Lung Cancer Detection with Deep Neural Network

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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/internship titled "**Lung Cancer Detection with Deep Neural Network**", submitted by Fahminul Islam Fahim, ID No: 201-15-13781 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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DECLARATION

I hereby declare that, this project has been done by us under the supervision of Md. Shahriar Shakil, lecturer, department of CSE. Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

By using state of the art deep learning models on the Iraq Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) dataset, a novel advancement in lung cancer prediction is demonstrated in this study. Our analysis shows the Compact Convolutional Transformers (CCT) to be the clear choice among five cutting edge models, with an incredible accuracy of 99.09%. Building on this achievement, we carried out an in depth ablation study to further optimize the CCT. The effects of optimizers, learning rates, loss functions, batch sizes, and pooling techniques were examined in detail in this study. A careful adjustment of these parameters produced a notable improvement in accuracy, highlighting the crucial part that fine tuning performs in building predictive models. Further, we conducted a thorough investigation using significant metrics such confusion matrices, classification reports, Area Under the Curve (AUC) scores, and loss curves to verify the robustness of our method. The model performed quite well, classifying cases properly and providing detailed insights into its recall and precision. The most significant conclusion of our research is that our best model reaches an astounding accuracy of 99.09%, highlighting its potential as an effective tool for early lung cancer identification. This achievement highlights the value of using deep learning in medical diagnostics in addition to marking a significant improvement in predicted accuracy.

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CCT	Compact Convolutional Transformers
GNN	Graph Neural Network
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
NPV	Negative Predicted Values
FRR	False Positive Rate
FNR	False Negative Rate

CHAPTER 1

Introduction

1.1 Introduction

Lung cancer remains a global health crisis, casting a formidable shadow due to its widespread prevalence, high mortality rates, and the imperative for early intervention. The World Health Organization (WHO) reported a staggering 2.2 million new cases of lung cancer in 2020 [1], solidifying its status as the most commonly diagnosed cancer worldwide. This alarming frequency is compounded by the harsh reality that lung cancer is the leading cause of cancer related deaths, claiming approximately 2 million [2] lives annually. The gravity of the situation is exacerbated by the stealthy progression of lung cancer, often advancing to late stages before manifesting discernible symptoms. Nearly 70% [3] of patients receive a diagnosis at an advanced stage, limiting treatment options and resulting in a disheartening five year survival rate of merely 19% [4]. This distressing statistic underscores the critical need for sophisticated diagnostic tools capable of detecting lung cancer in its nascent stages, offering a glimmer of hope for improved treatment outcomes and diminished mortality rates. While the association between smoking and lung cancer is well established, with approximately 85% [5] of cases attributed to tobacco use, it is crucial to recognize that non smokers constitute a significant portion of patients around 15% [6]. This nuance underscores the multifaceted nature of the disease, necessitating a nuanced approach to predictive modeling that accommodates diverse patient profiles. The somber reality of lung cancer extends beyond its sheer prevalence, manifesting in an alarming statistic that designates it as the leading cause of cancer related deaths, claiming the lives of approximately 2 million individuals annually [7]. This dire scenario is compounded by the insidious nature of the disease, with nearly 70% of patients receiving their diagnosis at advanced stages, resulting in a disheartening five year survival rate of merely 19% [8]. The urgency for early detection becomes evident as lung cancer often progresses silently, eluding clinical symptoms until its later, more challenging stages. While the correlation between smoking and lung cancer is a well established risk factor, accounting for approximately 85% of cases, it is imperative to recognize the substantial fraction of non smokers constituting around 15% [5] of all lung cancer patients. This underscores the complexity of the disease’s etiology, urging the adoption of a nuanced approach to predictive modeling that accommodates diverse patient profiles. Genetic predispositions, environmental factors, and lifestyle elements contribute to the intricate tapestry of lung cancer, demanding comprehensive diagnostic tools that can navigate its multifaceted origins [9], [10]. In response to these challenges, our research seeks to contribute to the evolving landscape of lung cancer diagnostics by harnessing the transformative capabilities of deep learning models. Utilizing the IQ-OTH/NCCD dataset, our study unveils a model achieving an unprecedented 99.09% accuracy. This achievement is not merely a statistical triumph but a testament to the potential of advanced technologies in reshaping the trajectory of lung cancer prognosis.

1.2 Motivation

The ongoing burden of lung cancer, which is characterized by a high death rate and broad prevalence, emphasizes how urgently new methods for early identification and detection are needed. Because most cases of lung cancer are found at an advanced stage, there are fewer available treatments and very low survival rates [1]. Though medical technology has advanced, lung cancer still has a very bad prognosis. The current diagnostic status, characterized by challenges in early detection, emphasizes how urgently novel strategies that may alter the course of lung cancer prognosis are needed. Dangerous lung cancer usually manifests in its early stages without any symptoms. This complicates the diagnosis and treatment of the illness. The lack of very accurate and efficient diagnostic tools makes this delayed detection much worse, particularly when it comes to distinguishing between benign, malignant, and normal cases. Acquiring accuracy in this regard becomes essential because early diagnosis can have a major influence on patient survival rates and treatment outcomes. Furthermore, the wide range of etiologies of lung cancer is highlighted by the substantial proportion of non smoker cases. Many times based on past risk factors like smoking, conventional diagnostic methods may miss a sizable patient population, calling for a more sophisticated and inclusive approach. The difficulty is in early disease detection as well as in modifying diagnostic models to fit the wide range of profiles of people who are at risk for lung cancer. Economically speaking, lung cancer is a terrible disease, and healthcare systems all over the world are burdened by the outrageous expense of treatment and care. The financial effects reach people and families outside of institutions, underscoring the need for affordable diagnostic methods. The creation of effective approaches not only enhances public health but also supports the financial viability of healthcare institutions struggling to meet the growing expenses related to lung cancer treatment.

1.3 Rationale of the Study

Lung cancer remains a global health crisis due to its high incidence and mortality rates. Despite advancements in medical technology, the prognosis for lung cancer is grim, primarily because the disease is often diagnosed at advanced stages when treatment options are limited and survival rates are low. The traditional diagnostic methods, which heavily rely on identifying risk factors such as smoking, fail to account for a significant portion of non-smoker cases, thus highlighting the necessity for more sophisticated and inclusive diagnostic approaches.

The economic burden of lung cancer is substantial, with costs running into billions annually, affecting healthcare systems and individual families alike. The dire need for cost-effective and efficient diagnostic tools that can identify lung cancer early and accurately is clear. Early detection not only improves survival rates but also enhances the quality of life for patients and their families.

Given these challenges, this study aims to leverage the potential of deep learning models to revolutionize lung cancer diagnosis. By developing and optimizing various deep learning models using the IQ-OTH/NCCD dataset, this research seeks to achieve unprecedented accuracy in lung cancer prediction. The high accuracy rate of 99.09% achieved in preliminary models underscores the promise of advanced technology in transforming lung cancer prognostication and treatment outcomes.

1.4 Research Questions

a. How can a deep learning algorithm be effectively tailored to classify lung cancer across a diverse dataset, considering variations in disease properties?
b. Which transfer learning model, among options such as MobileNetV2, ResNet, and Inception, demonstrates the highest accuracy and efficiency in predicting lung cancer diseases?

c. How can the performance of the developed algorithm be effectively validated, and what are the key metrics that indicate its reliability and efficacy in real world scenarios?
d. What methods can be incorporated into the algorithm to enhance interpretability and explain ability, allowing stakeholders to understand the decision making process and gain insights into disease classification?

1.5 Expected Output

The study is expected to yield the following outputs:

i. Development and Optimization of Deep Learning Models: Creation and fine tuning of various deep learning models (InceptionV3_network, Efficient network, ResNet152_network, MobileNetV2 network, VGG19 network) for accurate lung cancer prediction using the IQ-OTH/NCCD dataset.
ii. Identification of Optimal Model Configuration: Through an extensive ablation study, determination of the optimal model configuration for the Efficient Net network, considering factors such as pooling methods, batch size, loss functions, optimizers, and learning rates.
iii. High Accuracy Achievement and Validation: Attainment and rigorous validation of a high accuracy rate of 99.09% using the optimized Efficient Net network, ensuring robust performance across diverse subsets of the IQ-OTH/NCCD dataset.
iv. Detailed Performance Analysis: Comprehensive analysis of model performance using confusion matrices, classification reports, Area Under the Curve (AUC) scores, and Loss curves, providing insights into the model's classification capabilities and reliability.
v. Clinical Practice Insights: Actionable insights and recommendations for clinical practice, aimed at optimizing early detection strategies and improving lung cancer prognostication and treatment outcomes.

