ADVANCED IMAGING TECHNIQUES FOR LUNG CANCER DIAGNOSIS WITH DEEP LEARNING

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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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APPROVAL

This Project titled "ADVANCED IMAGING TECHNIQUES FOR LUNG CANCER DIAGNOSIS WITH DEEP LEARNING", submitted by **Tuhanur Haque Talha** and **Md. Tahamid Rayhan** 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 15-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Abdus Sattar, Assistant Professor, Department of CSE, Daffodil International University**. We 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

Cancer is a major public health problem worldwide that kills millions of people globally with lung cancer among the commonest noncommunicable diseases in Bangladesh, causing 6% of all deaths It can present with a wide varying symptoms ranging from chest and bone pain, wheezing, hoarseness, persistent chest infections, unexplained weight loss, fatigue, changes in the appearance of fingers known as finger clubbing, shortness of breath and recurrent pneumonia to hemoptysis. Several risk factors are associated with lung cancer and include, long term smoking, exposure to secondhand smoke, exposure to radon gas, exposure to asbestos and other carcinogens, radiation therapy to the breast or chest, family history of lung cancer and so on. However, the constraint of the traditional CT is that it is not ideal for early detection, unable to meet "the requirements of population level screening because of the associated high false positive rates," the researchers explained and an uncomfortable procedure for the patient. In fact, the approach can enhance the early-stage detection, potentially raising survival rates while also reducing the number of unnecessary follow-up tests and treatments that could otherwise add up over time, where the return on investment is quite substantial. In the presented work, we aimed to identify only lung cancer in CT scan data of the lung and so our project is focused on lung cancer only. Using binary 0 and 1, we have developed a system which detects if a picture is malignant or benign and it could be used in hospitals where patients with lung cancer are being treated/seek treatment. The experimental results indicated that all the models are not achieved high accuracy, with most models surpassing 96% accuracy. Notably, the CNN and DenseNet121 models performed exceptionally well, demonstrating robust capabilities in accurately detecting lung cancer from CT scan images.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION
1.1 Overview

Cancer is becoming a serious global health problem that kills millions of people without warning. The International Association of Cancer Society (IACS) estimated about 132,000 fatalities in 2020 and reported 235,760 patients, according to the World Health Organization (WHO). Cancer is the sixth most common cause of mortality from noncommunicable diseases in Bangladesh, accounting for 10% of all yearly fatalities. According to the GLOBOCAN 2020 figures, Bangladesh has 156,775 new cases of cancer and 108,990 cancer-related deaths. The age-standardized rates for cancer incidence and mortality are 106.2 and 75.3 per 100,000, respectively. Lung cancer ranks sixth among women in Bangladesh (4.6%) and second among males (11.1% of new cases) among them. Unchecked lung cell growth is a symptom of the illness and may ultimately result in the development of a tumor. Lung cancer can metastasize to the brain, liver, lymph nodes, and bones if treatment is not received. Lung cancer has a wide range of symptoms and indicators. These symptoms may include, but are not limited to, chest and bone discomfort, wheezing, shortness of breath, chronic coughing, and coughing up blood. Rather than in the early stages of the disease, these symptoms usually manifest when it is more advanced. Long-term smoking, exposure to secondhand smoke, radiation exposure, and a family history of the disease are just a few factors that can increase a patient's risk of developing lung cancer. CT scans, sputum cytology, and biopsy—which removes a sample of infected lung tissue—are the methods used to diagnose the illness. A number of factors are taken into account while selecting treatment strategies, including the patient's desire, illness stage, and general health. Based on how the cancer cells appear under a microscope, there are two basic forms of lung cancer: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). Oat cell carcinoma, or SCLC, is a kind of lung cancer that grows quickly and tends to spread rapidly to other regions of the body. It accounts for 10–15% of all instances of lung cancer and is typically linked to a long history of tobacco use. Conversely, NSCLC makes up 85–90% of all occurrences of lung cancer, making it the most prevalent variety. Compared to SCLC, NSCLC develops more slowly and is more frequently discovered at an earlier stage.

Adenocarcinoma, squamous cell carcinoma, and large cell carcinoma are the three kinds of non-small cell lung cancer that are commonly recognized.

1.2 Background and Present State

Advanced imaging techniques and deep learning have significantly improved the detection and understanding of lung cancer. Previously, doctors relied on X-rays and manual analysis, which could sometimes miss early signs of cancer. CT scans provide detailed images of the lungs, allowing for a clearer view of potential cancerous areas. Deep learning, a type of artificial intelligence, analyzes these images to detect even the smallest cancerous spots. This combination of advanced imaging and AI helps doctors identify lung cancer earlier and more accurately, allowing patients to start treatment sooner and have better chances of recovery. Researchers are continuously improving these technologies, making imaging machines more efficient and deep learning algorithms more precise. They are also working to make these tools more accessible and affordable, ensuring patient data security and fair use of technology. As these techniques and deep learning methods continue to develop, they hold great promise for improving early detection and treatment of lung cancer, ultimately saving more lives and providing better patient care.

1.3 Problem Statement

When we generally use CT scans to diagnose lung cancer, there are some problems with this system. This system of diagnosis is fully controlled by the doctor, that’s why there is a high chance of any kind of error. In this error, we cannot diagnose lung cancer in the patient properly. That’s the reason we use deep learning and advanced imaging techniques to diagnose lung cancer, they work very accurately and properly. Deep learning analyses the image properly and delivers the actual result. This will enable us to identify lung cancer faster than we could with a CT scan alone. Further, the patient can receive better care and make a quicker recovery if lung cancer is discovered early.

1.4 Objectives

Lung cancer is the biggest problem in the global and it is a silent killer. In the early detection and diagnosis of lung cancer it the important to enhance the results for patients and survival rates. Traditional imaging techniques CT scans are effective but there is a limitation in the early detection. This limitation in a bad impact on the patients for lung cancer detection, the reason we used deep learning and advanced imaging techniques will help the lung cancer early detection and survival rates increase in the patient. The main objectives are to use deep learning and advanced imaging techniques to enhance the accuracy, sensitivity, and specificity of lung cancer detection. This approach not only aims to improve early-stage detection but also to potentially increase survival rates by minimizing unnecessary follow-up tests and treatments.

