AN EFFECTIVE APPROACH TO IDENTIFICATION AND CLASSIFICATION OF LUNG CANCER FROM CT IMAGES BASED ON DEEP LEARNING MODELS.

BY

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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 **"AN EFFECTIVE APPROACH TO IDENTIFICATION AND CLASSIFICATION OF LUNG CANCER FROM CT IMAGES BASED ON DEEP LEARNING MODELS."** submitted by **Md. Atikur Rahman, ID: 201-15-3111** 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 25th January 2024.

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I hereby declare that this project has been done by me under the supervision of **Dr. Touhid Bhuiyan,** Professor**, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Lung cancer is the leading cause of cancer death in the globe. Early identification of lung cancer can help to prevent lung cancer from becoming chronic, severe and life threatening. Here, CT images are frequently used and an automated and appropriate method using deep learning technique that can potentially makes a huge contribute to make quick and accurate diagnosis for lung cancer. However, in the area of medical imaging using deep learnings techniques, there have two limitations. One huge training time and the other one is insufficient and imbalanced datasets. This study will present the number of image balancing and reducing the overall processing time. The dataset we use in this research work contains three cases normal, benign, and malignant. In the dataset, we use data augmentation techniques to increase the amount of data then we apply some image processing method on the dataset including some filter like GaussianBlur for reduce noise, Adaptive Thresholding for high component details and edge, lastly Image Negative and Bit Plane Slicing. We proposed a Customized Convolutional Neural Network (CCNN) model using 224 x 224 size images classify the lung cancer into three classes. Seven transfer learning models, VGG16, VGG19, ResNet50, ResNet101, DenseNet201, EfficientNetB4 and MobileNetV2 are applied with the same image and batch size and all the transfer leaning models are compared with the proposed CCNN model and we got the maximum test accuracy of 98.18% from CCNN model including the require time for per epoch 2 sec. Our proposed model may help medical expert for diagnosis the lung cancer from medical CT images and our aim to add more data in the dataset and use more deep learning models in our future study.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Lung cancer is responsible for the majority of cancer-related fatalities worldwide, making it the second most common cause of death worldwide. [15] A malignant tumor, lung cancer is typified by the uncontrollably growing cancerous nodules inside the lung tissue. Lung cancer is a fatal illness, meaning that it is dangerous enough to result in death. Lung cancer is the cause of more than one million fatalities each year.

According to estimates, lung cancer took the lives of 9.6 million people in 2018. If one discusses the various forms and their respective shares, lung cancer comes out on top. An estimated 2.09 million people are estimated to have lung cancer, and 1.76 million of those fatalities account for about 84% of all deaths. Lung cancer has earned its reputation as one of the worst illnesses because of this. However, compared to 1980, when 69% of cases were in industrialized nations, there has been a significant proportional increase in the number of lung cancer cases in developing nations, which now account for about half (49.9%) of all cases. The projected global incidence of lung cancer has grown by 51% since 1985, with a 44% increase in males and a 76% increase in women [19]. Lung cancer has the greatest mortality rates among both men and women, making it the primary cause of cancer-related fatalities globally. [21] Roughly 85% of occurrences of lung cancer are caused by smoking, making it the primary cause of the disease. When there are few treatment options available, lung cancer is frequently identified at an advanced stage. High-risk patients may be screened in order to increase survival rates significantly and enable early identification. Primary prevention can lower the incidence of lung cancer and save lives. Examples of primary prevention include tobacco control efforts and lowering exposure to environmental risk factors.

Lung cancer tumors are caused by the proliferation of aberrant cells. Because lung tissue contains both lymph fluid and blood streams, cancer cells have a tendency to spread quickly. Generally speaking, cancer cells often move to the center of the chest as a result of regular lymph flow. The spread of cancer cells to different tissues is known as metastasis. Since cancer tends to spread and is incurable in the event of a bigger spread, early detection is crucial. Lung cancer presents with symptoms only in its advanced stages, when survival is very impossible and diagnosis is challenging. Imaging methods including Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and X-ray are used to obtain images of the lungs for assessment. The most often used of the aforementioned techniques is the CT imaging technique since it provides a picture without overlapping structures. For physicians, diagnosing and understanding cancer is challenging. Lung cancer can be accurately diagnosed with CT scans. Deep learning techniques and image processing will be applied to diagnose lung cancer. These methods help to increase accuracy [16]. Scientists are working on automated solutions that lessen the workload of physicians, boost the accuracy of diagnostics by lowering the subjectivity factor, expedite the analysis, and lower medical expenses in anticipation of the anticipated rise in preventative and early detection measures. It is necessary to identify and quantify certain characteristics in order to find malignant nodules. Cancer likelihood can be evaluated based on the traits that have been found and how they combine. Even for a highly skilled physician, this endeavor is exceedingly challenging since there is a difficult correlation between the existence of nodules and a positive cancer diagnosis [17].

