enhance model interpretability and offer insights into feature contributions.

#### 3.1.2 Proposed Methodology

This study uses a number of successive procedures to create an image classification system that is both accurate and comprehensible. The first step is the dataset annotation phase, which entails methodically classifying the dataset's photos to make sure they are appropriate for supervised learning tasks. A pre-processing phase is used after annotation to improve the data's consistency and quality. There is also augmentation phase according to work such as rotation, crop, horizontal flip etc. In order to boost the diversity of the training data, this comprises processes like shrinking photos to standard dimensions, normalization to guarantee constant pixel value ranges and data augmentation techniques like flipping, rotating or scaling. After that, the dataset is separated into two subsets: testing images, which are used to assess how well the trained models perform on unobserved data and training images, which are used to train machine learning models. Advanced architectures such as Convolutional Neural Network (CNN), VGG16, ResNet50, ResNet101, ResNet152, InceptionNetV3, DenseNet121 and DenseNet169 are used to train deep learning models in the following stage. These architectures were selected due to their widespread use in picture classification problems and their shown ability to extract intricate characteristics from image data. Following training, the models' accuracy and

robustness are assessed by how well they can classify the test photos. SHAP (SHapley Additive exPlanations), an explainability tool that offers insights into the contributions of particular attributes to the model's predictions, is used to better evaluate the classification findings. By showing how the models make their judgments, SHAP improves transparency and increases the system's interpretability and reliability. This methodology guarantees a thorough approach to picture classification by integrating cutting-edge preprocessing techniques, cutting-edge deep learning models and strong interpretability frameworks, producing accurate results while preserving explainability. Last thing in overall, there is 60% of the data is for training, 20% of the data is for testing and 20% for the validation.

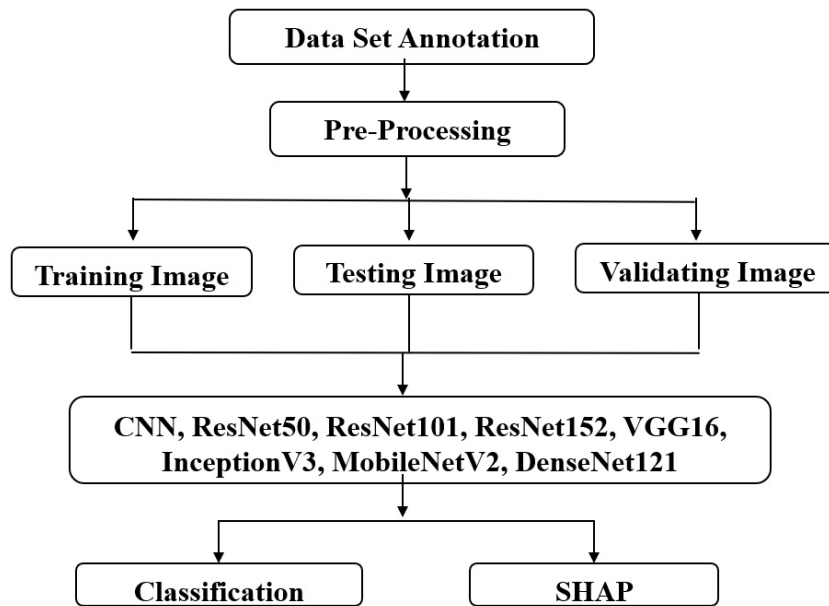


Figure 3.1: Proposed Methodology

### 3.1.3 Functional and Nonfunctional Requirements

Definition of both functional and non-functional requirements is essential while working with a system in order to guarantee that the end product satisfies user expectations and demands.

#### Functional Requirement:

1. Ingestion of data and preprocessing.
2. Training and assessing models (Convolutional Neural Network (CNN), VGG16, ResNet50, ResNet101, ResNet152, InceptionNetV3, DenseNet121 and DenseNet169).
3. Predictive and categorization models.
4. Analysis of feature importance with SHAP.

5. Interface for entering patient information and seeing forecasts.

**NonFunctional Requirement:**

1. High sensitivity and accuracy.
2. Prediction in real-time or almost real-time.
3. Resilience to missing data and noise.
4. The ability to scale to accommodate big datasets.
5. Explainability of SHAP-based model decisions.
6. Interface that is easy to use.
7. Patient data security and privacy.
8. System upgradeability and maintainability.

### 3.1.4 Context Diagram

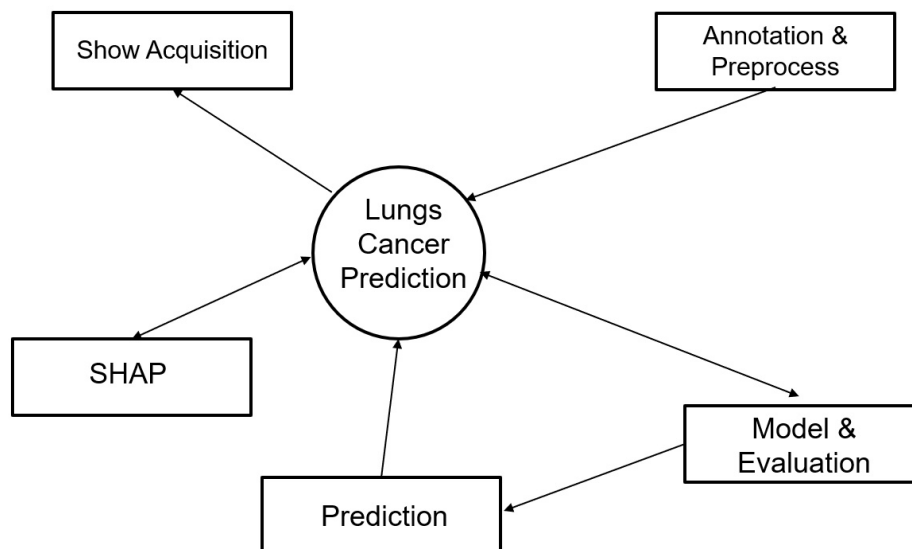


Figure 3.2: Context Diagram

For the context diagram-

**External Entities:**

Healthcare Providers: The system's main users, who supply patient data and may also get predictions.

Data sources include clinics, hospitals and research facilities that provide patient data and medical pictures.

**System Functions:**

**Data Acquisition and Annotation:** Accurate labeling for training is done after collecting medical images (such as CT scans) and related patient data.