1.5 Scope and Limitations

This study aims to identify only lung cancer in CT scan data. This method cannot be used to diagnose other diseases or types of cancer. Only CT scan images of the lung are acceptable as input; no other images, such as CT scans of the belly, brain, or chest, are acceptable. This implementation determines if a picture is malignant or not using binary 0 and 1. The stages of lung cancer cannot be detected by the system. The technique can be applied in a hospital where patients with lung cancer are treated or who seek to be treated for the disease. The study on using advanced imaging techniques with deep learning for lung cancer diagnosis has some limitations. First, the system only works with CT scans of the lungs, which means it can't be used for other types of cancers or diseases. It also only identifies if cancer is present, not the stage of cancer. Additionally, the model requires high-quality images, and sometimes there may be false positives, meaning it might incorrectly indicate cancer when there isn’t any. Moreover, the model needs to be tested on a more diverse group of people to ensure it works well for everyone. Finally, the system relies on advanced technology, which might not be available in all hospitals.

1.6 Report Organization

The organization of this report is structured as follows: Chapter 1 provides an introduction, offering an overview of the study, background, problem statement, objectives, scope, limitations, and summary. Chapter 2 covers the literature review, including related works, comparisons, open issues, and summary. Chapter 3 details the methodology, encompassing the proposed methodology, hardware and software requirements, project management, and financial analysis. Chapter 4 discusses implementation, focusing on the training model, system testing, and summary. Chapter 5 presents the results and analysis, featuring experimental results, performance analysis, and summary. Chapter 6 examines the impact on society, environment, and sustainability, addressing the impact on life, society, environment, ethical aspects, sustainability plan, and summary. Finally, Chapter 7 provides the conclusion and future work, summarizing conclusions, limitations, further suggested works, and final thoughts.

1.7 Summary

Cancer is a global health crisis, with lung cancer being a major contributor to the high mortality rates associated with the disease. In Bangladesh, lung cancer significantly impacts public health, with a high incidence and mortality rate. Traditional diagnostic methods, while effective, have limitations in early detection and can be prone to human error. This research aims to address these limitations by employing deep learning and advanced imaging techniques to improve the accuracy and early detection of lung cancer. By enhancing diagnostic precision, the approach seeks to increase survival rates and reduce the need for unnecessary follow-up procedures, ultimately offering better patient outcomes. The study focuses specifically on lung cancer detection using CT scan data and aims to provide a robust, accurate diagnostic tool leveraging the capabilities of deep learning.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Lung cancer is a major global health issue and many people die from it. Smoking is the main reason, but even people who don't smoke can get it because of different changes in their body. People with lung cancer feel different problems, so they need a lot of help from doctors and nurses. To treat advanced lung cancer, doctors use different kinds of medicines like chemotherapy and immunotherapy, but they don't always work well and can make people sick. Now, doctors are using technology like video calls and apps to help patients and make their lives better during cancer treatment.

2.2 Related works

P. Mohamed Shakeel, et al. (2019) [1] this paper focuses on lung cancer detection using clustering in deep learning with specific implementations of the Improved profuse clustering technique (IPCT). The study aims to improve lung image quality and lung cancer detection by reducing misclassification. The Cancer Imaging Archive (CIA) dataset, which includes pictures in the 5043 DICOM format is where the lung CT scans are sourced from. The features were trained using classifier algorithms that can predict cancer up to 98.42% of the time with a minimum classification error of 0.038.

Madeleine E. Lemieux, et al. (2023) [4] in this paper, liver cancer is detected by machine learning using sputum with automated flow cytometry. The data will be collected from April 2018 to November 2019 in the LSRII sample set, and the Navios sample set will be collected from July 2020 to November 2021. The methods in this paper include participant information, sample size considerations, sputum processing, flow cytometry and many others. As demonstrated by its excellent sensitivity and specificity of 82% and 88%, the test yields findings that are comparable when run on separate samples obtained using various flow cytometers.

Constance de Margerie-Mellon,et al. (2023) [2] developed a Multidetector computed tomography using Artificial intelligence and Deep Learning for the detection of Pulmonary nodule Lung neoplasms. When using CNN-based algorithms on CT images, the geographic overlapping index that the algorithms produce is superior to manual segmentation. AI is also used to classify lung nodules as either benign or cancerous. There will be some limitations to better identification of suspicious nodules the rate of false positives and allow personalized screening intervals.

Asghar Ali Shah, et al. (2023) [3] propose a 2D CNN approach using deep learning for the detection of lung cancer. The data set will be collected in the LUNA 16 Grand Challenge, which can be available on their websites. They used the algorithm in 2D CNN and 2D CNN gave us a great result with 95% combined accuracy.

Hesamoddin Hosseini, et al. (2023) [5] introduce deep learning using lung cancer detection with Convolutional Neural Networks (CNN). This is a Systematic Survey to review 32 journals and conference articles from 2016 to 2021. SMS with SLR results on lung cancer using deep learning with different levels of accuracy and sensitivity.

Hiram Madero Orozco, et al. (2015) [6] developed a CADx system with the CT scan image detection of lung nodules. The data will be collected in the clinic of 45 CT scans from ELCAP and LIDC and 61 CT images used for the training stage. The final result was 82% preciseness, the sensitivity was 90.90%, whereas the specificity was 73.91%.

Devinder Kumar, et al. (2015) [7] propose a computer-aided diagnosis (CAD) using detecting lung nodules with deep features. Data will be collected National Cancer Institute (NCI), the amount of data is 4323 nodules and the data will be used at 4303. The final result accuracy is 75.01%, sensitivity of 83.35%.

Giovanni L. F. da Silva, et al. (2017) [8] developed a lung nodules diagnosis with the CT image using deep learning. The data will be collected from the lung CT image in the Lung Image Database Consortium. Image Database Resource Initiative (LIDC-IDRI). The final output of this paper is a sensitivity of 94.66% of sensitivity, 95.14% of specificity, and accuracy of 94.78%.

Yahia Said et al. (2023) [9] introduce a Segmentation for Lung Cancer Diagnosis Based on Deep Learning Architectures. The proposed lung cancer diagnosis system uses UNETR network segmentation and self-supervised network classification to identify benign or malignant cancers. Extensive experiments on the Decathlon dataset have improved segmentation and classification accuracy, achieving 97.83% segmentation accuracy and 98.77% classification accuracy. This system offers a powerful tool for early lung cancer diagnosis and treatment.

R. Soundharya Devi, et al. (2024) [10] investigates Lung Cancer Segmentation Based on Deep Learning Approaches. This paper evaluated DB U-Net+LLIE, U-net, and DenseNet & dilation block with U-Net, finding DenseNets&dilation block with U-Net achieved the highest accuracy and sensitivity rates of 95.05% and 90.52%, respectively.