In the majority of nations, lung cancer is the most common malignant neoplasm and the leading cause of cancer-related death globally for all sexes combined. The primary aetiological factor in lung carcinogenesis, tobacco use, primarily determines the geographic and temporal patterns of lung cancer incidence as well as lung cancer mortality on a population level. Together with tobacco use, other variables including poor diet, genetic predisposition, occupational exposures, and air pollution may influence the descriptive epidemiology of lung cancer. Furthermore, new methods for classifying lung cancer based on genetic techniques have begun to shed light on the disease's aetiology, especially with regard to nonsmokers. Although tobacco use has been successfully identified as the primary risk factor for lung cancer, lung cancer is still one of the most frequent and deadly malignancies worldwide, despite being largely avoidable. Future research and preventative initiatives should concentrate on non-cigarette tobacco smoking products and get a deeper comprehension of the risk variables that contribute to lung carcinogenesis in non-smokers. [18] Cancer in nonsmokers differs histologically from cancer in tobacco users. Male smokers were more likely to develop squamous cell carcinoma than female smokers, who were more likely to develop lung adenocarcinoma. East Asian women and those who have never smoked have a higher chance of developing lung cancer. The EGFR, HER2, EML4-ALK, RET, and ROS1 gene mutation rates were higher in never smokers, but the K-ras gene mutation rate was lower in never smokers and more prevalent in tobacco smokers with lung cancer. Tumor samples from tobacco users exhibited a higher number of point mutations than tumor samples from nonsmokers, according to a paper by Govindan et al. Additionally, they stated that smokers have a mutational frequency that is ten times higher than that of non-smokers. These results imply that the carcinogenesis process for lung cancer differs in nonsmokers from smokers. Comprehending the distinctions between lung cancer in smokers and non-smokers will facilitate more accurate and effective lung cancer diagnosis and therapy for the latter group [19].

Early detection of the disease can help keep it from progressing to a serious, life-threatening, and chronic stage. Here, CT scans are commonly utilized in conjunction with an automated and suitable method that leverages deep learning techniques, which has the potential to significantly improve the speed and accuracy of lung cancer detection. There are two restrictions, nevertheless, when it comes to using deep learning methods to medical imaging. One involves extensive training time, and the other involves inadequate and unbalanced datasets. The quantity of images balanced and the total processing time reduced will be shown in this study. The contribution of the work summarized in below:

I. The dataset we used for this experiment that contains numbers of imbalance image data in different class that will performance poor in the model. So, we use data some augmentation technique’s to generate images. Such as: Rot90, Fliplr, Affine, Crop and Pad, Additive Gaussian Noise and Liner Contrast.
II. We proposed some image filter and processing techniques, such as: Gaussian Blur, Adaptive Thresholding, Image Negative, Bit plane Slicing and Normalization are applied to increase the quality of images and model performance.
III. We proposed CCNN model to reduce the high training time and compare with others pre-trained model based on various output of each models.

IV. Model Comparative analysis refers to compare the each generated out of models to find out the best fit model, We analysis VGG16, VGG19, ResNet50, ResNet101, DenseNet201, EfficientNetB4 and MobileNetV2 with our proposed CCNN model.

V. An ablation study is performed is to changing the different hyperparameters and the layer architecture of our proposed model to improve the model performance and reduce the number of parameters.

VI. In the section of the result analysis, we perform to show the various performance measurement matrix to show, how well our model is performed such as: accuracy, precision, recall, f1-score and support score.

From all used model, we got maximum test accuracy 98.18% from the CCNN model with the 2-3 second per epoch time, while other pre train achieve 48-95% test accuracy with average 17-20 second per epoch time. We keep value in total number of epoch, optimizer, image size, batch size and learning rate and we got different number of params for each models, different training time.

Our work primarily focused on utilizing deep learning techniques to identify lung cancer at an early stage using CT scans. We encountered and overcame two significant challenges: lengthy training time and unbalanced datasets. In order to address the second issue, data augmentation techniques were utilized, such as Rot90, Fliplr, Affine, Crop and Pad, Additive Gaussian Noise, and Linear Contrast. Moreover, many image filter and processing methods, including Gaussian Blur, Adaptive Thresholding, Image Negative, Bit plane Slicing, and Normalization, were suggested to improve the quality of images and boost the performance of the model. A unique Customized Convolutional Neural Network (CCNN) model was proposed to minimize training duration, and its efficacy was evaluated against pre-trained models including VGG16, VGG19, ResNet50, ResNet101, EfficientNetB4, and MobileNetV2.