Data preprocessing includes image scaling, normalization and augmentation in order to get the data ready for model training.

Model training is the process of using different deep learning models (such as CNN, ResNet variations etc.) to identify trends and characteristics in the training data.

**Model Testing and Evaluation:** Applying suitable measures (accuracy, precision, recall and F1-score) to evaluate the model's performance on unknown data.

**Explainability Analysis (SHAP):** Using SHAP to decipher model predictions and pinpoint important variables impacting the result.

**Prediction and Visualization:** Making predictions based on fresh patient data and displaying the findings to aid with comprehension.

**Data Flows:**

Patient data is sent to the system for analysis from data sources and healthcare providers.

**Predictions:** Produced by the system and sent to medical professionals.

Model parameters are those that the system learns during training and uses to make predictions in the future.

Clinical decision-making is aided by the explanation insights that SHAP analysis provides.

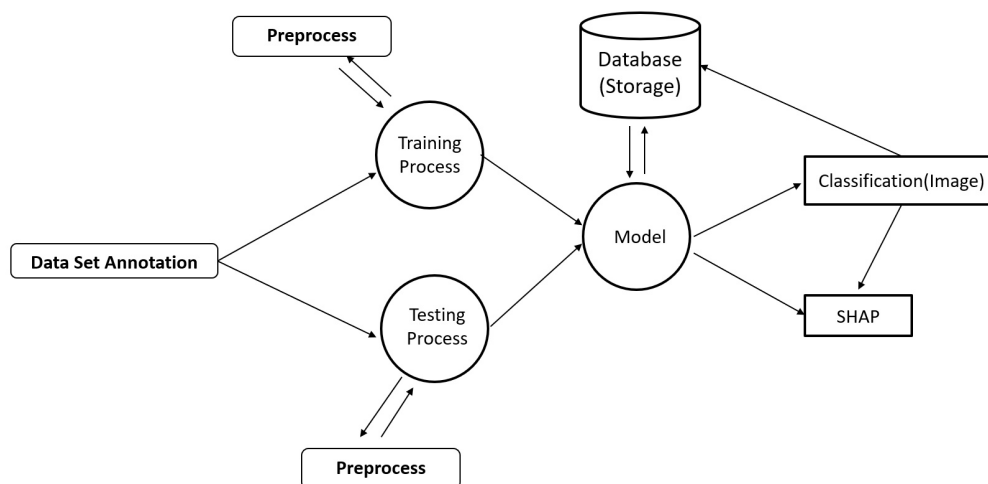
**3.1.5 Data Flow Diagram Level 1**

Figure 3.3: Data Flow Diagram Level 1

### 3.1.6 UI Design

We have two types of UI one of them is proposed UI as mobile application and another one is implemented UI for Web Application.