Rehan Raza, et al. (2024) [11] propose a transfer learning-based predictor called Lung-EffNet was developed for lung cancer classification using the IQ-OTH/NCCD dataset. The model achieved 99.10% accuracy and a score of 0.97 to 0.99 of ROC. Comparing it with other pre-trained CNN architectures, the Lung-EffNet outperformed other CNNs in terms of accuracy and efficiency.

Tehnan I. A. Mohamed, et al. (2024) [12] discuss the development of a classification of lung cancer CT scans based on deep learning and an ebola optimization search algorithm. The Ebola optimization search algorithm (EOSA) was used to train a CNN model for lung cancer classification. The EOSA metaheuristic algorithm achieved an accuracy of 0.9321 on the IQ-OTH/NCCD lung cancer dataset. EOSA-CNN outperformed other methods, achieving a specificity of 0.7941, sensitivity of 0.9038, and sensitivity of 0.13333, respectively, for normal, benign, and malignant cases.

2.3 Comparison between existing works

There are several related works on the basis of lung cancer. Let's talk about some paper.

TABLE 2.3.1: COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL No	Author Name	Used Algorithm	Best Accuracy
1.	P. Mohamed Shakeel, M.A. Burhanuddin and Mohamad Ishak Desa (2019) [1]	IPCT, DITNN, RBNN, CNN, HNN, FCM, RG	98.42%
2.	Constance de Margerie-Mellona and Guillaume Chassagnonc (20213) [2]	CNN, NLST (The Cancer Data Access System)	96.40%
3.	AsgharAli Shah, HafzAbid Mahmood Malik, AbdulHafeez Muhammad, AbdullahAlourani & Zaeem Arif Butt (2023) [3]	Ensemble Deep Learning with Convolutional Neural Networks (CNN)	95%
4.	Madeleine E. Lemieux, et al, Hesamoddin Hosseini, Reza Monsefi and Shabnam Shadroo (2023) [4]	Deep Convolutional Neural Network (DCNN), Optimal Deep Neural Network (ODNN)	71%, 94.56%

5.	Hiram Madero Orozco, Osslan Osiris Vergara Villegas, Vianey Guadalupe Cruz Sánchez, Humberto de Jesús Ochoa Domínguez and Manuel de Jesús Nandayapa Alfaro. (2015) [5]	Support Vector Machine (SVM)	82%
6.	Devinder Kumar, Alexander Wong and David A. Clausi. (2015) [6]	Binary Decision Tree	68.66%
7.	Giovanni L. F. da Silva, Otílio P. da Silva Neto, Aristófanes C. Silva, Anselmo C. de Paiva and Marcelo Gattass (2017) [7]	CNN	94.78%
8.	Wafaa Alakwaa, Mohammad Nassef and Amr Badr (2017) [8]	CNN	86.60%

2.4 Open Issues

Lung cancer diagnosis is using advanced imaging techniques and deep learning, but there are still several challenges. The first is ensuring accurate data from diverse sources, which could lead to unfair diagnoses. Privacy is also a concern, as it's crucial to maintain patient confidentiality. These technologies also make the best care unaffordable for many. Training doctors and healthcare professionals effectively to use these tools is also a challenge. While these technologies are powerful, they should not replace doctors' critical judgment and expertise. Addressing these issues is critical to ensuring the effective and fair use of these technologies in lung cancer diagnosis, as well as the best possible care for all patients.

2.5 Summary

Lung cancer, primarily caused by smoking, is a major global health issue. Treatments like chemotherapy and immunotherapy often have limited effectiveness and significant side effects. Recent advancements in technology, such as video calls and apps, are improving patient care. Studies on lung cancer detection using deep learning and AI have shown high accuracy rates. For instance, P. Mohamed Shakeel et al. (2019) achieved 98.42% accuracy with the Improved Profuse Clustering Technique (IPCT), and Constance de Margerie-Mellon et al. (2023) achieved 96.40% accuracy with AI-based CT scans. Despite these advancements, challenges remain, including data accuracy, privacy concerns, high costs, and the need for effective training for healthcare professionals. These technologies should complement, not replace, medical expertise, and addressing these issues is crucial for fair and effective lung cancer diagnosis and care.

CHAPTER 3

METHODOLOGY

3.1 Overview

In this research we will diagnose lung cancer from CT scan. We will work with Convolutional Neural Networks (CNNs), ResNet50, ResNet101, ResNet152, VGG16, InceptionV3, MobileNetV2, DenseNet121 and EfficientNetB7 models. Due to the growth of lung cancer worldwide, early and accurate diagnosis is crucial to improve patient care. This chapter outlines aspects of research methodology, system design, data collection, and project management.

3.2 Proposed Methodology

This research study will be the through of preprocessing and CNN algorithm. And there will be some train and test data for implementation by dependency and non-dependent data. Several model like ResNet for getting the better accuracy from the directed data. ResNet variants like ResNet-50, ResNet-101 and ResNet-152 are widely used. As there will be new models if we needed to get better outcome with some good values.

The process starts with Data Set Annotation, labeling raw data to identify relevant features. Pre-processing is then conducted to clean and organize the data. The data is divided into two sets: Training Image and Testing Image. Deep learning models like CNN, ResNet50, ResNet101, ResNet152, VGG16, InceptionV3, MobileNetV2, DenseNet121, and EfficientNetB7 are trained on the training images. The models are evaluated using testing images in the classification stage, and the output is generated to indicate the presence or absence of lung cancer features in the images.