Ablation research was conducted to investigate various hyperparameters and layer designs of the CCNN model in order to enhance performance and minimize the parameter count. The comparison research demonstrated that CCNN surpassed other models, with a maximum test accuracy of 98.18% with an impressive 2-3 seconds per epoch. In contrast, pre-trained models attained an accuracy range of 48-96% with an average duration of 17-20 seconds each epoch. The study maintained consistent settings for the total number of epochs, optimizer, picture size, batch size, and learning rate, emphasizing the efficiency and effectiveness of the proposed CCNN model. The extensive result analysis encompassed many performance parameters, including accuracy, precision, recall, f1-score, and support score. This further substantiates the superiority of CCNN in the early diagnosis of lung cancer.

1.2 Motivation

The growing incidence of lung cancer continues to be a substantial concern on a global scale, underscoring the urgent requirement for prompt detection of the illness in order to enhance patient results. Computed Tomography (CT) imaging is highly efficient in detecting abnormalities in the lungs and providing precise information about their anatomy. Nevertheless, the process of manually analyzing CT scans is arduous and susceptible to human fallibility, impeding the timely detection and treatment of lung cancer.

To tackle this dilemma, there is an urgent need for novel and efficient procedures to improve the speed and accuracy of lung cancer screening. Convolutional Neural Networks (CNNs), a specific branch of deep learning, have remarkable effectiveness in analyzing images, which makes them a compelling choice for converting CT scan interpretation.

The objective of our work is to utilize Convolutional Neural Networks (CNNs) to greatly enhance several elements of lung cancer diagnosis and classification based on CT scans.

- **Data analysis:** Automating the interpretation of complex CT scans expedites the detection of subtle cancer signs, hence minimizing delays in diagnosis and treatment.
- **Improved computational speed:** Deep learning algorithms have the ability to analyze CT images at a quicker pace than humans, allowing for quick and precise first interpretations.
- **Improved accuracy:** Convolutional Neural Networks (CNNs) are highly proficient in identifying complex patterns, which might potentially enhance detection rates and minimize the occurrence of false positives.

- **Rapid diagnosis:** Swift and accurate identification results in immediate intervention and enhanced treatment outcomes for individuals with lung cancer.
- **Enhanced patient care:** The use of consistent and unbiased analysis minimizes the occurrence of incorrect diagnoses, hence promoting patient confidence and guaranteeing appropriate treatment plans.
- **Enhancing the healthcare system:** Streamlining the diagnostic process decreases waiting periods, so preserving resources and yielding advantages for the whole healthcare system.

The conventional practice of visually inspecting CT images impedes the growth of screening initiatives and can lead to delays. The objective of our proposed deep learning model, which utilizes Convolutional Neural Networks (CNNs), is to effectively overcome these limitations by swiftly and precisely detecting lung cancer-associated patterns. This will ultimately enhance the overall efficiency of the diagnostic procedure.

We are motivated by our commitment to advance healthcare technology and solving the hurdles associated with rapid and accurate lung cancer diagnosis. The possible ramifications of our work transcend academic research and have implications for clinical practice. Our efforts aim to improve patient outcomes and assist to the fight against lung cancer by enabling faster and more precise identification of the disease.

1.3 Rationale of the study

The rising incidence of lung cancer necessitates novel approaches in the field of medical image analysis. The objective of the proposed study is to tackle the difficulties related to the duration of processing in the detection and categorization of lung cancer using CT images. The project aims to enhance the efficiency and accuracy of the diagnostic process by utilising Convolutional Neural Networks (CNNs) as a deep learning model. Given the importance of fast detection in determining treatment results, it is essential to improve processing speed by utilising sophisticated neural network designs. The study aims to enhance the efficiency of lung cancer detection by proposing an innovative CNN-based model, facilitating quicker and more efficient interpretation of medical images.

1.4 Research Question

Research Questions for a CNN-based Deep Learning Model to Improve Processing Time for Lung Cancer Identification and Classification from CT Images:

Precision and Applicability:

- Is it possible for a CNN-based model to surpass traditional approaches, such as radiologists, in terms of accuracy when it comes to finding and categorizing lung cancer nodules in CT images?
- To what extent can the model's performance be applied to various patient demographics, scanners, and picture qualities?
- Is the model capable of accurately detecting uncommon or unusual forms of lung cancer?

Time required for processing and level of efficiency:

- What is the extent of the reduction in processing time as compared to conventional diagnostic methods?
- Is there a trade-off between the accuracy of the model and its processing speed?
- Is it possible to optimize the model for real-time diagnosis in clinical settings?

Feature learning and interpretability:

- Which particular characteristics in CT pictures are the most important for the model's diagnosis?
- Is it possible to comprehend and elucidate the decision-making process of the model to medical professionals?
- By selectively emphasizing particular attributes or cancer categories, how can the model be modified to suit diverse clinical requirements?

Enhancing Data and Ensuring Model Resilience:

- What is the impact of data augmentation techniques such as rotation and scaling on the accuracy and generalizability of the model?
- Is it possible to enhance the model's resilience to noise, artifacts, and fluctuations in image quality?
- What modifications may be made to the model to effectively deal with datasets of CT scans that have limited or unbalanced data?