1.6 Report Layout

Chapter 1 presents the research introduction, objectives, and key research questions. Chapter 2 Brief summaries of the literature review are provided.

Chapter 3 describes the proposed methodology with a detailed description. Chapter 4 explains paper's experimental results and discussed. Chapter 5 concludes the present research along with a direction for future work.

CHAPTER 2

Background

2.1 Preliminaries/Terminologies

A number of research taken together highlight the variety of approaches used for COVID-19 diagnosis and automated lung cancer detection, including machine learning techniques and advanced graph-based neural networks as well as morphological reconstruction and segmentation models. Even if there has been progress, correct segmentation, feature extraction, and model interpretability are still difficult, which highlights the necessity of more study to improve and optimize these methods for strong and trustworthy diagnostic results.

2.2 Related works

Mohammad Hamid Asnawi et al. [17] explored 3D UNet and its modifications 3D Res uNet, 3D VGG-uNet, and 3D Dense-uNet for effective lung segmentation, shedding light on the diversity of architectural approaches in the pursuit of accurate segmentation. Extracting medically relevant features from ROIs and employing Graph Neural Networks (GNN), Artificial Neural Networks (ANN), or other machine learning models for disease classification have been explored by Huanhuan Liu et al. [18], Ya ni Duan et al. [19], and Chun Shuang Guan et al. [20]. These studies emphasize the importance of feature extraction from lung CT images, considering clinical and imaging differences in diverse populations, including pregnant women, children, and adults. Matthew Shardlow [21] delved into feature selection methods, determining that a hybrid method called 'Ranked Forward Search' proved most effective. Feature selection is crucial for optimizing model performance by identifying pertinent features from medical images. He Ma et al. [22] developed a Mask region-based CNN (RCNN) model, achieving a commendable accuracy of 81.7% for 3D medical image detection tasks. Asmaa Abbas et al. [23] introduced the Decompose, Transfer, and Compose (DeTraC) model for classifying COVID-19 using CXR images. This model demonstrated notable success in identifying COVID-19 X-ray images, showcasing its potential for discriminating between different respiratory syndromes. Shankar et al. [24] proposed the FM-HCF-DLF model, incorporating hand-crafted features and deep learning for COVID-19 classification. This unique fusion model, after applying Gaussian filtering based pre processing, achieved an accuracy of 94.08%. In exploring machine learning approaches, Emre AVUCLU et al. [25] experimented with various algorithms, where Naive Bayes (NB) emerged as the most effective for COVID-19 classification with a testing accuracy of 93.87%. The versatility of machine learning algorithms in classifying COVID-19 underscores their potential as alternative tools for diagnostic tasks. Recent studies have also explored the efficacy of Graph Neural Network (GNN) models for classifying medical diseases. Xiang Yu et al. [26] developed ResGNet C, a graph convolutional neural network under the ResGNet framework, achieving a test accuracy of 97.33% for classifying lung CT images into normal and COVID-19 pneumonia cases. Another noteworthy contribution comes from Pritam Saha et al. [27], who proposed Graph Covid Net, a Graph Isomorphic Network (GIN) based model, achieving an impressive accuracy of 99% for detecting COVID-19 from CT scans and CXRs.A. Asuntha et al., [11] detect the malignant lung nodules from the provided input lung image and categorize the degree of lung cancer. Using cutting-edge Deep learning techniques, this work locates the malignant lung nodules. The best feature extraction methods, including Zernike Moment, Local Binary Pattern (LBP), Scale Invariant Feature Transform (SIFT), Wavelet transform-based features, and Histogram of Oriented Gradients (HoG), are used in this work.

The optimal feature is chosen using the Fuzzy Particle Swarm Optimization (FPSO) algorithm following the extraction of textural, geometric, volumetric, and intensity characteristics. Lastly, deep learning is used to classify these attributes. The computational complexity of CNN is decreased via a novel FPSOCNN. The optimal accuracy was 94.67% for the proposed model. Ibrahim M. Nasser et al. [12]developed an Artificial Neural Network (ANN) to identify whether lung cancer exists in the human body or not. Lung cancer was diagnosed by looking for certain symptoms, including yellow fingers, anxiety, fatigue, chronic illness, allergy, wheezing, coughing, shortness of breath, difficulty swallowing, and chest pain. They served as input variables for our ANN along with additional personal data about the individual. Our artificial neural network (ANN) was developed, trained, and validated using the "survey lung cancer" data set. The model evaluation revealed that the ANN model had a 96.67% accuracy rate in detecting the presence or absence of lung cancer. Lung cancer prediction is made possible with the introduction of new, improved image processing and machine learning techniques proposed by P. Mohamed Shake et al. [13]. Images from the non-small cell lung cancer CT scan dataset are gathered to identify lung cancer. The afflicted region is segmented from the noise removed lung CT image using an enhanced deep neural network, which uses network layers to segment the region and extract different features. The hybrid spiral optimization intelligent generalized rough set strategy is then used to choose the useful features, and an ensemble classifier is used to classify those features. The method under discussion enhances the likelihood of predicting lung cancer, as demonstrated by MATLAB-based outcomes including logarithmic loss, mean absolute error, precision, recall, and F-score. The field of automated diagnosis of COVID-19 has witnessed a plethora of studies leveraging advanced techniques in deep learning and machine learning. S.A. Banday et al. [6][14]introduced a morphological reconstruction approach for segmenting and enhancing the detection of Ground Glass Opacities (GGOs) in CT lung images. Utilizing an Artificial Neural Network (ANN), they achieved an impressive classification accuracy of 99.5%. This highlights the efficacy of morphological reconstruction in enhancing the specificity of COVID-19 detection. Lorenzo Maiello et al. [15] employed a UNet segmentation model with a 3D transfer learning-based approach to identify lung volumes, aeration compartments, and lung recruitability. Despite achieving an accuracy of 89.02%, the study underscores the challenges in accurately delineating complex lung structures, necessitating further refinements in segmentation models. Junting Zhao et al. [16] introduced a novel cascaded two stage UNet model named Distraction Sensitive U-Net (DSU-Net) for extracting Regions of Interest (ROIs) from lung CT scan images.

These studies collectively underscore the diverse methodologies employed for automated lung cancer detection, COVID-19 diagnosis, ranging from morphological reconstruction and segmentation models to machine learning algorithms and sophisticated graph based neural networks. While advancements have been made, the challenges in accurate segmentation, feature extraction, and model interpretability persist, emphasizing the need for continued research to refine and optimize these approaches for robust and reliable diagnostic outcomes.

2.3 Comparative Analysis

A comparative analysis in the context of your thesis on lung cancer detection with deep neural networks would involve critically evaluating and comparing the authors' backgrounds, the deep learning models employed, the results achieved, and the limitations or constraints of each study or approach. This holistic assessment helps in understanding the strengths and weaknesses of different methodologies and contributes to advancing knowledge in the field.

Table 2.1: Comparative Analysis of Various Deep Learning Models

Author	Model	Result	Limitation
Mohammad Hamid Asnawi et al. [17]	3D UNet, 3D Res-uNet, 3D VGG-uNet, 3D Dense-uNet	Effective lung segmentation	Specific performance metrics not provided; diversity of datasets not discussed
Huanhuan Liu et al. [18], Ya-ni Duan et al. [19], Chun Shuang Guan et al. [20]	Graph Neural Networks (GNN), Artificial Neural Networks (ANN)	Importance of feature extraction from lung CT images	Specific classification accuracy and limitations not detailed
Matthew Shardlow [21]	Ranked Forward Search	Most effective feature selection method	Generalizability across different datasets not addressed
He Ma et al. [22]	Mask region-based CNN (RCNN)	Accuracy of 81.7% for 3D medical image detection tasks	Accuracy is lower compared to other advanced models; specific limitations not discussed
Asmaa Abbas et al. [23]	Decompose, Transfer, and Compose (DeTraC)	Success in identifying COVID-19 X-ray images	Focused on COVID-19, may not be directly applicable to lung cancer classification
Shankar et al. [24]	FM-HCF-DLF model	Accuracy of 94.08% for COVID-19 classification	Specific to COVID-19; the model's applicability to lung cancer is not explored