#### Proposed UI

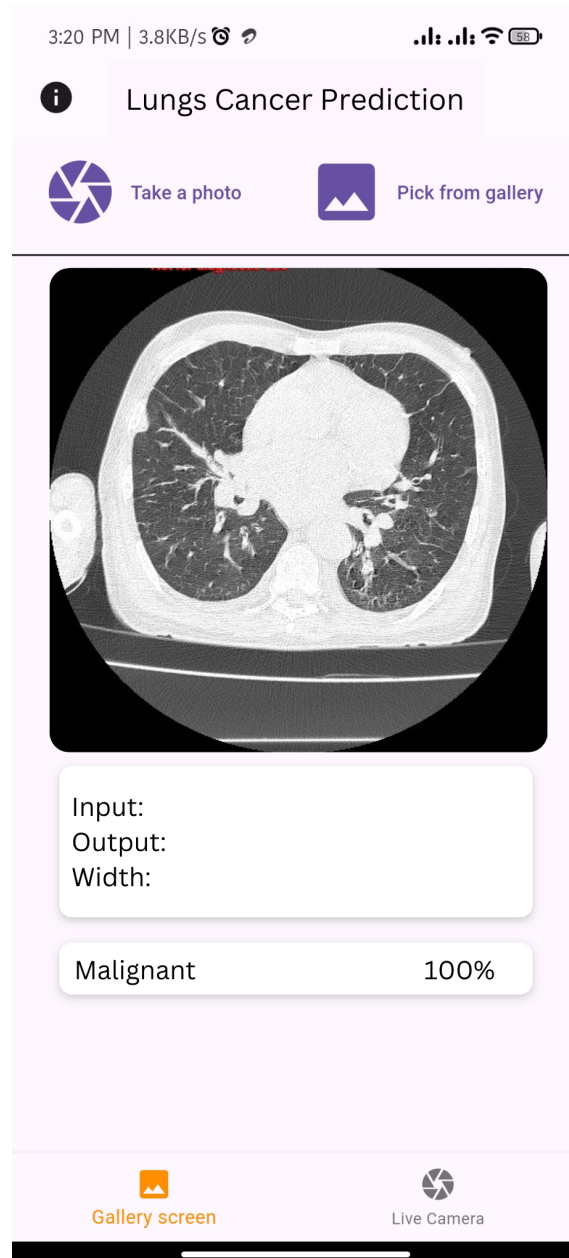


Figure 3.4: Proposed UI 1



Figure 3.5: Proposed UI 1

## Implemented UI

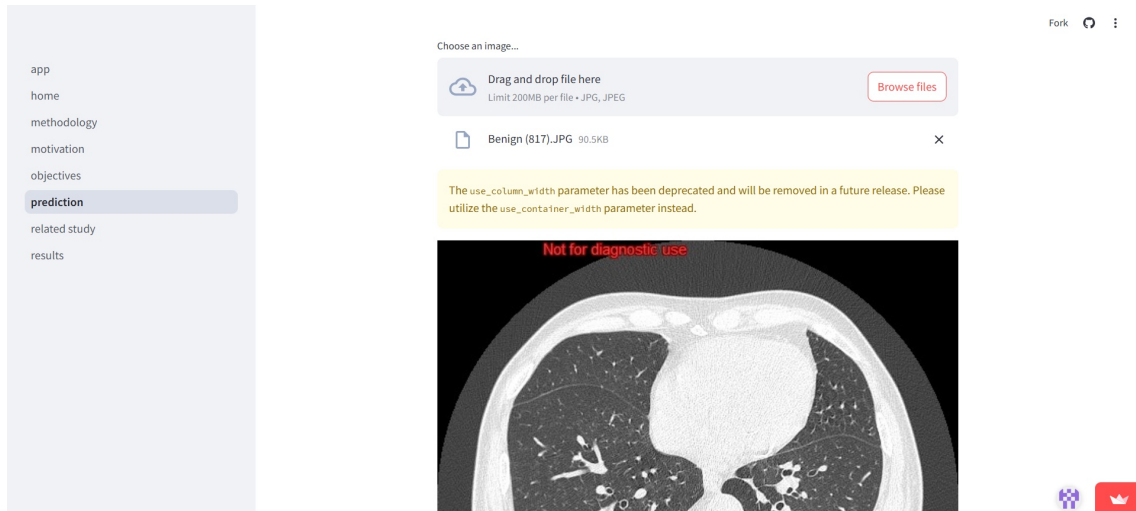


Figure 3.6: Implemented UI 1



Figure 3.7: Implemented UI 2

## 3.2 Detailed Methodology and Design

This study offers a thorough deep learning framework for reliable and accurate CT image-based lung cancer detection. Data preparation, feature extraction, classification, and model interpretation are some of the crucial steps that are included in the framework. We have the biggest dataset which one has been collected by us from NIDCH. And the size of that collected dataset is approx 8,00,000 image and after preprocessing there is approx 2500 image data. Annotating the dataset to add relevant labels for every image is the first step. The training and testing datasets are guaranteed to be appropriately constructed by this procedure. To guarantee that features in the dataset are accurately labeled, annotation tools and subject matter experts are frequently used. And A number of preprocessing techniques are used to improve image quality and eliminate noise before feeding the photos into the models. After augmentation, the dataset size is approx 3500 image. Then there is two split one is training, another one is Testing portion. We have made the validation by the physicians to get the better accuracy. The core of the approach is the feature extraction step, in which pertinent features are automatically extracted from the preprocessed CT images using deep learning models. Convolutional Neural Network (CNN), VGG16, ResNet50, ResNet101, ResNet152, InceptionNetV3, DenseNet121 and DenseNet169 are among the cutting-edge deep learning architectures that are investigated. Images are categorized into preset groups using trained models. The classification results are assessed using performance criteria like confusion matrix, F1-score, recall, accuracy, and precision. Multi-class categorization using categorical cross-entropy. SHAP assigns relevance ratings to each input feature in order to explain the machine learning model's output, is used to make the model interpretable. SHAP delivers a thorough comprehension of the ways in which distinct features influence the model's predictions. Clinicians can become more confident in the model's judgments and spot possible areas for additional research by displaying the feature importance ratings.

### 3.3 Project Plan

Table 3.1: Project Plan

Phase	Description	Week
Data Collection and Annotation	To ensure high-quality data for training and evaluation by curating a sizable dataset of medical pictures (such as CT scans) that have been labeled by experts in the field.	1-5
Pre-Processing	To increase dataset diversity and model robustness, standardize image dimensions, normalize pixel values.	5-7
Data Splitting	By making the division of two dataset in Training and Testing.	7-8
Model Training	Use cutting-edge deep learning models like CNNs, VGG16, InceptionV3, MobileNetV2, DenseNet121, and ResNet variations. To optimize performance, adjust hyperparameters such as batch size and learning rate.	7-10
Evaluation	By making utilization of metrics like F1-score, confusion matrix, recall, accuracy, and precision to evaluate the model's performance on the test dataset. Use SHAP to make predictions more comprehensible and interpretable..	10-11
Deployment	By using trained model in research, making sure it is scalable, reliable, and equipped to be updated in response to fresh data. Now we have work on Streamlit for Web Application	11-12

### 3.4 Task Allocation

Medical imaging experience and domain knowledge will curate and precisely annotate the dataset during the data gathering and labeling phase. Working with data science knowledge have handled pre-processing activities including image scaling, normalization. By gaining machine learning knowledge as a team member to implement and tune CNNs, ResNet variations and other models throughout the deep learning model training phase. We also need to adjust hyperparameters to attain the best possible performance. Both domain experts and machine learning technologists will be included in the model review process to make sure that measures like recall, accuracy, and precision match clinical norms. Our experience in explainable AI will do SHAP interpretability analyses to verify the model's decision-making procedures. And then we have go forwarded with our

web(implemented) and mobile application version according to the accuracy. All these task allocated to us (Student & Supervisor).

### 3.5 Summary

Using Convolutional Neural Network (CNN), VGG16, ResNet50, ResNet101, ResNet152, InceptionNetV3, DenseNet121 and DenseNet169, this study aims to enhance lung cancer prediction models. The procedure includes phases for model training, evaluation, deployment, preprocessing, and dataset annotation. To guarantee precise labeling for supervised learning tasks with experience in medical imaging annotate the dataset. To improve the quality and diversity of data, preprocessing techniques include image scaling, normalization. For the purpose of developing and assessing the model, the dataset is separated into subsets for training and testing. For model training, sophisticated CNN architectures are employed, and performance is optimized by hyperparameter adjustment. SHAP (SHapley Additive exPlanations) is used to explain feature contributions and improve model interpretability. Accuracy, precision, recall, and F1-score are model evaluation metrics that are in line with clinical norms. Data collection and annotation, preprocessing, data splitting, model training, evaluation, and deployment are the six stages listed in the project plan. With specialized knowledge in each phase—data curation, preprocessing, model training, and SHAP analysis, the study seeks to provide a dependable and significant lung cancer detection solution. The project adheres to a planned timeline, assigning specified weeks to each phase. Both functional and non-functional needs are taken into account at every stage in order to satisfy system demands and user expectations.

## Chapter 4

# Implementation and Results

### 4.1 Environment Setup

It's a vital step to ensure a smooth and effective workflow. This includes software and hardware setups that are specifically designed to meet the processing requirements of deep learning models. To handle huge datasets and speed up model training, high-performance computing hardware—such as strong CPUs, GPUs and enough RAM—is necessary. To handle the large amount of data produced, such as medical photos and trained model files, a reliable storage system is also necessary. When needed, networking features like dependable servers and fast internet are put up to support cloud-based operations and ease data transfer. Installing deep learning frameworks like TensorFlow, which offer the essential tools for model construction and training, is the first step in setting up the environment on the software side. To manage data pretreatment, manipulation and analysis, the Python programming language is set up in conjunction with necessary libraries including NumPy, Pandas, OpenCV and scikit-learn. To make coding and debugging more efficient, Kaggle Notebook is used as a platform. To create informative graphs and assess model performance, visualization libraries like Matplotlib and Seaborn are incorporated. Additionally, for scalable storage and computational resources, the system integrates cloud computing platforms such as Kaggle, guaranteeing accessibility and flexibility throughout the project lifecycle.