Integration and Clinical Impact:

- What are the methods for incorporating the model into current medical workflows and clinical decision support systems?
- What are the possible expenses and advantages of incorporating this paradigm into clinical practice?
- What are the ways in which the model may be utilized to enhance patient outcomes and facilitate the early diagnosis of lung cancer?

1.5 Expected Output

Improved Precision in Lung Cancer Detection: The CNN-based model is anticipated to surpass conventional approaches, such as human radiologists, in precisely detecting and classifying lung cancer nodules inside CT scans.

Versatility in Diverse Circumstances: The study aims to showcase the model's resilience when applied to a wide range of patient demographics, several CT scanners, and varied levels of picture quality.

Identification of Rare Lung Cancer Variants: The model is anticipated to demonstrate expertise in precisely identifying rare or unusual types of lung cancer, hence enhancing the overall diagnostic skills.

Substantial decrease in the amount of time required for processing: The objective of the study is to significantly decrease the amount of time required for processing in comparison to traditional diagnostic techniques, with a particular focus on highlighting the effectiveness of the CNN-based model.

Optimal Trade-off Between Precision and Efficiency: The study examines the presence of a harmonious trade-off between the precision of the model and its computational speed, offering valuable insights into the model's effectiveness.

Real-Time Diagnosis Optimization: The study investigates the feasibility of enhancing the CNN-based model for immediate diagnosis in clinical environments, hence enhancing prompt and efficient patient treatment.

Identification of Critical Diagnostic Characteristics: The objective of the research is to determine the key attributes in CT images that have a significant impact on the model's diagnostic judgements, hence facilitating comprehension of the fundamental process of feature acquisition.

Interpretability in the context of medical professionals: The focus is on clarifying the decision-making process of the model, so that it may be easily understood by medical practitioners and inspire confidence in its diagnostic skills.

Adaptable customization to accommodate a wide range of clinical needs: The study explores methods for selectively altering the model to highlight specific features or cancer classifications, in order to meet various therapeutic needs.

Enhanced capacity to withstand fluctuations in data: An evaluation is conducted to determine the influence of data augmentation strategies on the accuracy and generalizability of the model, focusing on improving its capacity to withstand noise, artefacts, and variations in picture quality.

Clinical integration strategies: The research offers valuable insights into techniques for smoothly integrating the CNN-based model into current medical processes and clinical decision support systems.

Cost-Benefit Analysis for Clinical Implementation: The study assesses the possible costs and benefits of incorporating the suggested paradigm into clinical practice, taking into account the economic consequences.

Enhancing Patient Outcomes: The anticipated result encompasses the various ways in which the model might be employed to improve patient outcomes, specifically by enabling early and precise detection of lung cancer.

1.6 Project Management and Finance

Efficient project management and meticulous financial preparation are crucial elements to guarantee the triumphant implementation of the research project. The subsequent delineates fundamental factors pertaining to project management and financial aspects:

Project Management:

Timeline and Milestones: Create an elaborate project timeline with precise milestones and deliverables.

Team Collaboration: Establish unambiguous communication routes among team members, collaborators, and stakeholders.

Risk Management: Identify prospective hazards and uncertainties. Create and implement methods to reduce or eliminate hazards.

Quality Control: Enforce methods to uphold the precision and dependability of study results.

Ethical Considerations: Maintain strict adherence to ethical norms in research, particularly when handling medical data.

Documentation: Ensure the maintenance of thorough documentation on the procedures, data sources, and outcomes.

Financial Planning:

Allocation of Funds: Create an elaborate budget that encompasses costs for data collecting, computing resources, and staff.

Sources of financing: Identify and get financing via research grants, institutional backing, or collaborative alliances.

Cost-Benefit Analysis: Conduct a cost-benefit analysis to evaluate the possible return on investment.

Financial Reporting: Establish an efficient financial reporting system to monitor and record expenses.

Resource Optimization: Maximise the efficiency of existing resources to achieve cost-effectiveness.

Contingency Planning: Allocate cash for contingencies in the budget to account for unexpected situations.

Grant Compliance: Ensure adherence to grant stipulations and fulfil reporting responsibilities.

Achieving Financial Sustainability: Investigate potential sources of long-term financial stability beyond the original financing period.

1.7 Report Layout

Chapter 1: Introduction

The research is introduced by providing a concise summary, explaining the reasons behind it, presenting a study that examines relationships, formulating specific research inquiries, specifying anticipated results, and briefly discussing project management and funding.

Chapter 2: Background

This document encompasses crucial terminology, evaluates relevant literature, conducts a comparative analysis and summary, establishes the boundaries of the topic, and tackles the obstacles linked to the research.

Chapter 3: Research Methodology

The text provides a description of the data gathering approach, an outline of the statistical analysis methods, details on data augmentations and image processing techniques, specifications for the dataset split, and an introduction to the suggested model along with its implementation requirements.