Emre AVUÇLU et al. [25]	Naive Bayes (NB)	Testing accuracy of 93.87% for COVID-19 classification	Specific to COVID-19; may not translate directly to lung cancer detection
Xiang Yu et al. [26]	ResGNet-C, Graph Convolutional Neural Network	Test accuracy of 97.33% for lung CT images	Focused on normal and COVID-19 pneumonia cases; generalization to other diseases not clear
Pritam Saha et al. [27]	GraphCovidNet, Graph Isomorphic Network (GIN)	Accuracy of 99% for detecting COVID-19	Focused on COVID-19, may not directly apply to lung cancer classification
A. Asuntha et al. [11]	FPSO-CNN	Accuracy of 94.67% for detecting malignant lung nodules	High computational complexity; specific challenges in feature extraction not detailed
Ibrahim M. Nasser et al. [12]	Artificial Neural Network (ANN)	Accuracy of 96.67% in detecting lung cancer	Relies on symptom-based input variables, which may not capture all relevant clinical features
P. Mohamed Shakee et al. [13]	Enhanced Deep Neural Network	Improved prediction of lung cancer	Complex hybrid model; specific limitations in practical application not discussed
S.A. Banday et al. [6] [14]	Morphological Reconstruction, ANN	Classification accuracy of 99.5% for COVID-19	Specific to COVID-19; applicability to lung cancer not addressed
Lorenzo Maiello et al. [15]	UNet with 3D transfer learning	Accuracy of 89.02% in lung volume identification	Challenges in accurately delineating complex lung structures; further refinements needed

Junting Zhao et al. [16]	Distraction-Sensitive U-Net (DSU-Net)	Effective ROI extraction from lung CT scan images	Specific performance metrics and broader applicability not discussed

2.4 The Problem's Scope

Within the contours of our study, the scope of the problem centers on the automated detection of lung cancer, deploying advanced deep learning models for predictive analysis. Leveraging the Iraq-Oncology Teaching Hospital National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset, our research encompasses the exploration and optimization of five distinct deep learning architectures InceptionV3 network, Efficient network, ResNet152 network, MobileNetV2 network, and VGG19 network. The problem scope extends to the enhancement of the Efficient network through a comprehensive ablation study, probing the impact of pooling methods, batch size, loss functions, optimizers, and learning rates on diagnostic accuracy. Additionally, our investigation delves into the evaluation of model performance using metrics such as confusion matrices, classification reports, Area Under the Curve (AUC) scores, and Loss curves. The overarching goal is to contribute not only to the technical advancements in lung cancer detection but also to provide insights into the clinical significance of our proposed models, fostering a paradigm shift in the precision and efficacy of lung cancer prognosis.

2.5 Challenges

The pursuit of automated lung cancer detection using deep learning models is accompanied by a set of intricate challenges that necessitate careful consideration and innovative solutions. One primary challenge lies in the inherent complexity and heterogeneity of lung cancer itself. The varied manifestations of benign and malignant cases, coupled with the potential presence of com orbidities, demand robust models capable of discerning subtle patterns and features within medical imaging data. Another formidable challenge pertains to the scarcity and quality of labeled datasets for lung cancer. The availability of comprehensive, well-annotated datasets is pivotal for training deep learning models effectively. The limited size and diversity of datasets can hinder the generalization of models across different patient demographics and disease variations, potentially leading to overfitting or biased predictions. The interpretability of deep learning models in the medical domain poses a significant challenge. Understanding the decision-making process of these complex models is crucial for gaining the trust of healthcare practitioners and ensuring the seamless integration of automated diagnostic tools into clinical workflows. The black-box nature of some deep learning architectures requires efforts to enhance model interpretability while maintaining high accuracy. Optimizing model parameters and configurations presents a challenge in itself. The ablation study conducted to refine the Efficient network underscores the intricate interplay of factors such as pooling methods, batch size, loss functions, optimizers, and learning rates. Balancing these parameters to achieve optimal performance without overfitting or compromising computational efficiency is a delicate yet crucial challenge in model development. The translational aspect of deploying deep learning models in real-world clinical settings introduces challenges related to scalability, computational resources, and model deployment. Integrating automated lung cancer detection tools seamlessly into existing healthcare infrastructures while ensuring scalability and real time performance necessitates careful consideration of deployment challenges. Evaluating the economic impact and cost effectiveness of the proposed models poses additional challenges. While achieving high accuracy is paramount, it is essential to assess the economic feasibility and practicality of implementing these advanced technologies within healthcare systems, considering factors such as infrastructure requirements, maintenance costs, and accessibility.

Furthermore, the lack of standardized protocols for model evaluation in the field of medical imaging introduces challenges in comparing the performance of different models across studies. Harmonizing evaluation metrics and methodologies would facilitate more meaningful comparisons and advancements in the broader research community. In summary, the challenges inherent in automated lung cancer detection encompass the complexities of the disease itself, data limitations, model interpretability, parameter optimization, translational deployment, economic considerations, and the need for standardized evaluation protocols. Addressing these challenges will not only advance the field of automated diagnostics but also pave the way for more effective and accessible tools in the early detection and prognosis of lung cancer.

CHAPTER 3

Research Methodology

3.1 Proposed Methodology/Applied Mechanism

Figure 3.1 below provides a visual representation of the whole workflow, including all of the sequential steps and interactions that went into developing and testing our deep learning model for classifying benign and malignant cases.

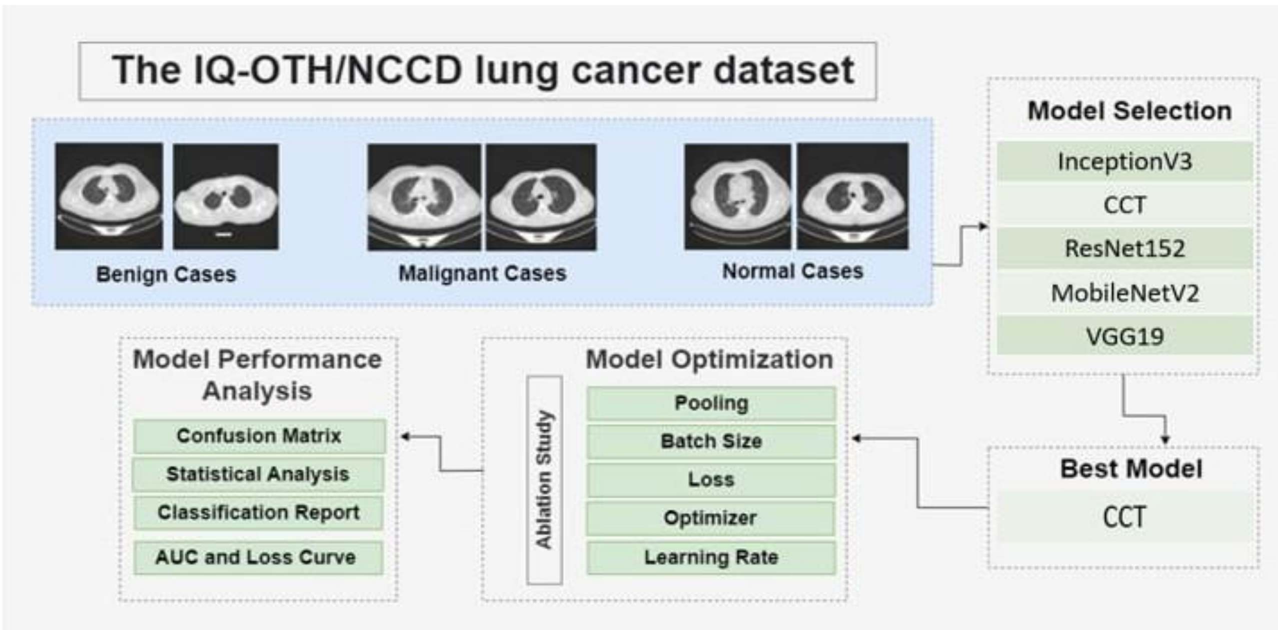

Figure 3.1: Demonstration of the entire methodology of this study.

The methodology section illustrated in the image presents a detailed process for evaluating and optimizing deep learning models to classify lung cancer using the IQ-OTH/NCCD lung cancer dataset, which includes benign, malignant, and normal cases. The process begins with model selection, where five different convolutional neural network (CNN) architectures are chosen for initial assessment: InceptionV3, CCT (Compact Convolutional Transformer), ResNet152, MobileNetV2, and VGG19. Each model is comprehensively evaluated using several key metrics, including the confusion matrix, statistical analysis, classification report, and AUC (Area Under the Curve) and loss curves. To enhance the model's performance, optimization is performed through ablation studies, systematically altering hyper parameters such as pooling strategies, batch size, loss function, optimizer, and learning rate to understand their impact. Through this rigorous process of evaluation and optimization, the CCT (Compact Convolutional Transformer) model is identified as the best performing model, demonstrating superior capability in classifying lung cancer cases from the dataset.