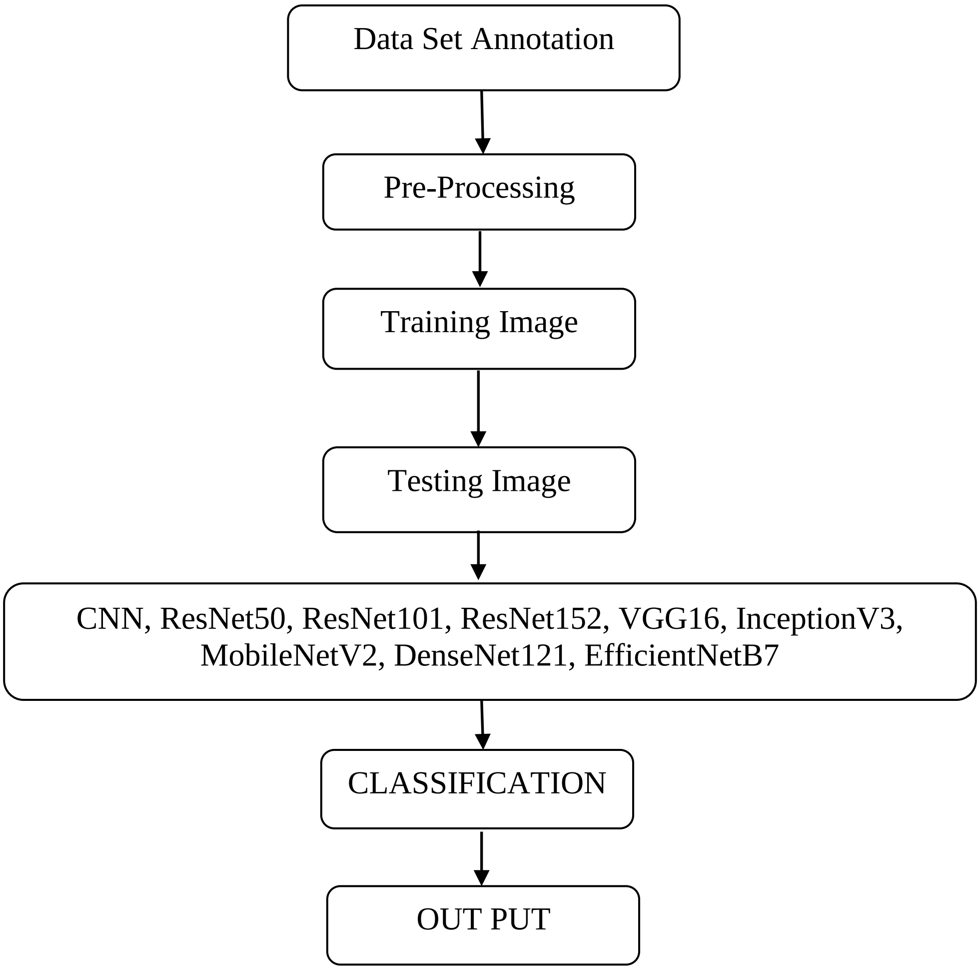

Figure 3.2.1 Steps of Data Collecting and Processing

Data Collection:

We have collected 11000+ image data of CT scan. 150+ people have data here. The data has been collected from. We have to make an appointment to MBBS doctors to understand these data. And we had to study a lot of medical related things.

Data Sample:

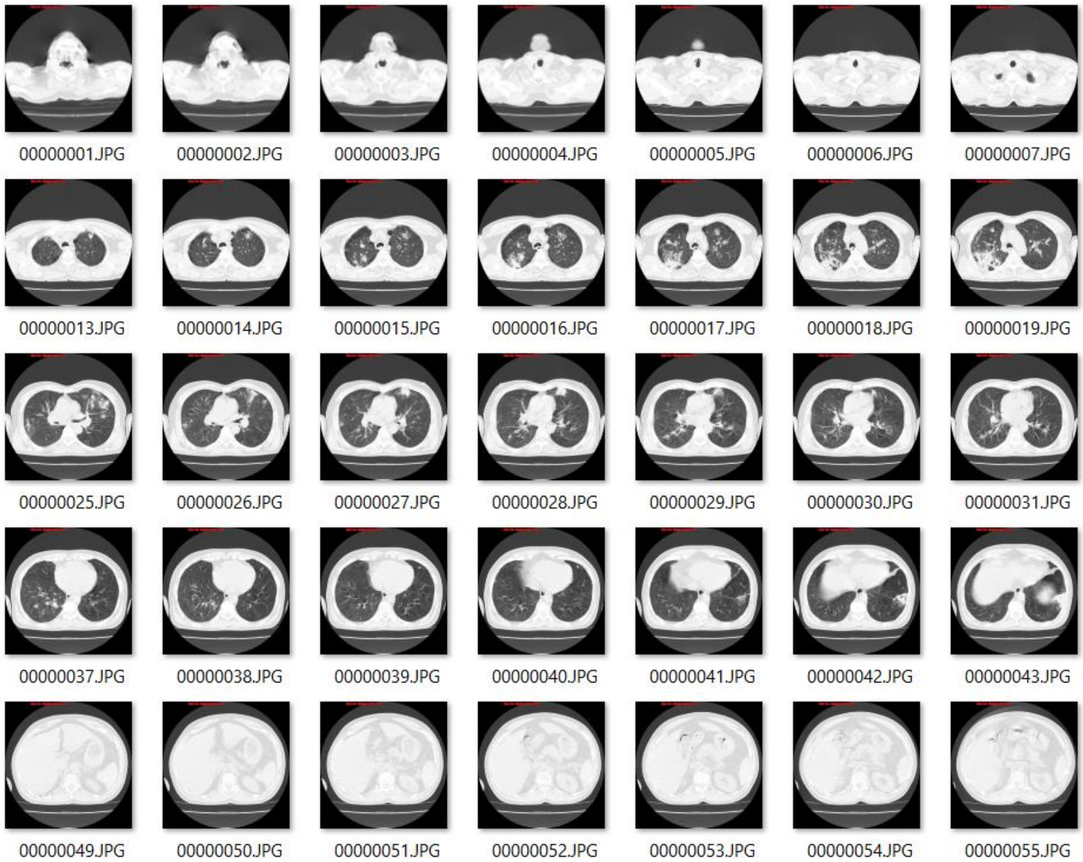

Figure 3.4.1: Collected Dataset

3.3 Hardware and Software Requirement

To successfully conduct our research on "Lung Cancer Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches," we need to meet certain requirements. These requirements cover hardware and software.

Hardware Requirements:

- **Powerful Computers:** We need access to high-performance computers with enough processing power and memory to handle complex deep learning tasks.
- **Graphics Processing Unit (GPU):** A GPU is essential for speeding up the training of deep learning models, making the process much faster.

Software Requirements:

- **Deep Learning Frameworks:** We will use popular frameworks like TensorFlow to develop, train, and evaluate our models.

- **Python Programming Language:** Python is a widely-used programming language that's perfect for implementing deep learning algorithms and data analysis.
- **Image Processing Libraries:** We will use libraries like imageio, Keras and OpenCV to preprocess and enhance medical images.