Chapter 4: Experimental Results and Discussion

Describes the methodology used in the experiment, examines and assesses the experimental data, and engages in a comprehensive analysis of the outcomes.

Chapter 5: Impact on Society, Environment, and Sustainability

Examines the effects of the study on society and the environment, considers ethical considerations, and presents a sustainability strategy for the suggested model.

Chapter 6: Summary, Conclusion, Recommendation, and Implication for Future Research

This text provides a concise overview of the study, presents logical deductions, proposes suggestions for action, and delineates possible avenues for further investigation.

CHAPTER 2
Background

2.1 Terminologies

This study utilizes Convolutional Neural Networks (CNNs) as a robust tool for image identification and processing, particularly designed for the complex job of recognizing and categorizing lung cancer from Computed Tomography (CT) pictures. Convolutional Neural Networks (CNNs) are highly effective at capturing the arrangement of elements in space, making them particularly valuable for identifying intricate patterns in medical imaging. An advanced deep learning model, known for its several layers and ability to learn from intricate data, is utilized to improve the processing time involved in identifying lung cancer from CT images. The main focus of this research is to enhance efficiency by reducing the time it takes to analyze and interpret images. The ultimate objective is to enable quick and accurate diagnosis. The classification component of the deep learning model entails assigning discovered areas in CT scans to distinct forms of lung cancer, surpassing simply detection to provide a sophisticated comprehension of the disease. Image processing techniques are essential in the overall methodology, since they contribute to the efficient analysis and interpretation of lung CT data. The study's efficiency measurements include enhancements in processing time, accuracy, precision, recall, F1 score, and other indicators. These metrics together evaluate the usefulness of the model in accurately and promptly detecting lung cancer. The objective of this research is to enhance early detection by utilizing the capabilities of the built deep learning model. This will lead to better patient outcomes by enabling prompt intervention and precise identification of lung cancer from CT scans.

2.2 Related works

In their study [1], the authors introduced a three-dimensional multipath VGG-like network. This network was tested using three-dimensional cubes that were obtained from the Lung Image Database Consortium and Image Database Resource Initiative (LIDCIDRI), Lung Nodule Analysis 2016 (LUNA16), and Kaggle Data Science Bowl 2017 datasets. The final findings were obtained by combining predictions from U-Net with a 3D multipath VGG-like network. The lung nodules were categorized and the presence of malignancy was determined using this framework, achieving an accuracy of 95.60% and a logloss value of 0.387732. The conventional approach of directly inputting the segmented CT images into 3D CNNs for categorization has been shown to be insufficient. In reference [2], a modified U-Net model was employed, which had been trained on LUNA16 data, for the purpose of identifying nodule candidates. The U-Net output identified the regions of CT scans with segmented lungs where the most probable nodule candidates were situated. These regions were then inputted into 3D Convolutional Neural Networks (CNNs) to classify the CT scan as either positive or negative for lung cancer. The performance of the suggested computer-aided design (CAD) system surpassed that of existing CAD systems, offering improved training and detection efficiency as well as enhanced generalizability to different types of malignancies.

The author of the paper [3] discusses the deployment of a convolutional neural network to develop a lung cancer prediction system, which addresses the limitations associated with manual cancer prediction.

CT scan images are collected and processed using a neural network layer that automatically extracts image features. These features are then processed using deep learning to predict cancer-related features, utilizing a large volume of images. The authors have developed a method that aids in decision-making during the analysis of a patient's CT scan result. In the 22nd iteration [4], I successfully predicted the presence of lung nodules in CT scan pictures using the convolutional neural network technique. Throughout this procedure, photos from the LIDC IDRI database are gathered and inputted into the stack encoder (SAE), convolution neural network (CNN), and deep neural network (DNN) to accurately classify lung cancer-related features as either benign or malignant. The author has created a technique that guarantees an accuracy rate of up to 84.32%. Authors have discussed that CT scans are analyzed by segmentation and optimized machine learning techniques to accurately predict malignancy. This research investigates the classification of lung cancer using an enhanced clustering technique called Improved Profuse Clustering Technique (IPCT) and a neural network trained immediately using deep learning, known as Deep Learning based immediately Trained Neural Network (DITNN). The next section provides an explanation of this approach.

Due to the scope of our study, we will only provide a selection of current discriminative approaches, as a thorough examination is beyond our present focus. The majority of image detection methods primarily focus on two-dimensional images. One example is the introduction of faster-RCNN by [5], in which the model suggests bounding boxes in an early step and estimates the class decision in a second stage. In addition, the existing approaches operate in a single stage, where both class probability and bounding boxes are predicted directly [6]. Alternatively, class probabilities can be predicted for default boxes without creating proposals [7]. In general, single stage procedures are quicker, however two-step methods are more optimal. In a recent study, [8] introduced a new training approach that combines partial supervision with a unique weight transfer function. This approach allows for training instance segmentation models on a wide range of categories, all of which have bounding box annotations. However, only a tiny portion of these categories have mask annotations. Subsequently, the novel technique known as group normalization [9] is integrated into deep learning and utilized, for instance, in a cascaded manner for image detection [10].