3.2 Data Collection Procedure/Dataset Utilized

The Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset serves as a crucial foundation for our study, collected meticulously over three months in fall 2019 from specialized medical centers. Comprising CT scans obtained using the Siemens SOMATOM scanner, this dataset encapsulates a comprehensive view of lung cancer cases at various stages, alongside scans from healthy subjects. The scans, initially in DICOM format, underwent meticulous annotation by oncologists and radiologists in the specified hospitals. In total, the dataset comprises 1190 CT scan slices extracted from 110 cases, encompassing a diverse representation of lung cancer scenarios. The distribution of cases across the three classes is as follows: 40 cases diagnosed as malignant, 15 cases as benign, and 55 cases classified as normal. Each scan, acquired with a CT protocol of 120 kV and a 1 mm slice thickness, represents an image of the human chest taken at full inspiration. The specified window width ranging from 350 to 1200 HU and window center from 50 to 600 were employed during scanning. Notably, all images underwent de-identification prior to analysis, adhering to ethical guidelines. The study received approval from the institutional review board of the participating medical centers, with written consent waived by the oversight review board. Figure 3.2 can illustrate more with three distinct classes.

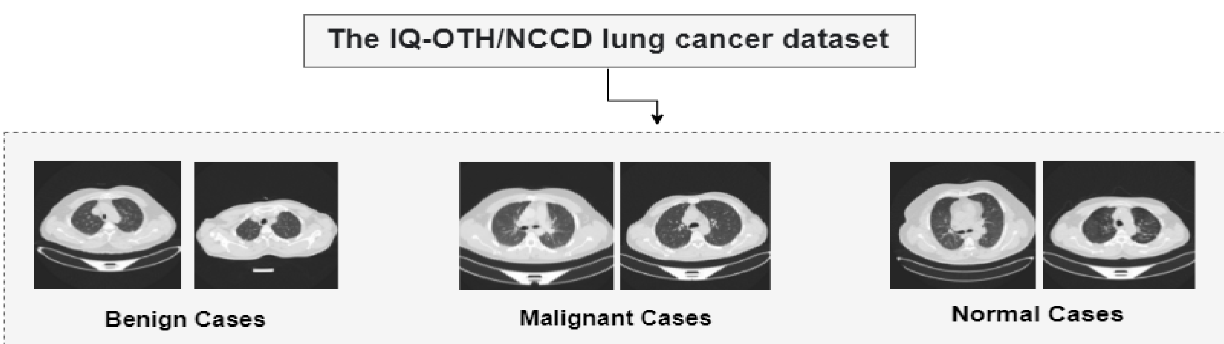

Figure 3.2: Illustration of three classes used in the dataset for this research.

These CT scans reveal a rich diversity, with each case presenting a variable number of slices ranging from 80 to 200. Each slice provides a unique perspective of the human chest, captured at different sides and angles, offering a comprehensive portrayal of the lung's structure. The cases within the dataset encompass a wide demographic spectrum, including variations in gender, age, educational attainment, area of residence, and living status. Occupationally, individuals from diverse backgrounds such as employees of Iraqi ministries of Transport and Oil, farmers, and gainers contribute to the heterogeneity of the dataset. Geographically, the majority hail from the central region of Iraq, particularly the provinces of Baghdad, Wasit, Diyala, Salahuddin, and Babylon.The number of images of each class shown in Table 3.1

Table 3.1: Image count details of from each class of the dataset.

Dataset Classes	**Image Quantity**	**Image Type**
Benign	120	JPG
Malignant	561	
Normal	416	

This dataset, with its meticulous annotation, diverse representation, and adherence to ethical standards, forms the cornerstone of our study, enabling the development and evaluation of advanced deep learning models for accurate lung cancer detection.

3.3 Method & Proposed Model

The image presents a detailed methodology section that describes a thorough process for assessing and improving models for lung cancer classification. This process utilizes the IQ-OTH/NCCD lung cancer dataset, which consists of instances of benign, malignant, and normal lung cancer. At first, a range of models including InceptionV3, CCT, ResNet152, MobileNetV2, and VGG19 are chosen for evaluation. The performance of these models is evaluated by the utilization of many metrics such as the confusion matrix, statistical analysis, classification report, AUC (Area Under the Curve), and loss curves. Model optimization is conducted by doing ablation experiments, which specifically target hyper parameters including pooling, batch size, loss function, optimizer, and learning rate. The most effective model resulting from this procedure is referred to be CCT.

3.3.1 InceptionV3

The InceptionV3[28] model architecture, a pivotal member of the Inception family, represents a landmark in convolutional neural network (CNN) design, particularly for image classification and object recognition tasks. With an input layer accepting RGB images of dimensions 299x299 pixels, InceptionV3 sets the stage for hierarchical feature extraction. The initial convolutional layers lay the groundwork by capturing low level features from the input images. The distinctive feature of Inception models, the inception module, dominates the architecture, fostering the simultaneous exploration of multiple filter sizes (1x1, 3x3, 5x5) and max-pooling branches. This parallel processing allows the model to capture features at different scales, enhancing its ability to discern complex patterns. Interspersed between the inception modules, reduction blocks further optimize spatial dimensions, typically incorporating a mix of convolutional layers and max-pooling. Noteworthy are the auxiliary classifiers strategically placed within the network, assisting in mitigating the vanishing gradient problem and promoting convergence during training. Global average pooling precedes the fully connected layers, contributing to parameter reduction and preventing overfitting. The architecture of InceptionV3 shown in Figure 3.3.

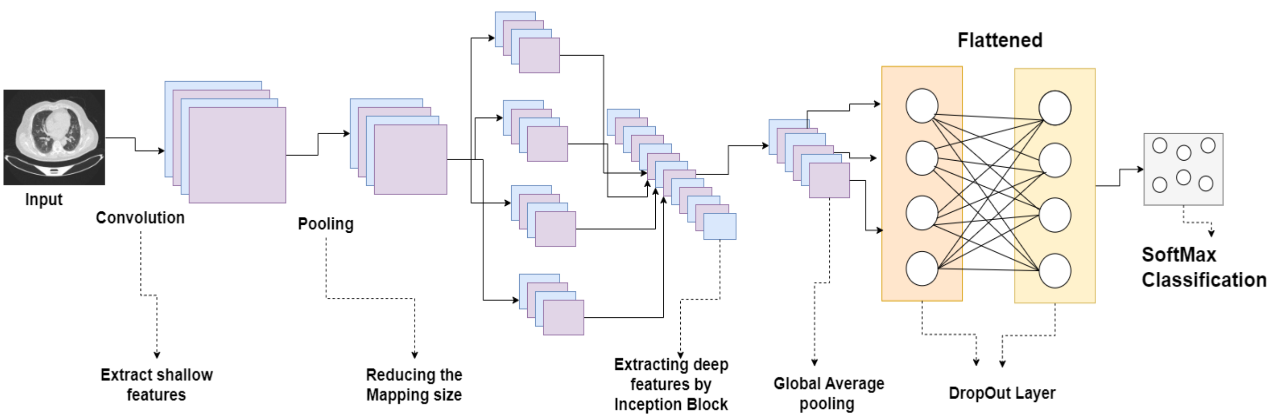

Figure 3.3: Architecture of InceptionV3

With a total of approximately 23 million parameters, InceptionV3 showcases its depth and capacity to comprehend intricate image structures. The architecture is equipped with pre trained weights, often leveraging extensive datasets like ImageNet, making it adept at transfer learning for various image-related tasks. The model's modular design, innovative inception modules, and factorized convolutions collectively position InceptionV3 as a versatile and powerful tool in the realm of deep learning, underscoring its effectiveness in extracting multi-scale features and achieving high accuracy in image classification. As a testament to its success, InceptionV3 continues to find applications in diverse domains, contributing to advancements in computer vision and pattern recognition.