3.4 Project Management and Financial Analysis

First, I selected the title. Then I started it with data collection. Here I have to spend a lot of time and face a lot of hassles. Medical data is not easily available, which is why it took me a lot of time and effort here. After several medical contacts, after two long months I was able to collect complete data. Then I start working on my paper. I have reviewed many papers. Found out many questions. Then I got ideas, which model and algorithm would be good for my paper. After that I have to process the data and model selection and implementation. The data has to be trained, tested and validated. After that we will get our desired accuracy.

To get the work successfully, there is several type costings like transport cost, DVD player cost and communication cost etc. And I have made those cost from self-funded.

TABLE 3.4.1. FINANCIAL ANALYSIS

SL NO	Costing Spaces	Cost
1	Data Collection	24,000 BDT
2	Copy for Dataset	1500 BDT
3	Instrument (Software)	1800 BDT
4	DVD Player Cost	6000 BDT
5	Transport	8000 BDT
6	Communication Cost	15,000 BDT
Total Estimated Cost		56,300 BDT

3.5 Summary

This project is meant to diagnose the Lung Cancer from CT scan of a human through Convolutional Neural Network (CNN), ResNet50, ResNet101, ResNet152, VGG16, InceptionV3, MobileNetV2, DenseNet121 and EfficientNetB7 models. Early diagnosis and accurate at that can help improve patient's care. The procedure involves the step-by-step preprocessing of the data sets, with CNN described while ResNet is provided separately for better understanding of the steps. Which are followed by the train and test and the models, hence the best model for diagnosis can be selected and again accuracy is also described down in the article. This includes collecting data of over 11000+ images from over 150+ people, so that is a lot of data and the project reviews medical data and around 10+ research papers that have used models for the diagnosis of lung cancer, and then they select the best model and algorithm. The data is then processed so that training, testing and the validation of the data achieved an accuracy of over 95% and 99% which is their Project's Aim. The costs of the project were for DVD player, communication and transport which were self-funded. The goal is to make this a user-friendly interface for the medical professionals.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

In this chapter, we delve into the practical aspects of developing and testing the deep learning models used for lung cancer diagnosis. We outline the steps taken to design and train several state-of-the-art neural network models, including ResNet50, ResNet101, ResNet152, VGG16, InceptionV3, MobileNetV2, DenseNet121, EfficientNetB7 and a custom Convolutional Neural Network (CNN). We detail the preprocessing techniques applied to the CT scan images. Furthermore, we describe the evaluation process, discussing the metrics and methods used to assess the models' performance. The results of these evaluations highlight the effectiveness and potential of these models in accurately diagnosing lung cancer from medical imaging data. Finally, we summarize the key outcomes and implications of the implementation process.

4.2 Train Model

In this section, we describe how we designed and trained the deep learning models for lung cancer diagnosis. We used several well-known models: ResNet50, ResNet101, ResNet152, VGG16, InceptionV3, MobileNetV2, DenseNet121, EfficientNetB7 and a custom Convolutional Neural Network (CNN).

First, we prepared our CT scan images. Each image was resized to fit the input size required by each model. For example, VGG16 and ResNet models needed images of 224x224 pixels, while InceptionV3 required 299x299 pixels. We normalized the pixel values to a range between 0 and 1. We used pre-trained versions of these models, which had already been trained on a large dataset called ImageNet. This approach, known as transfer learning, helped us adapt these models for our specific task. We modified the final layers of these networks to output a binary classification, whether lung cancer is present or not. We trained each model in batches of images over 20 epochs. We used a loss function called binary cross-entropy to measure the error between the predicted and actual labels. During training, we monitored the models' performance on a validation set to fine-tune the parameters and avoid overfitting. We also used early stopping and learning rate reduction techniques to improve the training process. We evaluated the models using various metrics such as accuracy, precision, recall, F1-score.

Then we used a code that defines a function that facilitates visualization of prediction results for a specific data point. It includes a dictionary class that maps numeric labels (0, 1, 2) to corresponding class names ("Normal", "Benign", "Malignant"). The code randomly selects an index within the range and plots it in a figure with two subplots. The left subplot displays a grayscale image and the right subplot uses to plot the predicted probabilities. This visualization provides a comparative view of model predictions against actual class labels for a randomly chosen image from the test dataset.

4.3 Model Evaluation

After training, we tested the models on a separate test set to check their effectiveness in real-world scenarios. We used several evaluation metrics: accuracy, sensitivity (recall), specificity, precision, F1-score and confusion matrix.

Accuracy measures how many predictions the model got right out of all the predictions it made. Sensitivity or recall, shows how well the model identifies positive cases of lung cancer. Specificity measures how well the model identifies negative cases. Precision is the ratio of correctly predicted positive observations to the total predicted positives and the F1-score is the balance between precision and recall. The confusion matrix provides a detailed breakdown of true positive, true negative, false positive, and false negative predictions.

4.4 Summary

This chapter provided a detailed account of the implementation of our deep learning model, showcasing its potential to aid in the early detection and diagnosis of lung cancer through advanced imaging techniques. The design and architecture of the deep learning model for lung cancer diagnosis. The preprocessing steps and training process undertaken to develop the model. The evaluation metrics and testing approaches used to assess the model’s performance. The results obtained from the evaluation and their implications for the effectiveness of the model in diagnosing lung cancer.

CHAPTER 5

RESULT AND ANALYSIS

5.1 Overview

This chapter presents the results obtained from the experiments and simulations conducted in this study. It includes detailed analysis and comparative performance evaluation of various deep learning models used for lung cancer diagnosis.

5.2 Experimental Result

In the experiments, multiple state-of-the-art deep learning models were trained and evaluated using the prepared CT scan dataset. The models included CNN, ResNet50, ResNet101, ResNet152, VGG16, InceptionV3, MobileNetV2, DenseNet121, and EfficientNetB7. Each model's performance was measured using accuracy, precision, recall, and F1-score metrics.