The method suggested by Hua et al. [11] streamlines the image processing process of traditional computer-aided diagnosis for lung cancer. Sun et al. [12] conducted experiments utilizing convolutional neural networks (CNN), deep belief networks (DBNs), and statistical denoising autoencoder (SDAE) on the Lung Image Database Consortium image collection (LIDC-IDRI) [13]. Their respective accuracies were 79%, 81%, and 79%.

The National Lung Screening Trial (NLST) was a randomized controlled trial conducted in the USA, involving over 50,000 individuals at high risk for lung cancer. The trial demonstrated that annual lung cancer screening using low-dose computed tomography (CT) resulted in a 20% reduction in lung cancer mortality compared to annual screening with chest radiography [14].

Kapil and Rana [16] introduced a modified decision tree method called a weight enhanced decision tree. They used this methodology to the WBCD dataset and another breast cancer dataset obtained from the UCI repository. Utilizing the Chisquare test, they have assessed the ranking of each characteristic and retained the pertinent features for this classification job.

The suggested approach achieved an accuracy of around 99% for the WBCD dataset and around 85-90% for the breast cancer dataset.

Yue et al. [17] conducted thorough evaluations of Support Vector Machines (SVM), K-Nearest Neighbours (K-NN), Artificial Neural Networks (ANN), and Decision Tree approaches in the context of predicting breast cancer using the benchmark Wisconsin Breast Cancer Diagnosis (WBCD) dataset.

The authors assert that the use of deep belief networks (DBNs) with artificial neural network (ANN) architecture, known as DBNs-ANNs, has yielded more precise outcomes. The architecture achieved an accuracy of 98.68%, while the SVM approach, when combined with the two-step clustering algorithm, achieved a classification accuracy of 98.10%. The ensemble approach, employing SVM, Naive Bayes, and J48, was reviewed, utilising the voting technique. The ensemble approach achieved an accuracy of 97.13%.

In 2013, the US Preventive Services Task Force (USPSTF) assigned a grade B recommendation to low-dose CT screening for adults at high risk [36]. In early 2015, the US Centers for Medicare and Medicaid Services (CMS) authorized CT lung cancer screening for Medicare enrollees [37].

The recently initiated "LUNA16" challenge [38] seeks to forecast the precise location of a nodule inside a specified lung area. Zatloukal et al. [39] conducted a study on the localization of non-small lung cancer cells using chemotherapeutic approaches.

Chabat et al. [40] have developed a 13-dimensional vector that captures local texture information. This vector includes statistical moments of CT attenuation distribution, acquisition-length parameters, and co-occurrence descriptors.

A supervised Bayesian classifier is utilized for feature segmentation. In this case, the feature vector's dimensionality is lowered by utilizing five scalar values: maximum, entropy, energy, contrast, and homogeneity. These measurements are retrieved from each cooccurrence matrix produced. The textural properties of Solitary Pulmonary Nodules (SPNs) discovered by CT were reported and assessed by Yanjie Zhu et al. [41].

A total of 67 traits were initially retrieved, and around 25 features were ultimately chosen after 300 genetic generations. The classification task is performed using a Support Vector Machine (SVM) based classifier. In their study, Sang Cheol Park et al. [42] utilized a genetic algorithm to identify the most suitable picture attributes for Interstitial Lung Disease (ILD). Hiram and his colleagues (Hiram et al., [43] have categorized lung nodules by utilizing the frequency domain and support vector machines (SVM) with radial basis function (RBF). Hong et al. [44] have developed an algorithm that can automatically detect solitary lung nodules. The SVM classifier is utilized to accurately identify genuine nodules and assign them labels on the original pictures. Antonio et al. [45] have categorized lung nodules by utilizing the LIDC-IDRI imaging database. The SVM algorithm is utilized to apply taxonomic diversity and taxonomic distinctness indexes from ecology for classification [46]. The results indicate an average accuracy of 98.11%.

Ashwini Rejintal, often known as Aswini N. [47], Several studies have been conducted on the detection and classification of lung cancer using different image processing techniques implemented in MATLAB. MATLAB is very suitable for algorithm creation, but it has limited speed. Therefore, in order to implement your method effectively, it is necessary to convert it to an object-oriented programming language. Therefore, this entire process is more laborious in terms of time. The name is Mena Bansil. The user's text is [48]. Several classification and pattern recognition algorithms integrated into the CAD system still exhibit redundancy issues when dealing with a large number of histopathological datasets. However, this problem can be resolved by implementing a large and easily accessible repository with an efficient data search engine within the system.