3.3.2 VGG19

VGG19[29], a prominent member of the Visual Geometry Group's (VGG) family of convolutional neural network (CNN) architectures, has emerged as a stalwart in the realm of image classification tasks. Introduced by the Visual Geometry Group at the University of Oxford, VGG19 is celebrated for its simplicity and effectiveness. This architectural design, while straightforward, has proven to be highly impactful, earning its place in the pantheon of influential deep learning models. At the core of VGG19 lies a focus on convolutional layers with small receptive fields. The model is adept at capturing intricate features through the repeated use of 3x3 convolutional filters, fostering a deep and hierarchical understanding of image patterns. Operating on RGB images with a fixed size of 224x224 pixels, VGG19 initiates its convolutional journey with an input layer that efficiently processes the intricate details within each image. The architecture of VGG19 shows in Figure 3.4

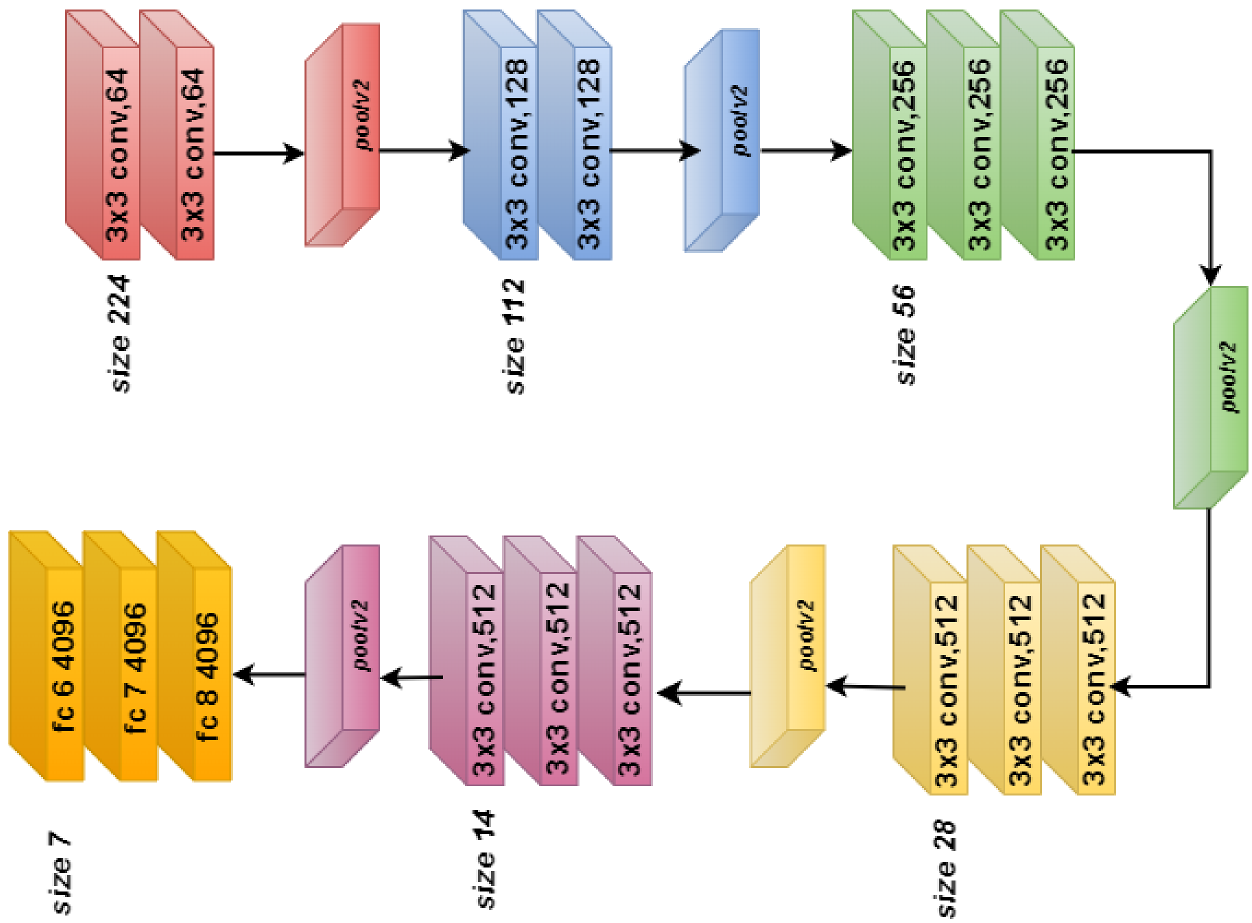

Figure 3.4: Architecture of VGG19

The architecture unfolds through a sequence of five convolutional blocks, each containing one to four convolutional layers followed by max-pooling. This stacking of convolutional layers allows the model to progressively learn complex hierarchical features. The rectified linear unit (ReLU) activation function is employed throughout the model, contributing to the efficient learning of non linear relationships within the data. Each convolutional block is strategically designed to capture different levels of abstraction, facilitating the extraction of features at varying scales. Pooling layers, specifically max-pooling with a 2x2 window and a stride of 2, are interspersed between the convolutional layers. These pooling layers serve a dual purpose of down sampling the spatial dimensions of the feature maps and promoting translation invariance. The ability to capture local patterns while progressively reducing the spatial resolution contributes to the model's capacity to discern intricate structures within images. Following the convolutional blocks, VGG19 incorporates three fully connected layers, each comprising 4,096 neurons with ReLU activation. This transition to fully connected layers enables the model to capture high-level features and intricate relationships between the learned features. The final layer of the network is a fully connected layer with 1,000 neurons, corresponding to the 1,000 classes in the ImageNet dataset. The softmax activation function is applied to produce probability scores, providing a nuanced prediction for each class. In terms of model parameters, VGG19 is a heavyweight, boasting approximately 143.7 million parameters. This extensive parameterization is a testament to the model's capacity to learn intricate representations, making it suitable for a wide range of image classification tasks. The model is often utilized with pre trained weights on large-scale image datasets such as ImageNet. This pre training strategy enables the model to leverage knowledge gained from extensive data, facilitating effective transfer learning to new tasks. VGG19's architectural simplicity and its efficient use of small convolutional filters have positioned it as a versatile and powerful tool for image classification tasks. Despite its deep architecture, the model's clear and modular design makes it easy to understand and implement. Additionally, variants within the VGG family, such as VGG16, offer flexibility to practitioners based on specific task requirements. In conclusion, VGG19's architectural design, characterized by its emphasis on small receptive fields, hierarchical feature extraction, and a deep network stack, has cemented its status as a robust and reliable model for image classification. The model's expressive learning capabilities, coupled with its simplicity and ease of understanding, have contributed to its widespread adoption in the deep learning community. VGG19's influence extends beyond its initial introduction, serving as a foundational reference in the evolution of deep learning architectures.

3.3.3 ResNet152

ResNet152[30], an influential member of the ResNet (Residual Network) family, stands as a pinnacle in deep convolutional neural network (CNN) architecture. Developed by Microsoft Research, ResNet152 addresses the challenges associated with training extremely deep networks by introducing the innovative concept of residual learning. The hallmark of ResNet architectures, including ResNet152, lies in the incorporation of residual blocks, which facilitate the learning of residual functions capturing the difference between the input and output of a given layer.

ResNet152 consists of 152 layers, showcasing its depth and capacity for hierarchical feature extraction. The fundamental building block, the residual block, comprises two or more convolutional layers with shortcut connections that allow the network to bypass one or more layers. These shortcut connections mitigate the vanishing gradient problem, enabling the successful training of extremely deep networks. Within each residual block, batch normalization and rectified linear unit (ReLU) activation functions contribute to stable and efficient feature learning. The architecture follows a pattern of down-sampling and up-sampling layers, with down-sampling achieved through strided convolutions and up-sampling using transposed convolutions. ResNet152 concludes with a global average pooling layer, which reduces spatial dimensions and serves as a transition to fully connected layers. The final layer is a fully connected layer with softmax activation, producing probabilities for different classes. ResNet152, with approximately 60 million parameters, showcases a careful balance between depth and parameter efficiency. The architecture ofResNet152 shows in Figure 3.5