### 4.2 Testing and Evaluation

This section explains the process we used to create and train the deep learning models for the diagnosis of lung cancer. We employed a number of popular models: A proprietary Convolutional Neural Network (CNN), VGG16, ResNet50, ResNet101, ResNet152, InceptionNetV3, DenseNet121 and DenseNet1697 also contribute. We started by getting our CT scan pictures ready. Every picture was adjusted to match the input size that each model needed. For instance, InceptionV3 required 299x299 pixels for pictures, whereas VGG16 and ResNet models need 224x224 pixels. The pixel values were adjusted to fall

between 0 and 1. We employed pre-trained iterations of these models, which had previously undergone training on the sizable ImageNet dataset. We were able to modify these models for our particular objective with the use of this strategy, called transfer learning. In order to produce a binary classification—whether or not lung cancer is present—we altered the last layers of these networks. Maximum 20 epochs, we used batches of photos to train each model. Binary cross-entropy is a loss function that we utilized to quantify the discrepancy between the real and predicted labels. To enhance the training process, we also employed learning rate reduction strategies and early halting. Several criteria, including accuracy, precision, recall and F1-score, were used to assess the models. The code that specifies a function that makes it easier to visualize the prediction results for a particular data point was then used. It has a dictionary class that associates class names ("Normal", "Benign" and "Malignant") with numeric labels (0, 1, 2).

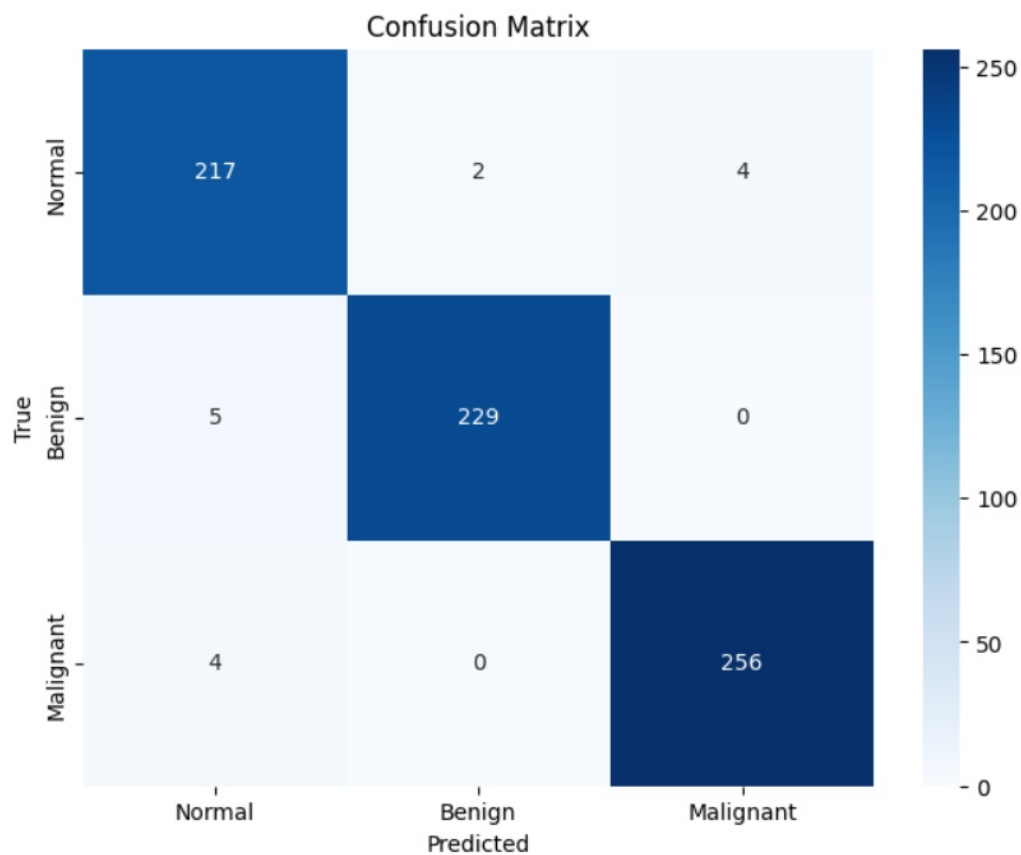


Figure 4.1: Confusion matrix

The code plots an index in a figure with two subplots after choosing it at random from the range. A grayscale image is shown in the left subplot and the projected probabilities are plotted in the right subplot. For a randomly selected image from the test dataset, this display shows how the model predictions compare to the actual class labels. We evaluated the models on a different test set after training to see how well they performed in actual situations. Accuracy, sensitivity (recall), specificity, precision, F1-score and confusion

matrix were among the evaluation metrics we employed. The number of correct predictions the model made out of all of its forecasts is known as accuracy. The model's sensitivity or recall indicates how well it detects positive lung cancer cases. The model's ability to detect negative cases is measured by its specificity. The F1-score represents the equilibrium between precision and recall, whereas precision is defined as the ratio of properly predicted positive observations to the total number of expected positives. A thorough analysis of true positive, true negative, false positive and false negative predictions is given by the confusion matrix.

### 4.3 Results and Discussion

In this portion we have to go through image classification where we have three part. Class names ("Normal", "Benign" and "Malignant") are linked to numerical labels (0, 1, 2) by its dictionary class.