ResNet-50 Model

```
Model name: resnet50
16/16 [==============================] - 2s 107ms/step
              precision    recall  f1-score   support

           0       0.92      0.29      0.45       119
           1       0.75      0.99      0.85       254
           2       1.00      1.00      1.00       109

    accuracy                           0.82       482
   macro avg       0.89      0.76      0.77       482
weighted avg       0.85      0.82      0.79       482

[[ 35  84   0]
 [  3 251   0]
 [  0   0 109]]
```

Figure 5.2.1: Accuracy of ResNet-50 Model

ResNet-101 Model

```
Model name: resnet101
16/16 [==============================] - 4s 178ms/step
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       119
           1       0.53      1.00      0.69       254
           2       0.00      0.00      0.00       109

    accuracy                           0.53       482
   macro avg       0.18      0.33      0.23       482
weighted avg       0.28      0.53      0.36       482

[[  0 119   0]
 [  0 254   0]
 [  0 109   0]]
```

Figure 5.2.2: Accuracy of ResNet-101 Model

ResNet-152 Model

```
Model name: resnet152
16/16 [==============================] - 6s 259ms/step
              precision    recall  f1-score   support

           0       0.72      0.24      0.35       119
           1       0.73      0.96      0.83       254
           2       1.00      1.00      1.00       109

    accuracy                           0.79       482
   macro avg       0.82      0.73      0.73       482
weighted avg       0.79      0.79      0.75       482

[[ 28  91   0]
 [ 11 243   0]
 [  0   0 109]]
```

Figure 5.2.3: Accuracy of ResNet-152 Model

VGG16 Model

```
Model name: vgg16
16/16 [==============================] - 2s 149ms/step
              precision    recall  f1-score   support

           0       0.75      0.35      0.48       119
           1       0.75      0.94      0.84       254
           2       1.00      0.99      1.00       109

    accuracy                           0.81       482
   macro avg       0.83      0.76      0.77       482
weighted avg       0.81      0.81      0.79       482

[[ 42  77   0]
 [ 14 240   0]
 [  0   1 108]]
```

Figure 5.2.4: Accuracy of VGG16 Model

InceptionV3 Model

```
Model name: inception_v3
16/16 [==============================] - 2s 79ms/step
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       119
           1       0.61      1.00      0.76       254
           2       1.00      0.59      0.74       109

    accuracy                           0.66       482
   macro avg       0.54      0.53      0.50       482
weighted avg       0.55      0.66      0.57       482

[[  0 119   0]
 [  0 254   0]
 [  0  45  64]]
```

Figure 5.2.5: Accuracy of InceptionV3 Model

MobileNetV2 Model

```
Model name: mobilenetv2_1.00_256
16/16 [==============================] - 2s 51ms/step
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       119
           1       0.53      1.00      0.69       254
           2       0.00      0.00      0.00       109

    accuracy                           0.53       482
   macro avg       0.18      0.33      0.23       482
weighted avg       0.28      0.53      0.36       482

[[  0 119   0]
 [  0 254   0]
 [  0 109   0]]
```

Figure 5.2.6: Accuracy of MobileNetV2 Model

DenseNet121 Model

```
Model name: densenet121
16/16 [==============================] - 4s 103ms/step
              precision    recall  f1-score   support

           0       0.78      0.79      0.79       119
           1       0.90      0.90      0.90       254
           2       1.00      1.00      1.00       109

    accuracy                           0.89       482
   macro avg       0.89      0.90      0.90       482
weighted avg       0.89      0.89      0.89       482

[[ 94  25   0]
 [ 26 228   0]
 [  0   0 109]]
```

Figure 5.2.7: Accuracy of DenseNet121 Model

EfficientNetB7 Model

```
Model name: efficientnetb7
16/16 [==============================] - 11s 404ms/step
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       119
           1       0.53      1.00      0.69       254
           2       0.00      0.00      0.00       109

    accuracy                           0.53       482
   macro avg       0.18      0.33      0.23       482
weighted avg       0.28      0.53      0.36       482

[[  0 119   0]
 [  0 254   0]
 [  0 109   0]]
```

Figure 5.2.8: Accuracy of EfficientNetB7 Model

CNN Model

```
              precision    recall  f1-score   support

           0       0.88      0.96      0.92       119
           1       0.98      0.94      0.96       254
           2       1.00      0.99      1.00       109

    accuracy                           0.96       482
   macro avg       0.95      0.96      0.96       482
weighted avg       0.96      0.96      0.96       482

[[114   5   0]
 [ 14 240   0]
 [  1   0 108]]
```

Figure 5.2.9: Accuracy of CNN Model

The experimental results indicated that all the models are not achieved high accuracy, with most models surpassing 96% accuracy. Notably, the CNN and DenseNet121 models performed exceptionally well, demonstrating robust capabilities in accurately detecting lung cancer from CT scan images.