2.3 Comparative Analysis and Summary

The comparative analysis and the summary of the analysis is given below:

Table 1: The table represent the comparative analysis with the existing work.

References	**Models**	**Result**	**Training Time**	**Key Points**

Kareem, Hamdalla F, et al. [33]	SVM	Accuracy: 89.88%	Not Mentioned	1. Image filter: After bit-plane slicing, After Gaussian filter, erosion operation, Extracting the lung borders, Defining the lung areas 2. The IQ-OTH/NCCD dataset
Al-Huseiny et al. [34]	GoogleNet	Accuracy: 94.38%	57.41 min	1. Variations in training brought on both more complicated data and uneven imaging circumstances. 2. Possibility of bias in the identification of cancer when benign problems are grouped together. 3. Limited understanding of the model's generalizability outside of the particular dataset it was applied to.
Ren et al. [35]	AlexNet	Accuracy 97.74%	5-6 min	1. Small Dataset Constraint: Limited to 100 CT scans, the model's generalizability may be hindered. 2. Augmentation Bias: Dependency on augmentation techniques could introduce biases due to the small original dataset. 3. Dataset Feature Constraints: Applicability may be limited as the model relies on specific features from a publicly accessible dataset.
Marentakis et al. [49]	LSTM + Inception, Inception, Radiomics (kNN), Radiomics (SVM)	Accuracy 74%, 70%, 67%, 58%	Not Mentioned	1. Limited cross-dataset generalisation. 2. Sensitivity to the amount and calibre of data. 3. Interpretability is lowered because of the intricate architecture.

The material presented provides a concise overview of the findings derived from many research that explore the utilization of diverse deep learning architectures for the purpose of identifying lung cancer from CT scans. In their study, Silva et al. [33] employed a Convolutional Neural Network (CNN) model and achieved an accuracy of 82.3%. They also reported a sensitivity of 79.4% and a specificity of 83.8%. Sahu et al. [34] utilized a Multi-View Convolutional Neural Network (MVCNN) to train models on several cross-sections of lung nodules from diverse viewpoints. This approach resulted in a commendable accuracy of 93.18%. Ren et al. [35] developed the Manifold Regularized Classification Deep Neural Network (MRC-DNN) specifically for classifying 3D CT images. The network achieved an accuracy of 90%, a sensitivity of 81%, and a specificity of 95%. Marentakis et al. [49] investigated several models, such as LSTM + Inception, Inception, and classic Radiomics using kNN and SVM. The hybrid LSTM + Inception model exhibited a higher accuracy of 74%, surpassing the accuracy of pure Inception (70%), as well as conventional radiomics techniques using kNN (67%) and SVM (58%). These research demonstrate that various deep learning architectures effectively increase the accuracy of lung cancer classification from CT scans. These gains are achieved using unique techniques such as manifold regularization and hybrid models that combine LSTM and Inception.

2.4 Scope of the Problem

- Assess the effectiveness of convolutional neural network (CNN) models in improving the precision of diagnosing lung cancer using CT images.
- Evaluate the performance of the model across various patient demographics, imaging equipment, and picture quality.
- Examine the model's capacity to identify atypical or rare manifestations of lung cancer in CT images.
- Quantify the decrease in processing time in relation to conventional diagnostic techniques.
- Analyze potential trade-offs between the accuracy of the model and the speed at which it processes data.
- Evaluate the practicality of enhancing the model to enable real-time diagnosis in clinical environments.

- Determine and rank certain aspects essential for the model's diagnostic capabilities.
- Assess the model's capacity to clarify its decision-making process for medical experts in order to determine its interpretability.
- Investigate techniques to adapt the model for varied clinical needs by prioritizing particular characteristics or cancer types.
- Evaluate the influence of data augmentation approaches on the accuracy and generalizability of the model.
- Explore alterations to improve the model's robustness against noise, artefacts, and variations in image quality.
- Investigate methodologies for managing datasets of CT scans that have limited or imbalanced data.
- Analyze techniques for the smooth incorporation of the model into current medical workflows.
- Evaluate the prospective costs and benefits linked to integrating the model into clinical practice.
- Investigate the impact of the model on improving patient outcomes and expediting the early detection of lung cancer.

2.5 Challenges

- Insufficient labelled data available for effectively training resilient CNN models.
- Difficulties in ensuring uniform data quality and managing diversity across various healthcare organizations.
- Challenges in creating comprehensible CNN models for medical practitioners.
- There is a trade-off between the speed at which data is processed and the accuracy of the model.
- Modifying the model to enable immediate clinical diagnosis.
- Ethical concerns pertaining to the protection of patient privacy and the acquisition of informed consent.
- Ensuring the robustness of the model to various scenarios and atypical manifestations of lung cancer.