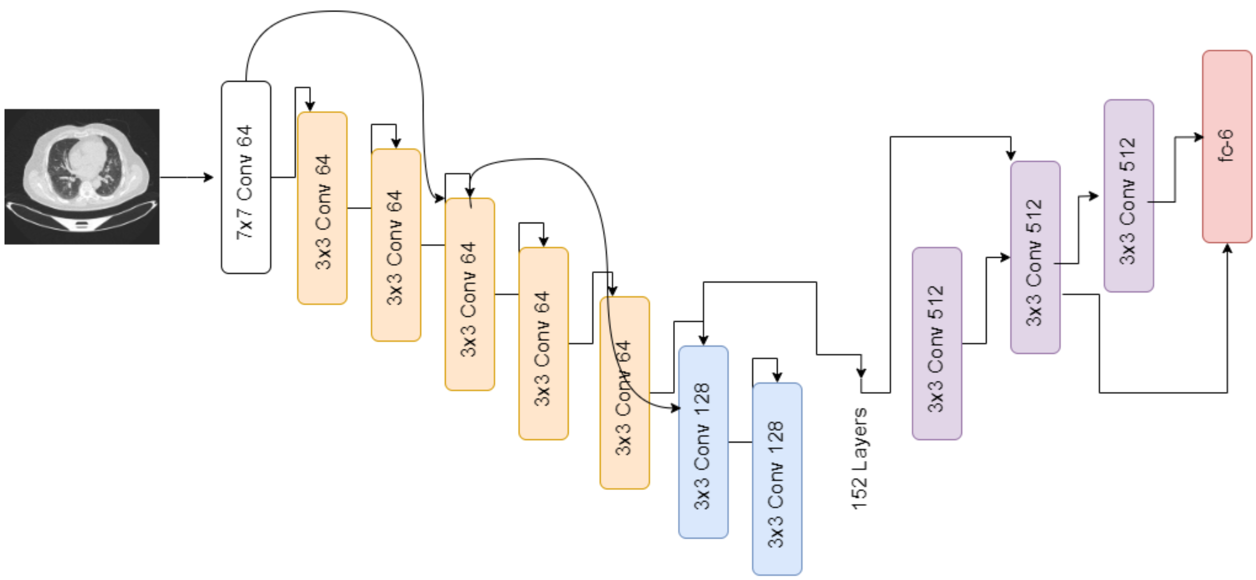

Figure 3.5: Architecture of ResNet152

This architecture is often employed with pre-trained weights on large-scale image datasets like ImageNet, facilitating transfer learning across various computer vision tasks. The depth and skip connections of ResNet152 enable the model to capture intricate features, making it particularly effective in image recognition tasks. Its influence extends beyond image classification, finding applications in tasks such as object detection and segmentation. In summary, ResNet152's architecture, characterized by residual blocks and skip connections, represents a breakthrough in training deep neural networks. The meticulous design addresses the challenges of deep learning, fostering the development of highly accurate and efficient models. ResNet152, with its depth, parameter efficiency, and adaptability, continues to serve as a cornerstone in the evolution of deep learning architectures, influencing advancements in various domains of computer vision and artificial intelligence.

3.3.4 MoblieNetV2

MobileNetV2 [31], a lightweight convolutional neural network (CNN) architecture developed by Google, has been meticulously designed for efficient deployment on mobile and edge devices with resource constraints. At the core of its innovation are the inverted residual blocks, each comprising a depth wise separable convolution, a linear bottleneck, and shortcut connections. These inverted residual blocks efficiently capture complex features while minimizing computational overhead. The linear bottlenecks maintain a linear path through the network, and shortcut connections facilitate information flow across layers, mitigating the vanishing gradient problem. MobileNetV2 strategically employs down sampling through strided convolutions within these blocks, optimizing spatial dimensions and computational efficiency. The architecture of MobileNetV2 shows in Figure 3.6.

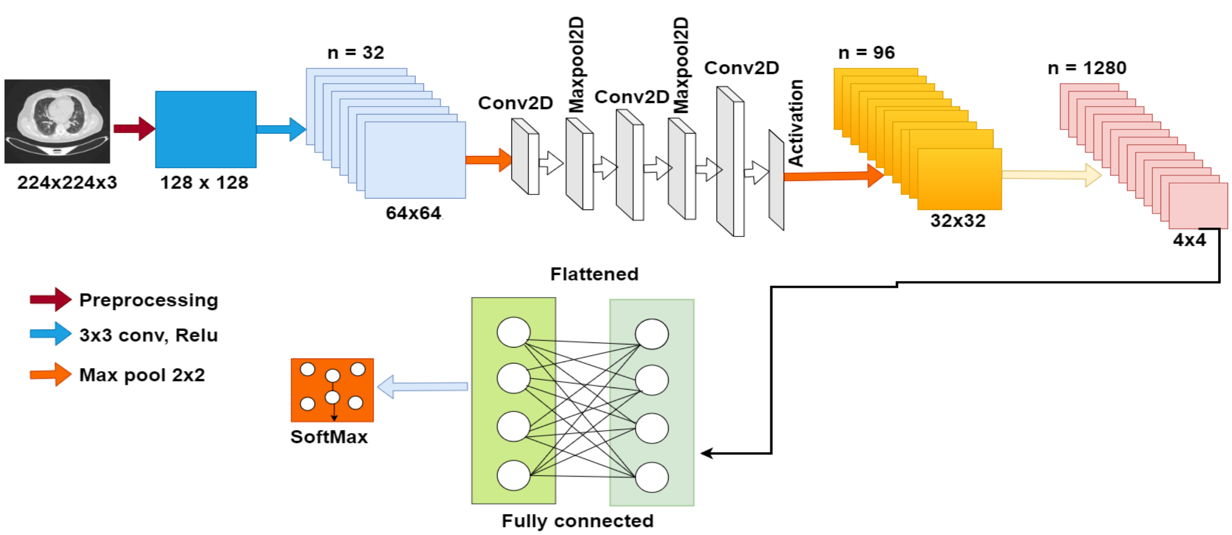

Figure 3.6: Architecture of MobileNetV2

The network's final layers include global average pooling for adaptability to varying input resolutions and a fully connected layer with soft max activation for classification tasks. With fewer parameters compared to larger CNN architectures, MobileNetV2 strikes a balance between efficiency and performance, making it a go to choice for image classification and computer vision tasks on mobile and edge devices, particularly when initialized with pre trained weights for effective transfer learning. With a focus on effective handheld consumption, MobileNetV2 [32], a lightweight and optimized convolutional neural network, represents a significant improvement over its predecessor, MobileNetV1. Designed to minimize computational complexity and achieve high accuracy, MobileNetV2 is a more efficient architectural evolution. In contrast to its predecessor, MobileNetV2 exhibits enhanced accuracy on identical hardware, rendering it a perfect option for environments with limited resources. MobileNetV2's architecture places equal emphasis on improved resilience against adversarial assaults and input noise as it does on greater accuracy. Because of this robustness, the model can be used in situations where it is subjected to a variety of potentially difficult real world conditions. Furthermore, MobileNetV2 is especially well suited for applications like picture segmentation and object detection because it is built to maximize battery life and reduce latency on mobile devices. MobileNetV2 is composed of two kinds of blocks, each with three levels, and each block has eleven convolutional layers. Each block's first, third, and second layers have 32 filters that are carefully crafted to collect and handle complex features. The longitudinal bottlenecks between layers are note worthy, this is an important characteristic that keeps a significant amount of data from being negatively impacted by non linearity. The two block’s distinct strides block 2 has a stride of two, while block 1 has a stride of one address the network's flexibility and effectiveness in processing a variety of geographical data.

3.3.5 Proposed CCT Model

The two main components of the CCT model architecture are Transformer with sequential pooling and Convolutional Tokenization. The coordination of these blocks enables the model to efficiently process input images [32]. In the Convolutional Tokenization block, the model transforms inputs of dimensions $H \times W \times C$intoanm length sequence. This is achieved through operations involving a convolutional layer (Conv2D) with 64 filters and strides of 2, followed by the ReLU activation function, and a MaxPool layer for down sampling. Notably, this block accommodates input images of varying sizes, eliminating the need for uniform patch sizes, and preserving local spatial information through convolutional patches. Positional embeddings are learned by the transformer encoder through layer normalization, GELU activation, and drop out after positional embedding. Theoutput of the transformer backbone is then pooled via the sequence pooling layer by means of a mapping transformation called $T{:}\mathrm{R}^{b\times n\times d}\rightarrow\mathrm{R}^{b\times d}$. This sequence pooling strategically lever ages the transformer's sequential embeddings, enhancing data correlation across he input data.