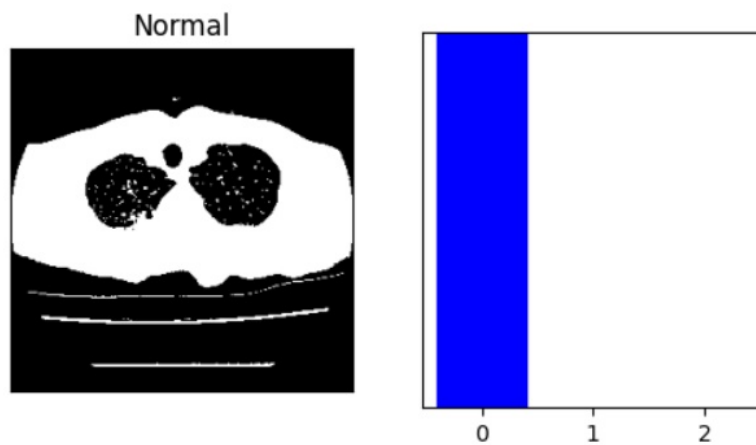


Figure 4.2: Prediction of Normal Image

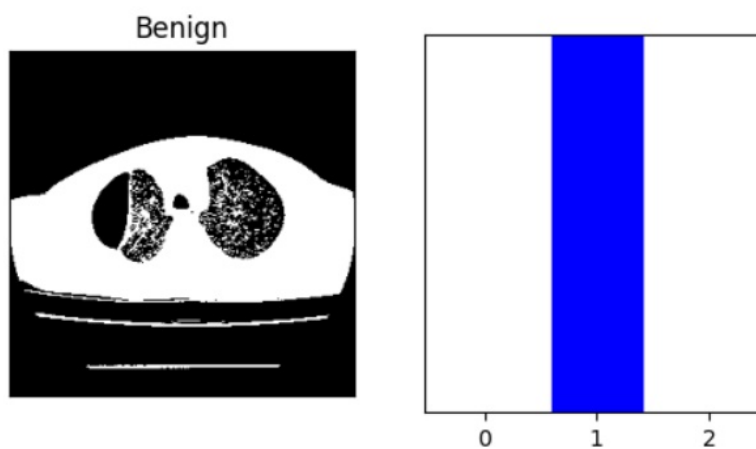


Figure 4.3: Prediction of Benign Image

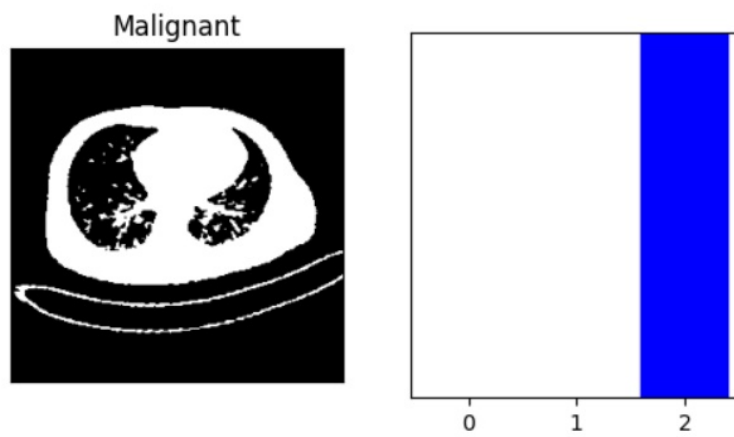


Figure 4.4: Prediction of Malignant Image

Now there is the portion of model where it goes with model accuracy, precision, recall, f1-score. Here is the uses of Convolutional Neural Network (CNN), VGG16, ResNet50, ResNet101, ResNet152, InceptionNetV3, DenseNet121 and DenseNet169.

## ResNet-50 Model

```

Model name: resnet50
23/23 ————— 12s 295ms/step
      precision  recall  f1-score  support
0      0.83      0.99      0.90      257
1      0.99      0.85      0.91      238
2      1.00      0.91      0.95      222

accuracy                0.92      717
macro avg               0.94      0.92      0.92      717
weighted avg            0.93      0.92      0.92      717

```

Figure 4.5: Accuracy of ResNet50

## ResNet-101 Model

```

Model name: resnet101
23/23  14s 394ms/step
      precision    recall  f1-score   support

     0       0.83       0.97       0.90       258
     1       0.99       0.81       0.89       240
     2       0.96       0.97       0.97       219

 accuracy                   0.92       717
 macro avg       0.93       0.92       0.92       717
 weighted avg    0.93       0.92       0.92       717

```

Figure 4.6: Accuracy of ResNet101

## ResNet-152 Model

```

Model name: resnet152
23/23  22s 625ms/step
      precision    recall  f1-score   support

     0       0.95       0.55       0.70       255
     1       0.70       1.00       0.82       236
     2       0.93       0.95       0.94       226

 accuracy                   0.83       717
 macro avg       0.86       0.83       0.82       717
 weighted avg    0.86       0.83       0.82       717

```

Figure 4.7: Accuracy of ResNet152

## VGG16 Model

```

Model name: vgg16
23/23  32s 677ms/step
      precision    recall  f1-score   support

     0       0.97       0.78       0.87       255
     1       0.82       0.98       0.90       236
     2       0.97       1.00       0.98       226

 accuracy                   0.91       717
 macro avg       0.92       0.92       0.91       717
 weighted avg    0.92       0.91       0.91       717

```

Figure 4.8: Accuracy of VGG16

## InceptionNet V3 Model

```

Model name: inception_v3
23/23 ----- 20s 428ms/step
           precision    recall  f1-score   support

     0       0.62       0.73       0.67       255
     1       0.73       0.83       0.78       236
     2       0.88       0.59       0.71       226

 accuracy                   0.72       717
 macro avg                   0.74       717
 weighted avg                 0.74       717

```

Figure 4.9: Accuracy of InceptionNetV3

## DenseNet121 Model

```

Model name: densenet121
23/23 ----- 14s 356ms/step
           precision    recall  f1-score   support

     0       0.98       0.93       0.95       258
     1       0.94       0.98       0.96       240
     2       0.98       0.99       0.99       219

 accuracy                   0.97       717
 macro avg                   0.97       717
 weighted avg                 0.97       717

 [[239  15   4]
 [  4 236   0]
 [  1   1 217]]

```

Figure 4.10: Accuracy of DenseNet121

## DenseNet169 Model

Model name: densenet169					
23/23	—————			28s 693ms/step	
	precision	recall	f1-score	support	
0	0.69	0.99	0.81	258	
1	0.97	0.91	0.94	240	
2	1.00	0.55	0.71	219	
accuracy			0.83	717	
macro avg	0.89	0.82	0.82	717	
weighted avg	0.88	0.83	0.82	717	

Figure 4.11: Accuracy of DenseNet169

## Proposed CNN Model

Model name: CNN					
23/23	—————			1s 19ms/step	
	precision	recall	f1-score	support	
0	0.98	0.99	0.98	267	
1	0.98	0.98	0.98	232	
2	1.00	0.99	0.99	218	
accuracy			0.98	717	
macro avg	0.99	0.98	0.99	717	
weighted avg	0.98	0.98	0.98	717	