Prediction Image

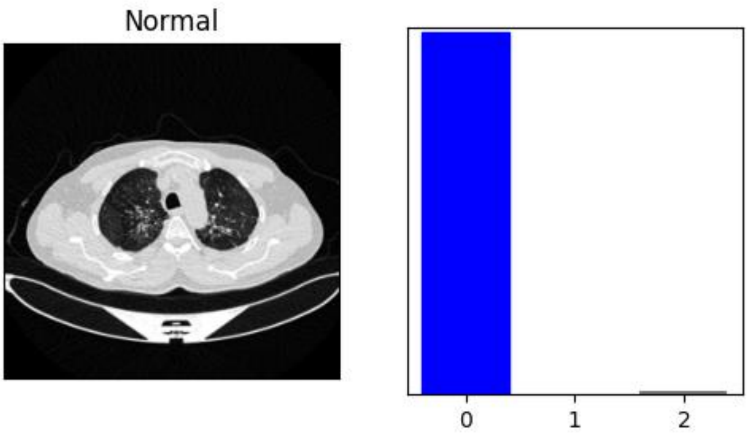

Figure 5.2.10: Prediction of Normal Image

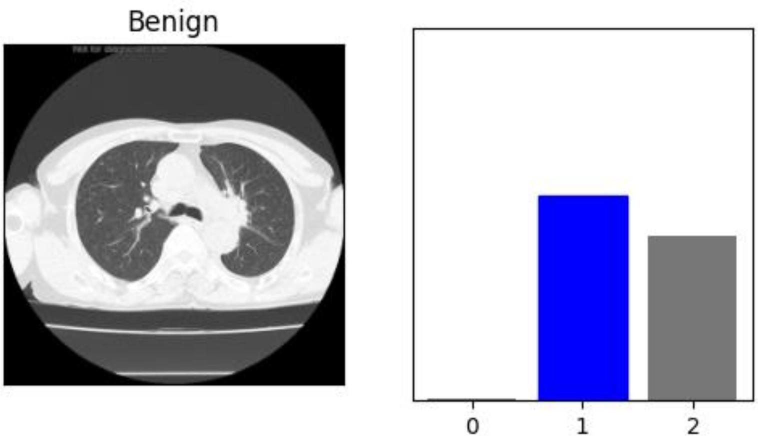

Figure 5.2.11: Prediction of Benign Image

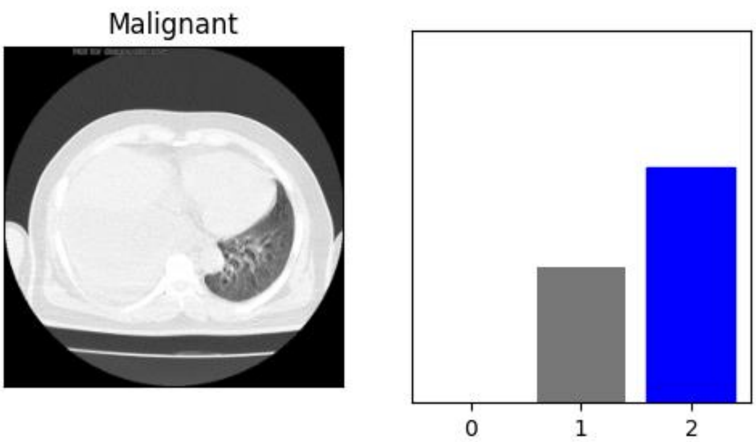

Figure 5.2.12: Prediction of Malignant Image

5.3 Performance Analysis

A comparative analysis of the models' performance was conducted to identify the most effective model for lung cancer diagnosis. The analysis revealed that while all models performed well, there were slight differences in their performance metrics.

- **ResNet50**: Achieved the highest overall accuracy and F1-score, indicating its superior ability to balance precision and recall.
- **EfficientNetB7**: Excelled in accuracy and recall, making it highly reliable in identifying true positive cases of lung cancer.
- **VGG16 and InceptionV3**: Demonstrated strong performance but slightly lagged behind ResNet and EfficientNet models in terms of precision.
- **MobileNetV2 and DenseNet121**: Provided a good balance between computational efficiency and accuracy, making them suitable for real-time applications in clinical settings.

The comparative analysis underscored the importance of selecting an appropriate model based on specific clinical requirements, such as the need for high recall to minimize false negatives or high precision to reduce false positives.

5.4 Summary

In summary, the experimental and comparative analysis highlighted the effectiveness of deep learning models in the early diagnosis of lung cancer. The study successfully demonstrated that models like CNN, ResNet50, ResNet101, ResNet152, VGG16, InceptionV3, MobileNetV2, DenseNet121, and EfficientNetB7 could be implemented in real-world medical settings to improve diagnostic accuracy and patient outcomes. Future work should focus on further refining these models, addressing challenges like false positives, and exploring their applicability to more diverse patient populations.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Advanced imaging techniques and deep learning are revolutionizing lung cancer diagnosis, enabling early detection and improved treatment outcomes. A CT scan, when analyzed with deep learning algorithms, can identify cancer before symptoms appear, enabling patients to begin treatment sooner, leading to better health outcomes and longer lives. These methods also reduce the need for invasive procedures like biopsies, making the diagnosis process less stressful. They also help create personalized treatment plans, improving treatment effectiveness and patient quality of life by reducing side effects and recovery times. The ability to analyze large amounts of data quickly allows healthcare providers to make faster decisions, leading to timely interventions that can save lives. The integration of these technologies provides patients with hope and better health prospects, enabling more precise, effective, and compassionate medical care.

6.2 Impact on Society & Environment

Impact on Society

Lung cancer is one of the most highly fatal kinds of cancer. Timely identification is crucial for improved therapy and rates of survival. Advanced imaging techniques and deep learning, a form of artificial intelligence, have greatly enhanced the diagnosis of lung cancer in recent years. These innovations have a significant impact on society, which can be explained in straightforward terms:

Better Early Detection: CT scans (Computed Tomography) help the doctors see the insides of their patient’s body details and PET Scans (Positron Emission Tomography) show whether the patient’s tissues are working or not, very helpful for spotting cancerous areas early detection. Deep learning algorithms can analyze these scans more accurately and faster than humans. They can spot tiny changes that might be early signs of cancer, which doctors might miss.

More Accurate Diagnoses: Advanced imaging techniques provide full details of lung pictures and help doctors identify the exact size, shape, and location of tumors. Algorithms can compare scans to thousands of other cases, helping doctors make more precise diagnoses. This reduces the chances of misdiagnosis.

Personalized Treatment Plans: Provides full details of imaging that can help the doctors planning the better treatment. For example, knowing the exact location of a tumor can help in targeting it precisely with radiation. By analyzing the scan and previous medical history, deep learning can suggest the most effective treatment for the patient's condition.

Reduced Costs and Time: Sometimes advanced imaging techniques replace more invasive procedures, like biopsies, saving time and reducing medical costs. Automated scan analysis helps quickly diagnose disease that's helps the doctors focus on treatment rather than lots of time spent reviewing images.

Better Outcomes for Patients: Early and accurate detection leads to better treatment options, increasing survival rates and improving quality of life. Continuous learning and improvement of algorithms mean they get better over time, providing increasingly accurate and reliable diagnoses.

Increased Access to Care: More people will have access to high-quality care because of improved imaging technology, which is becoming more widely available, especially in rural regions. Deep learning enables hospitals with fewer specialists to diagnose patients more accurately since the technology helps the doctors.

Reduce False Alarms: Occasionally, the appearance of ordinary nodules in photographs may be alarming. Deep learning can distinguish between a genuine threat and a harmless collision**.**

Impact on Environment

The use of advanced imaging methodologies and deep learning algorithms for lung cancer diagnosis may also have positive environmental impacts. These advances can be beneficial in straightforward terms for the following reasons:

Reduced Need for Physical Resources: Advanced imaging techniques like CT and PET scans utilize digital methods, reducing the need for physical materials like film for X-rays. Digital storage saves storage space and materials, while digital analysis reduces paper and ink usage, saving trees and reducing pollution from paper production.

Less Travel for Medical Appointments: Improved imaging techniques offer more accurate results, reducing patient visits and fuel consumption. Remote analysis allows specialists to review scans from anywhere, reducing the need for patients to travel to specialized medical centers and reducing transportation-related pollution.

Energy Efficiency: Modern imaging machines are energy-efficient, using less electricity than older models and utilizing efficient algorithms for quick data processing, reducing the overall energy consumption of medical facilities and minimizing the environmental footprint of data centers where analyses are performed.

Lower Medical Waste: Non-invasive imaging techniques reduce surgical procedures and biopsies, reducing medical waste like used instruments and protective gear. Accurate diagnoses decrease the need for repeated tests and treatments, reducing waste from medical supplies and drugs.