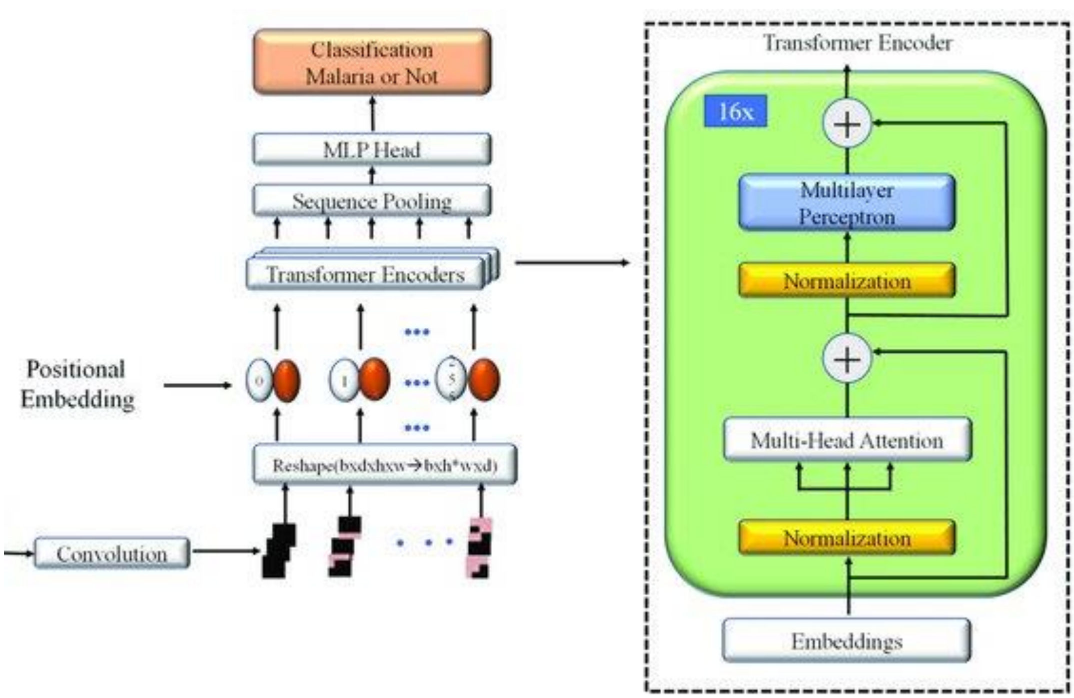

Figure 3.7: Architecture of CCT

3.4 Ablation Study

A concentrated ablation study has been carried out with great care and attention to forecast sweet pumpkin disorders; the results are presented in the Results section. In order to shed light on the intricate details of the model's architecture, this study seeks to identify the unique contributions made by each component. The ablation study offers important insights into the significance and efficacy of each enhancement by methodically disabling and assessing the effects of various variables. This enables a more intelligent and optimal transfer learning model that is specifically designed for the categorization of sweet pumpkin diseases. The ablation study's findings advance knowledge of the robustness and functionality of the model as a whole, opening the door to more efficient and knowledgeable decision making in the field of agricultural disease prediction.

CHAPTER 4

Experimental Results and Discussion

4.1 Evolution Methods

Accuracy, precision, recall, and F1 score are among the confusion matrix metrics used in the evaluation. In actuality, genuine positive (TP) values are true. misleading positives (FP) are results of incorrect labeling of misleading information. When a proper value is mistakenly seen as negative, it results in the third form, known as false negative (FN). The alternatives for fourth and fifth place are TN and FN. A positive value mistakenly classified as negative is called a true negative (TN). True negative (TN) comes in fourth [23].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{F1 Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{4}$$

Additional evaluation matrices include root mean square error (RMSE), mean absolute error (MAE), negative predicted values (NPV), false positive rate (FPR), and false negative rate (FNR).

4.2 Results and Discussion

The findings of this paper will be reviewed in this section. The DR dataset is first put to the test using transfer learning models. The base model for the ablation study is determined by selecting the best outcome from the outcomes of the transfer learning models. The accuracy (training, testing, and validation) and loss (train, test, and validation) for each of the five transfer learning models are displayed in Table 4.1.

Table 4.1: Comparison of Deep Learning Models

Model	**Image Size**	**Time (s)**	**Epoch**	**Test Accuracy (%)**
InceptionV3	224x224	53	100	72.66
ResNet152	224x224	55	100	91.41
MobileNetV2	224x224	54	100	89.84
VGG19	224x224	53	100	94.53
CCT	32x32	51	400	99.09

The performance of various deep learning models was assessed for lung cancer classification using the IQ-OTH/NCCD dataset. InceptionV3, ResNet152, MobileNetV2, VGG19, and CCT models were evaluated with their respective configurations. InceptionV3, with an image size of 224x224, required 53 seconds per epoch and achieved a test accuracy of 72.66% after 100 epochs. ResNet152, also with an image size of 224x224, took 55 seconds per epoch and reached a test accuracy of 91.41% after 100 epochs. MobileNetV2, maintaining the same image size, took 54 seconds per epoch and achieved 89.84% accuracy in 100 epochs. VGG19, with similar parameters, required 53 seconds per epoch and attained a 94.53% accuracy. Notably, the CCT model, using a smaller image size of 32x32, completed training in 51 seconds per epoch and achieved an impressive test accuracy of 99.09% after 400 epochs, making it the top performing model in this evaluation.

4.2.1 Results of the Ablation study

The accuracy of classification can be increased by changing a number of design elements. The proposed model is modified in a total of four experiments that are conducted as ablation research. Below are the findings of the ablation investigation are shown in table 4.2.

Table 4.2: Summary of Experimental Configurations.

Case Study 01: Changing polling Layer				
Configuration No.	**Polling layer types**	**Epochs x training times**	**Test_accuracy (%)**	**Findings**
1	Flatten	400 x 34s	93.26	Best Accuracy
2	Global Max pooling	400x 34s	93.22	Good Accuracy
3	Global Average pooling	400x 34s	92.88	Poor Accuracy

Case Study 02: Changing the batch size

Configuration No.	Batch size	Epochs x training times	Test_accuracy (%)	Findings
1	16	400x 61s	94.23	Poor Accuracy
2	32	400x 34s	94.87	Best Accuracy
3	64	400x 28s	94.26	Good Accuracy

Case Study 03: Changing the Loss Function

Configuration No.	Loss Functions	Epochs x training times	Test_accuracy (%)	Findings
1	Categorical Cross entropy	400x 34s	95.51	Best Accuracy
2	Mean Squared Errors	400x 34s	94.87	Poor Accuracy
3	Mean absolute errors	400x 34s	93.23	Good Accuracy

Case Study 04: Changing the Optimizer

Configuration No.	Optimizers	Epochs x training times	Test_accuracy (%)	Findings

1	Adam	400x 34s	97.28	Best Accuracy
2	Nadam	400x 34s	96.88	Good Accuracy
3	SGD	400x 34s	96.51	Good Accuracy

Case Study 05: Changing the Learning Rate

Configuration No.	Learning rates	Epochs x training times	Test_accuracy (%)	Findings
1	0.01	400x 34s	98.8	Good Accuracy
2	0.001	400x 34s	99.09	Best Accuracy
3	0.0001	400x 34s	96.2	Good Accuracy

• **Case Study 1:** Modifying the Layer of Polling

The effects of changing the pooling layer are investigated in Case Study 1. Among the options, the flatten layer proves to be the most efficient and produces the highest accuracy. Using the flatten layer, the findings show that neither global averages nor global maximums contribute favorably to accuracy, with an accuracy of 93.26%. By comparison, 93.22% and 92.88% accuracy are obtained when using global averages and global maximums, respectively.

• **Case Study 2:** Modifying the Size of the Batch

The impact of batch size variation on model performance is the main topic of Case Study 2. The results show that the maximum accuracy is obtained with a batch size of 32, followed by 64 and 16. More specifically, the test accuracy is 94.87% when a batch size of 32 is used.

• **Case Study 3:** Loss Function Change

Examining the effects of various loss functions, Case Study 3 demonstrates that categorical cross-entropy produces the best outcomes, with a noteworthy accuracy of 95.28%.

• **Case Study 4:** Optimizer Change

When the optimizer selection is examined in Case Study 4, it is discovered that the Adam optimizer performs better than the Nadam, SGD, and Adamax optimizers. Using the Adam optimizer results in the maximum accuracy, which is 97.28%.

• **Case Study 5:** Learning Rate Change

Case Study 5 compares 0.001, 0.0001, and 0.01 to examine the impact of different learning rates. According to the study, the best accuracy is obtained with a learning rate of 0.01; this rate achieves 87.50%, which is higher than the accuracy attained with learning rates of 0.001 and 0.0001.

4.2.2 The final configuration of the model

Following the ablation study, table 4.3 presents the proposed model's final configuration.

Table 4.3: Configuration of the proposed model

Configuration	**Value**
Image sizes	32x32
Epochs	400
Optimization Functions	Adam
Learning rates	0.001
Batch sizes	32
Activation functions	Softmax
Dropouts	0.5

Momentum	0.9
Accuracy	99.09

4.2.3 Performance and statistical analysis

The most robust and hyper-tuned CNN model has the following FPR, FNR, FDR, KC, MCC, and RMSE, as table 4.4 illustrates.

Table 4.4: Statistical analysis of the proposed model

Statistics	**Value (%)**
Accuracy	99.09
Sensitivity	96.00
FPR	0.03
FNR	0.13
MCC	93.83
RMSE	34.43
Precession	97.09
F1 Score	96.66
Specificity	96.18

4.2.4 Confusion Matrix and Accuracy curve, loss curve and ROC curve

As decision-makers navigate the complexities of selecting the most effective model for their specific dataset, the analysis of confusion matrices and associated metrics becomes pivotal, guiding the optimization of these models for accurate and reliable lung cancer diagnostics. The confusion matrix of CCT is shown in Figure 4.1.