Figure 4.12: Accuracy of Proposed CNN

To find the best method for identifying lung cancer, a comprehensive evaluation of different deep learning models was done. Although all models had excellent performance, the research revealed minor differences in their performance indicators. With its outstanding balance between precision and recall demonstrated by its higher overall accuracy and F1-score, CNN emerged as the best performer. Although they marginally lagged behind the ResNet152, DenseNet169 and InceptionNetV3 models showed strong performance. DenseNet121, ResNet50, ResNet101 and VGG16 provided an excellent trade-off between accuracy and computing economy, making them appropriate for real-time clinical applications. Though best performance comes from CNN. The significance of choosing a suitable model based on particular clinical criteria was highlighted by this comparative analysis. For example, some models would be favored when good recall is essential to reduce false

negatives. On the other hand, different models would be more appropriate when accuracy is crucial to lowering false positives.

### SHAP analysis for CNN

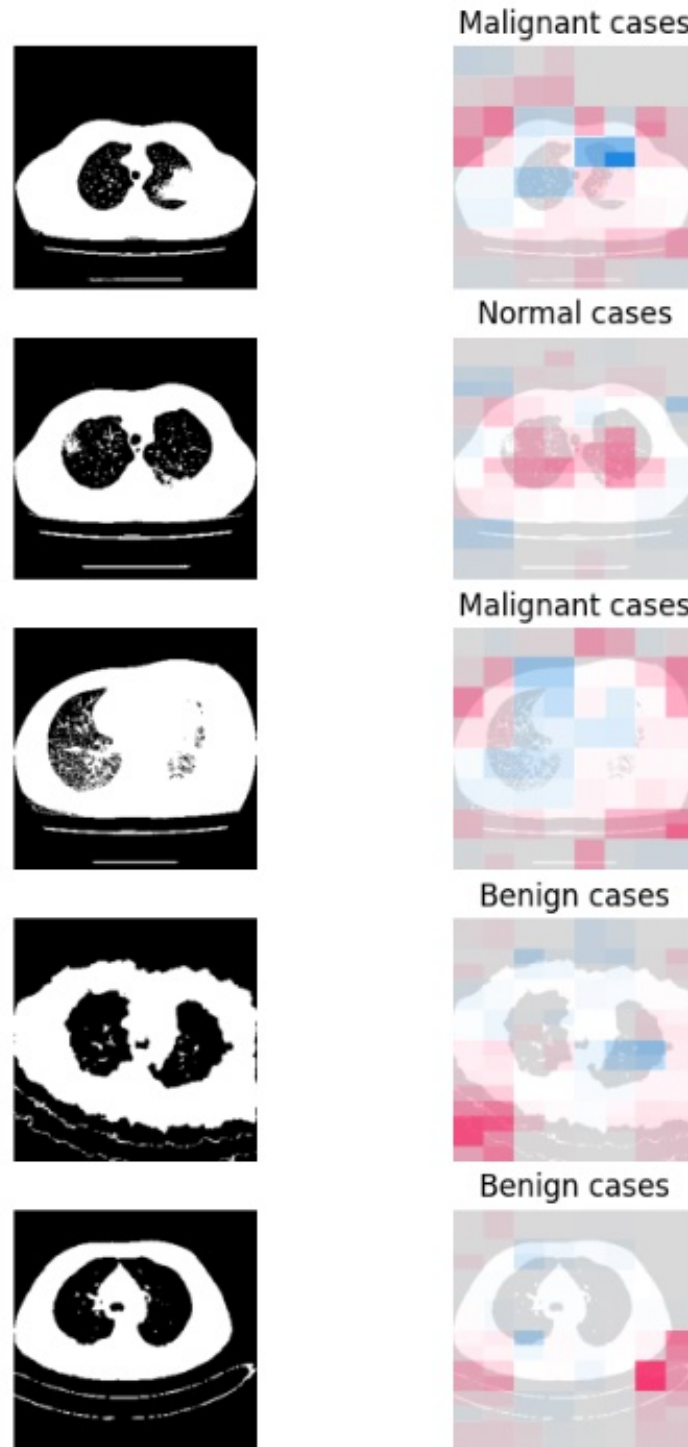


Figure 4.13: SHAP Analysis

## 4.4 Summary

In conclusion, the comparative and experimental research demonstrated how well deep learning models work for early lung cancer detection. The study effectively shown that models such as CNN, VGG16, ResNet50, ResNet101, ResNet152, InceptionNetV3, DenseNet121 and DenseNet169 could be used in actual medical settings. Future research should concentrate on improving these models even more, tackling issues like false positives, and determining whether they can be used to a wider range of patient populations.

# Chapter 5

## Engineering Standards and Design Challenges

### 5.1 Compliance with the Standards

#### 5.1.1 Software Standards

These Things are important to make proper specification of this study and work-

- Python Programming Language: Python is a popular programming language that is perfect for carrying out data analysis and putting deep learning techniques into practice.
- Storage Platforms: Using Kaggle storage is the perfection for the practice in better way.
- Working Platform: Kaggle is a free cloud-based Jupyter notebook environment that gives users access to GPUs and CPUs, among other high-performance computing capabilities. Its powerful characteristics and ease of use make it a popular option for data research, machine learning, and education. And we also have the uses of Streamlit and Github for application.
- Visualization Tools: Model performance and assessment metrics can be analyzed and visualized using libraries such as Matplotlib, Seaborn and TensorBoard.

#### 5.1.2 Hardware Standards

Along with software, there is also importance of these hardware things-

- Powerful Computers: The ability to use powerful computers that have the memory and processing capability to tackle challenging deep learning tasks.
- GPU: Graphics processing unit is crucial for speeding up deep learning model training and cutting down on computation time.

- High-capacity storage: Enough room to store trained models and manage big datasets, such as CT scans and previously processed photos.
- Backup Power Supply: Continuous power supplies to avoid interruptions or data loss during project milestones.

For smooth data transfer, particularly when integrating cloud-based solutions or accessing distant datasets, high-speed internet is necessary.