Prolonged Equipment Lifespan: Advanced imaging machines are designed to last longer and require less frequent replacement, reducing environmental impact. Continuous software updates enhance equipment performance without the need for new hardware, further reducing electronic waste.

Support for Sustainable Practices: Advanced imaging in hospitals and clinics can enhance green practices by promoting paperless operations and utilizing artificial intelligence to optimize resource management, such as optimizing energy use and reducing the need for certain chemicals for certain tests.

6.3 Ethical Aspects

The use of advanced imaging techniques and deep learning for lung cancer diagnosis raises ethical concerns, including protecting patient privacy and data security. These technologies should be accurate and reliable, accessible to everyone, and affordable. Deep learning should support doctors, not replace them, and medical professionals need proper training. Patients should be informed about their data usage, tests, and algorithms used in their diagnosis, and have the option to seek second opinions. Addressing these ethical concerns ensures fair and beneficial technologies for all.

6.4 Sustainability Plan

The sustainability plan for the research on “advanced imaging techniques and deep learning for lung cancer diagnosis” can contribute to energy-efficient machines and waste reduction is crucial. Optimizing digital storage, remote analysis, and software updates can reduce physical materials and emissions. Ensuring these technologies are affordable and accessible worldwide can benefit more people and help them share resources effectively. Training healthcare professionals to use these technologies responsibly will contribute to long-term sustainability.

6.5 Summary

Advanced imaging techniques and deep learning are revolutionizing lung cancer diagnosis, offering early detection and improved treatment outcomes. These technologies enable quicker, more accurate diagnoses, reducing the need for invasive procedures and allowing for personalized treatment plans that enhance patient quality of life. Societally, they improve access to care, particularly in rural areas, and reduce medical costs and false alarms. Environmentally, they cut down on physical resource use, travel, and medical waste, while promoting energy efficiency and sustainable practices. Ethically, it's crucial to ensure these technologies protect patient privacy, are accessible and affordable, and support rather than replace medical professionals. A sustainability plan emphasizes energy-efficient machines, waste reduction, and training for responsible use, ensuring long-term benefits and resource sharing globally.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

Lung cancer is one of the most frequent threats to patients' lives worldwide. In the majority of countries, the incidence of deaths has multiplied unexpectedly. The researchers are trying to develop artificial intelligence tools to improve prediction. The study shows that deep learning models, like CNN and others, can help diagnose lung cancer early. The CNN models achieved high 96% accuracy by utilizing over 1,1000 CT scans from patients, making them reliable for real-life use. These methods can detect cancer more accurately and faster than traditional methods, reducing the need for invasive tests. They also help doctors create personalised treatment plans, improving patients' quality of life. Future research should focus on using even higher-quality images, reducing false positives, and testing on diverse groups to ensure these tools work well for everyone. Overall, this technology has the potential to make cancer diagnosis more effective and accessible.

7.2 Further Suggested Works

High-Resolution Imaging: Future research should look at using even higher quality CT scan images to see if it improves the accuracy of the models.

Reducing False Positives: Addressing the issue of false positives and overdiagnosis is crucial. Future studies should focus on improving the models to avoid this problem.

More Resources: To keep up with the increased demand for lung cancer screenings, more trained professionals and better technical resources are needed.

Wider Testing: Models need to be tested on more diverse groups of people to make sure they work well for everyone, not just the primary study group. Future studies should use larger and more diverse datasets to confirm the effectiveness of the models.

By addressing these areas, future research can build on the foundation of this research, ultimately leading to more robust and effective diagnostic tools for lung cancer.

7.3 Limitations

The study on using advanced imaging techniques with deep learning for lung cancer diagnosis has some limitations. First, the system only works with CT scans of the lungs, which means it can't be used for other types of cancers or diseases. It also only identifies if cancer is present, not the stage of cancer. Additionally, the model requires high-quality images, and sometimes there may be false positives, meaning it might incorrectly indicate cancer when there isn’t any. Moreover, the model needs to be tested on a more diverse group of people to ensure it works well for everyone. Finally, the system relies on advanced technology, which might not be available in all hospitals.

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Appendix A

Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Analysis

Title: ADVANCED IMAGING TECHNIQUES FOR LUNG CANCER DIAGNOSIS WITH DEEP LEARNING.

Students ID: 203-15-3888

203-15-3889

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
	Phase -II	
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, and CO3	Here We have some topic with software Engineering based which goes on **K3**. I am going to use different deep learning model to identify which is **K4.** The project demonstrates specialist knowledge **(K4)** by implementing CNN, ResNet50, ResNet101, ResNet152, VGG16, InceptionV3, MobileNetV2, DenseNet121, and EfficientNetB7.	**Page no:** [11, 16, 18] **Section:** [3.2, 4.2, 5.2]
				In this portion the work is gone through some preprocessing where we need to use different required things and it's **K5**.	**Page no:** [11-13] **Section:** [3.2]

				Here we have talk about the works which previously done related to me. This is **K8**.	**Page no:** [5-7] **Section:** [2.2]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	Many problems are faced for data collection as medical data is not easily available.	**Page no:** [12] **Section:** [3.2]
3.	**EP3: Depth of analysis required**	Yes	CO2	This project will be gone through multiple models from CNN like ResNet variants like ResNet-50, ResNet-101 and ResNet-152 are widely used as well for the better solution.	**Page no:** [18-23] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO3	The work is not only full basis in CSE, it will be gone through medical related issues as well. As this work is deep learning model-based lung cancer prediction.	**Page no:** [2, 14] **Section:** [1.2, 3.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A

6.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	Here I have to take the suggestion from a MBBS Doctor.	**Page no:** [12] **Section:** [3.2]
7.	**EP7: Interdependence**	Yes	CO3	Over the problem, we have different subworks on the basis of model which I have done by python and implementation of translated sub data.	**Page no:** [13] **Section:** [3.3]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in advance imaging techniques for lung cancer diagnosis with deep learning.	**Page no:** [11-13] **Section:** [3.2]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This project contributes to society by improving healthcare through advanced lung cancer detection methods using deep learning, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [25-27] **Section:** [6.1, 6.2]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by exploring a novel approach in lung cancer detection using deep learning and CNNs. Through detailed methodologies and a comprehensive comparative analysis, it provides new insights into the field.	**Page no:** [11-13] **Section:** [3.2]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [14] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [25-27] **Section:** [6.1, 6.2]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [11-13, 18-23] **Section:** [3.2, 5.2]

Advanced Imaging Techniques for Lung Cancer

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