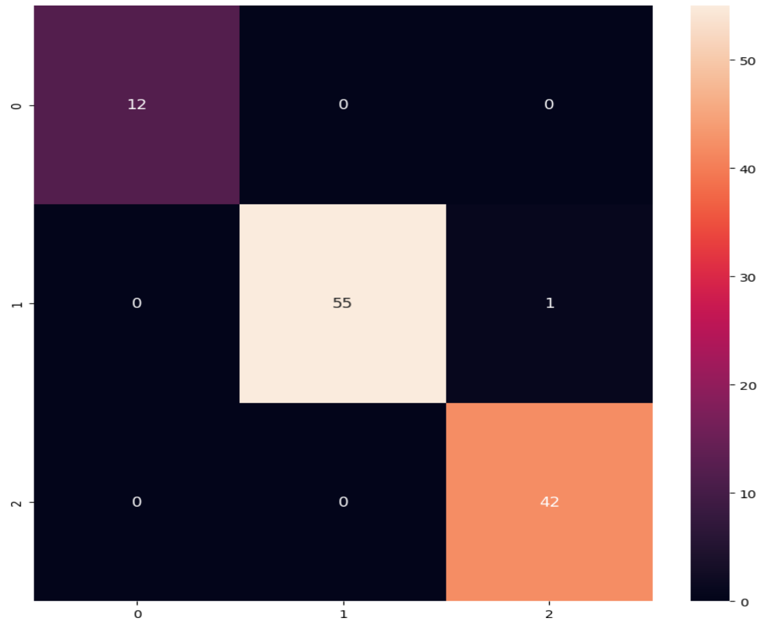

Figure 4.1. Confusion Matrix of the InceptionV3model.

The AUC and Loss Curve of this models shown in Figure 4.2.

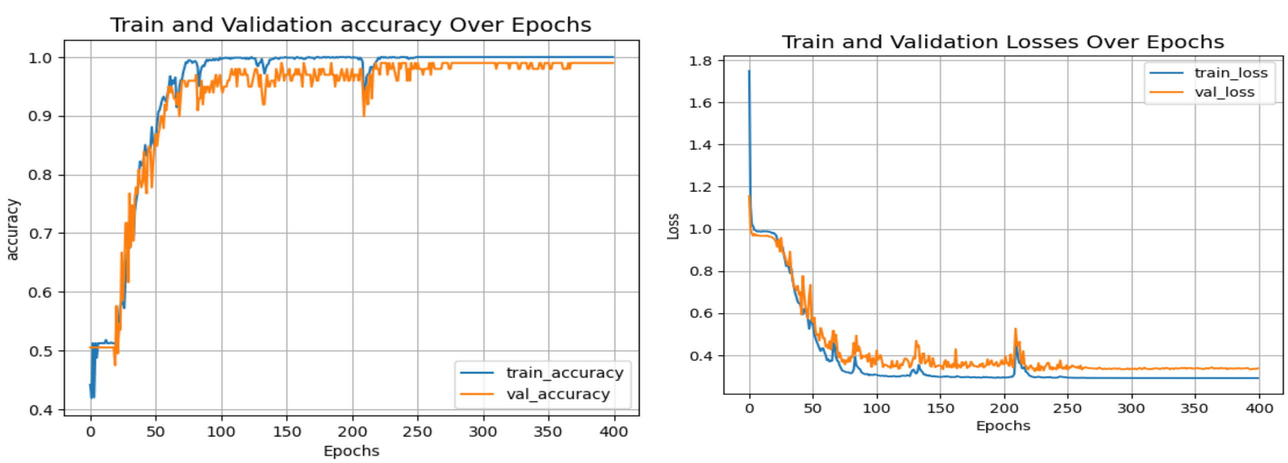

Figure 4.2. Accuracy and Loss curve of the CCT model.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Lung cancer classification has a profound impact on society by potentially revolutionizing early detection and treatment strategies. With lung cancer being a leading cause of cancer-related deaths globally, accurate classification models offer hope for improved survival rates and better patient outcomes. By enabling early identification of lung cancer cases, these models can facilitate timely interventions, reducing the societal burden of disease and enhancing overall public health. Additionally, increased accuracy in lung cancer classification can help mitigate disparities in access to healthcare, ensuring that all individuals, regardless of socioeconomic status or geographical location, have equitable opportunities for early detection and treatment.

5.2 Impact on Environment

The development and implementation of advanced lung cancer classification models have significant implications for healthcare systems worldwide. By streamlining the diagnostic process and enhancing the accuracy of disease detection, these models can improve resource allocation within healthcare facilities, leading to more efficient utilization of medical personnel, equipment, and financial resources. Moreover, early identification of lung cancer cases can potentially reduce the overall cost of treatment by minimizing the need for extensive interventions at later disease stages. This, in turn, can alleviate the financial strain on healthcare systems and contribute to the sustainability of healthcare delivery.

5.3 Ethical Aspects

The ethical implications of lung cancer classification extend to various aspects of healthcare delivery, including patient privacy, consent, and equity. Ensuring the privacy and confidentiality of patient data is paramount in the development and deployment of classification models, necessitating robust data security measures and adherence to regulatory guidelines such as GDPR and HIPAA. Moreover, there is a need to address potential biases in dataset collection and algorithmic decision-making to ensure equitable access to accurate diagnosis for all patient populations. Transparency in model development and validation processes is essential to foster trust among healthcare professionals and patients, promoting informed decision-making and ethical practice.

5.4 Sustainability Plan

A sustainable approach to lung cancer classification involves long-term strategies aimed at maximizing the impact of classification models while minimizing potential risks and limitations. This includes ongoing research and development efforts to improve the accuracy and generalizability of classification algorithms through collaboration between multidisciplinary teams of researchers, clinicians, and data scientists. Additionally, investment in education and training programs can empower healthcare professionals to effectively utilize classification models in clinical practice, ensuring their widespread adoption and sustainability. Furthermore, continuous monitoring and evaluation of model performance, coupled with feedback mechanisms from end-users, are essential for identifying areas of improvement and adapting classification algorithms to evolving healthcare needs. By prioritizing sustainability in the development and implementation of lung cancer classification models, we can maximize their potential to positively impact patient outcomes and public health.

CHAPTER 6

Conclusion and Future Work

6.1 Summary of the Study

This study aimed to enhance lung cancer prediction using advanced deep learning models, leveraging the IQ-OTH/NCCD dataset, which includes benign, malignant, and normal cases. We evaluated several state of the art convolutional neural network (CNN) architectures: InceptionV3, ResNet152, MobileNetV2, VGG19, and the Compact Convolutional Transformer (CCT). Each model's performance was meticulously analyzed using various metrics, including confusion matrices, statistical analyses, classification reports, and AUC and loss curves. Additionally, we conducted ablation studies to optimize model performance by adjusting key hyper parameters such as pooling strategies, batch size, loss functions, optimizers, and learning rates. The CCT model emerged as the most effective, achieving an impressive test accuracy of 99.09%.

6.2 Conclusion

The culmination of our study underscores the transformative potential of deep learning technologies in lung cancer diagnostics. Among the models tested, the CCT model demonstrated superior performance, achieving a remarkable 99.09% accuracy. This model's robustness in distinguishing between benign, malignant, and normal cases highlights its potential for reliable lung cancer predictions. Through detailed performance evaluations, we validated the models' predictive capabilities and gained nuanced insights into their strengths and areas for improvement. The societal impact of our findings is significant, suggesting that these advanced models can facilitate early detection, improve treatment outcomes, and optimize resource planning within healthcare systems. These advancements not only contribute to early diagnosis but also reduce the economic burden on healthcare, positioning deep learning models as valuable tools in combating lung cancer.

6.3 Implications for Further Study

While this study has demonstrated the efficacy of deep learning models, particularly the CCT, in predicting lung cancer, several avenues for future research remain. Further studies could explore the integration of additional data types, such as genomic and proteomic data, to enhance model accuracy and robustness. Moreover, real-world application and validation of these models in clinical settings are essential to confirm their practical utility and reliability. Expanding the dataset to include a more diverse population could also improve the generalizability of the models. Additionally, exploring the impact of explainable AI techniques on model transparency and clinician trust could foster broader adoption in healthcare settings. Finally, continued research into optimizing computational efficiency will be crucial for deploying these models in resource-limited environments, thereby broadening their accessibility and impact.

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