### 5.1.3 Communication Standards

Weekly scheduled meetings held on using video conferencing software such as Zoom or Google Meet to plan future work, discuss changes and resolve issues. As well as we have some physical meeting with supervise whom give us the proper guideline everytime. Google Docs, Latex(Ovrleaf), Kaggle and other collaborative tools will be used to maintain documentation and progress reports. Furthermore, precise rules for email correspondence will be set, guaranteeing succinct and expert messages. In order to ensure that project goals are met effectively and efficiently, these communication standards will promote a cohesive and productive atmosphere.

## 5.2 Impact on Society, Environment and Sustainability

### 5.2.1 Impact on Life

By providing early and accurate lung cancer detection, which can result in timely interventions that lower mortality rates and improve patient outcomes, the proposed project seeks to significantly impact individual lives. By utilizing deep learning and artificial intelligence, the system offers a non-invasive, effective, and scalable solution to a crucial healthcare challenge, potentially improving the quality of life for countless people.

### 5.2.2 Impact on Society & Environment

With significant effects on healthcare accessibility, resource allocation, and environmental sustainability, the socioeconomic ramifications of this lung cancer prediction study go well beyond its immediate technical capabilities. The project reduces healthcare inequities globally by democratizing access to sophisticated diagnostic technologies, especially in locations with limited resources. With the use of this technology, underprivileged areas can gain access to state-of-the-art diagnostic capabilities, which could save countless lives and enhance global health outcomes. The project has important ramifications for the cost-effectiveness and efficiency of the healthcare system as well. Because less expensive therapies are required at later stages of the disease, early identification of lung cancer eases the strain on healthcare systems. In addition to improving patient outcomes, this move toward early intervention dramatically lowers the medical expenses related to treating late-stage cancer. If this technology is widely adopted, it may result in a significant

realignment of healthcare resources, making it possible to allocate money and staff more effectively. Lastly, by encouraging digital workflows, the project reduces the need for tangible resources like films and paper-based records in the healthcare industry. There are numerous environmental advantages to this shift to digital data management and documentation. The concept helps to significantly reduce the carbon footprint connected with healthcare operations by eliminating the requirement for medical records to be physically stored and transported. Furthermore, the digitization of medical data improves data interoperability and accessibility, which may result in better research capacities.

### 5.2.3 Ethical Aspects

The development and implementation of this lung cancer prediction system are heavily influenced by ethical considerations. Maintaining patient confidentiality and data privacy is of utmost importance. Strong security measures must be put in place by the system to guard against breaches or illegal access to private patient data. This entails encrypting data while it's in transit and at rest, putting strong access controls in place, and routinely checking access logs and data consumption. Model decision-making places a high priority on transparency. The system should break down feature contributions using methods like SHAP (SHapley Additive exPlanations) and clearly explain how predictions are made. Establishing confidence between patients and healthcare providers depends on this openness.

### 5.2.4 Sustainability Plan

The project includes a thorough plan for regular updates and maintenance of the AI system to guarantee long-term viability. A key element is the constant retraining of the model with fresh data, which keeps the solution accurate and pertinent in the face of new technology and changing medical knowledge. By upgrading the model proactively, the system is kept up to date with the most recent developments in lung cancer detection and treatment techniques. In order to promote broad acceptance and integration into current medical infrastructures, the project also encourages cooperation with legislators and healthcare providers. The system can be customized to match certain clinical requirements and to handle any issues that may come up during implementation thanks to this cooperative effort. The project can ensure that the AI solution is in line with actual clinical procedures and can be successfully incorporated into current workflows by interacting with healthcare professionals at different levels, ranging from frontline physicians to policymakers. The project also includes systems for continuous assessment and enhancement. Finding areas for improvement is aided by routine evaluations of the system's performance in comparison to current clinical standards. The system's effectiveness and relevance are maintained throughout time by this ongoing cycle of evaluation, enhancement, and re-deployment. The initiative also recognizes the importance of flexibility in healthcare environments. The system can adapt to new diagnostic methods, evolving imaging technology, and mod-

ifications in medical practices because it was designed with flexibility in mind. Because of its versatility, the AI solution can develop in tandem with the quickly progressing field of lung cancer detection and therapy.

### 5.3 Project Management and Financial Analysis

The main goal is to create an accurate, comprehensible and scalable system for identifying lung cancer utilizing cutting-edge AI approaches in clinical settings. The main focus of this work has gone through data collection and title selection. Because title selection and further work is quite tough, because on that time you have to think about the whole project and the best way to do the work. And after selecting title, it's not so easy to manage data and make the process in two split portion to successfully run the whole work. And then the Ai potionmakes it more critical where we need to do the validation of the output explanation. And lastly the application making procedure another portion to go through. And it's a crucial part to understand the User Interface. Risk management techniques use techniques like thorough validation, hyperparameter tweaking and utilizing reliable cloud solutions to solve possible problems such data quality problems, model underperformance and deployment hurdles.

Table 5.1: Financial Analysis

SL NO	Costing Spaces	Cost
1	Data Collection	35,000 BDT
2	Web Application	3,500 BDT
3	Instrument (Software)	30,000 BDT
4	Pendrive	2,000 BDT
5	Transport	15,000 BDT
6	Communication Cost	20,000 BDT
<b>Total Estimated Cost</b>		<b>1,05,500 BDT</b>

## 5.4 Complex Engineering Problem

### 5.4.1 Complex Problem Solving

Over here, We are going to map complex problem solve according to this study-

Table 5.2: Mapping with complex problem solving.

EP1 Dept of Knowl- edge	EP2 Range of Con- flicting Require- ments	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applica- ble Codes	EP6 Extent of Stake- holder Involve- ment	EP7 Inter- dependence
√	√	√	√		√	√

#### Mapping with Knowledge Profile for EP1

This table 5.3) is designed to map the EP1 to the Knowledge Profile.

Table 5.3: Mapping with knowledge Profile.

K2 Mathematics	K3 Engineering Funda- mentals	K4 Specialist Knowl- edge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
√	√	√	√	√	√

#### Explanation:

EP1: This work Follows K2 and K3, because we have used confusion matrix and accuracy, recall, f1 score. The suggestion from the doctor accomplish K4. K5 and K6 goes through the design part and machine learning work where we have multiple diagram. And lastly, K8 is fully on previous work which is literature review.

EP2: As we have colleted the data from NIDCH, though it's not so easy to collect data. We have sacrificed some requirements to gain data from the source.

EP3: In this work, there is multiple uses of model and SHAP as well. We have got the better accuracy by using the models according to the SHAP.

EP4: This work is partially medical-based and partially computer science-based. Because over here the uses of machine learning to predict lung cancer.

EP5: This work doesn't follow EP5.

EP6: As it's a medical based work, we have to take the suggestion and guideline from the doctor to make the implementation.

EP7: We have many subworks based on the model that I created using Python and the data that I gathered from the hospital. It goes through EP7 for that reason.

### 5.4.2 Engineering Activities

Here this study goes through by this Engineering activities

Table 5.4: Mapping with complex engineering activities.

EA1 Range of re- sources	EA2 Level of Inter- action	EA3 Innovation	EA4 Consequences for society and envi- ronment	EA5 Familiarity
√	√	√	√	√

#### Explanation:

EA1: In order to guarantee systematic research and support developments in advanced imaging techniques for lung cancer diagnosis with deep learning, our project makes use of a variety of resources, including high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations. We also paid money and had to see the doctor. For this reason, we can declare it to be satisfied EA1.

EA2: As we have to take the proper suggestion from the doctor, it goes with EA2.

EA3: As there is new accuracy and something new to elaborate, EA3 fulfilled.

EA4: By enhancing healthcare through deep learning-based enhanced lung cancer detection techniques and encouraging environmental sustainability through the use of effective computational resources and adherence to ethical standards for patient data protection, this initiative benefits society.

EA5: This study have the focus on Machine Learning and Artificial Intelligence. We have this practice in our previous study.

## 5.5 Summary

This research adheres to the design problems and engineering criteria for a deep learning-based lung cancer prediction system. It highlights how crucial it is to adhere to hardware, software, and communication standards. The project makes use of Google Colab for development, Google Cloud for storage, and Python as its main programming language. Strong processors, GPUs, and large-capacity storage are necessary pieces of hardware for effective data handling and model training. To forecast lung cancer, the system uses a variety of CNN architectures, including ResNet50, EfficientNetB7, VGG16, InceptionV3, MobileNetV2, and DenseNet121. Model decisions are explained using interpretability based on SHAP. The project's goals are to decrease false positives and false negatives and increase the accuracy of lung cancer detection. By giving data protection and transparency a priority during model decision-making, it allays ethical worries. The system is made to be adaptive to changing imaging technology and medical procedures. To guarantee accuracy and long-term sustainability, regular updates and maintenance are scheduled. To maximize resource allocation and minimize any problems, the project is subjected to risk management and financial analysis.

# Chapter 6

## Conclusion

### 6.1 Summary

This paper is mainly about how explainable machine learning (XAI) can help find and predict lung cancer, which is the main reason people die from cancer around the world. It starts by emphasizing the limitations of traditional diagnostic methods like CT scans, which often struggle with early detection. This causes a need for advanced technologies such as deep learning models to improve sensitivity, specificity, and accuracy. Models like CNN, ResNet50, ResNet101, DenseNet121, and VGG16 were employed, giving robust feature extraction capabilities for image classification. The study integrates explainable AI techniques like SHAP to ensure transparency in the decision-making process, allowing healthcare workers to trust model predictions. Data collection was conducted from medical sources which is NIDCH. The dataset was divided into subgroups for testing and training in order to assess the model's performance in real-world scenarios. Effectiveness was evaluated using metrics such as confusion matrices, F1-score, accuracy, and recall. High accuracy was attained by models trained via transfer learning; CNN was the top performer, while DenseNet121 and VGG16 provided computational efficiency. Clinicians were able to comprehend predictions thanks to the insights into feature relevance that SHAP analysis gave. Also this research emphasizes the moral necessity of secure system design and patient data protection. The solution's sustainability is also covered, with an emphasis on scalability, frequent upgrades, and flexibility to accommodate evolving medical requirements. The study highlights the advantages of early cancer identification for society, including higher survival rates and lower medical expenses. By using fewer physical resources, it also investigates how digital solutions affect the environment. Notwithstanding its achievements, the project encountered difficulties managing computing needs and preserving model interpretability. To do further increase diagnostic accuracy, future research will incorporate multimodal data, such as clinical history and genomic information, and expand datasets. By giving low-resource settings access to cutting-edge diagnostic technologies, the project helps democratize healthcare. The system's design was influenced by engineering principles, while clinical relevance was ensured by collaboration with medical

professionals. The study comes to the conclusion that explainable machine learning is a game-changing technology in healthcare that can strike a balance between innovation and social and ethical issues.

## 6.2 Limitation

There are a number of drawbacks, even though explainable machine learning has demonstrated significant potential in enhancing the interpretability and reliability of AI models in medical diagnostics:

- Because of their intricate design and several layers, deep CNNs like DenseNet can be difficult to completely understand. Because of this, it is challenging to comprehend how characteristics affect final predictions throughout the network.
- Although methods such as SHAP provide light on feature contributions, they could miss interactions or non-linear correlations between several characteristics that affect model choices.
- As considered by our study of MS-CNN across multiple datasets, model accuracy may decline as class sizes or dataset complexity increase. For accurate forecasts, balanced, high-quality datasets are still essential.
- Inference durations for real-time applications may be slowed down by sophisticated explainable AI approaches, which can dramatically increase CPU needs.
- Maintaining explainability requires constant work since models' interpretability may vary as they are updated or improved. [16]

## 6.3 Future Work

To increase its potential and influence, this lung cancer prediction system's future development will concentrate on a few crucial areas. Initially, efforts will be focused on growing the dataset to incorporate more thorough and varied medical imaging data from different clinical settings and populations. The goal of this extension is to increase the model's generalizability across various patient populations and medical settings. Furthermore, by offering a more comprehensive picture of the illness, combining several imaging modalities, such as MRI and PET scans, with CT scans is anticipated to greatly increase diagnosis accuracy. In order to develop a more complete diagnosis system, research will also examine the integration of multimodal data analysis, merging imaging data with patient demographics, genomic data, and clinical history. Deeper insights into the model's decision-making process will be obtained through the pursuit of advancements in explainable AI techniques. This could hasten the system's adoption in clinical practice by improving the data' interpretability and fostering trust between patients and practitioners. To ensure

that the system satisfies strict clinical standards and usability criteria, collaboration with medical institutions will be strengthened in order to carry out pilot deployments and real-world validation tests. In order to provide accessibility in low-resource situations where lung cancer screening may be especially important, efforts will also be directed toward streamlining the deployment process for mobile and edge devices. [17]

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