- Addressing the issue of limited or imbalanced data in the training dataset.
- Evaluating the expenses, available resources, and financial consequences of implementing the model.
- Managing regulatory compliance and adhering to healthcare standards for AI-driven medical applications.
- Addressing the reluctance and doubt among healthcare professionals towards the implementation of AI.
- Iterative enhancement of the model through feedback and developing medical expertise.
- Ensuring the efficacy of the model in various patient groups.
- Dealing with unexpected clinical situations or picture features that were not seen during training.
- Ensuring the enduring stability and dependability of the model's performance.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The research methodology unfolds in a systematic sequence, commencing with the collected dataset. This is the initial phase involves the collection of data for establishing the foundation for subsequent analysis. Then we focus to shifts to data augmentations and that is aimed to diversifying and enriching the dataset. Though techniques like, rotation, flipping, affine, crop and pad, additive gaussian noise and linear contrast to augmented data that provides the model with a more robust understanding of variations within the dataset. Additionally, the process delves inti image processing, where the collected and augmented data undergoes refining and standardization. Techniques such as normalization and resizing are applied to enhance model efficiency and performance. Moving forward, the proposed approach is section that outlines the unique model designed for the specific research problem. Elucidating the steps taken to address challenges and achieve the desired outcomes. The used models come to comparative analysis, where the proposed approach or model is performed better against all models. This phase critically evaluates the strengths and proposed approach stands out in comparison. Following this, the result analysis phase interprets the outcomes to the experiments conducted. It involves a meticulous test of metrics, such as accuracy, precision, recall, f1-socre and support values that assess the efficacy of the proposed model. In proposed model analysis, we analysis the model's performance based on changing the learning rate, optimizer and number of images. Lastly, the methodology diagram of the work is given to the below **figure-1**.

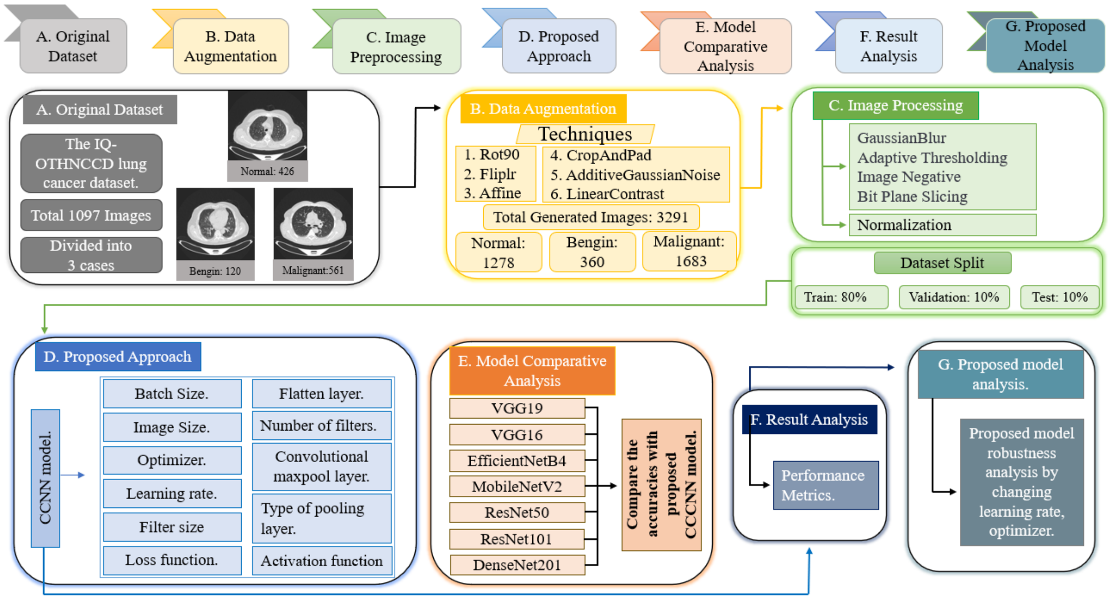


Figure 1: The process of classify CT images into their classes using CCNN with each phase.

3.2 Data Collection Procedure

In our, this research, we evaluate the proposed model on a publicly available “The IQ-OTHNCCD lung cancer dataset” that we collected from “Kaggle”. The dataset contains three class with total 1097 lung cancer CT images. The Normal class has 416 images, the Bengin class has 120 images and the Malignant class has 561 images. All the image data are in 512 x 512 pixels in grayscale format. The whole summary of the dataset is given **Table 1**[20] and the percentage of images in each classes is given in the figure-2 in pie chart.

Figure 2: The figure shows sample images for each class from the dataset.

3.3 Statistical Analysis

We analysis the full dataset in table with the total number of images in dimensions 512 x 512 including the number of images in each class. Also, we add a pie chart that represent the percentages of images in each class.

Table-2: Description of dataset.

Name	Description
Total number of images.	1097
Dimension	512 x 512
Images types	CT
Normal	416
Bengin	120
Malignant	561

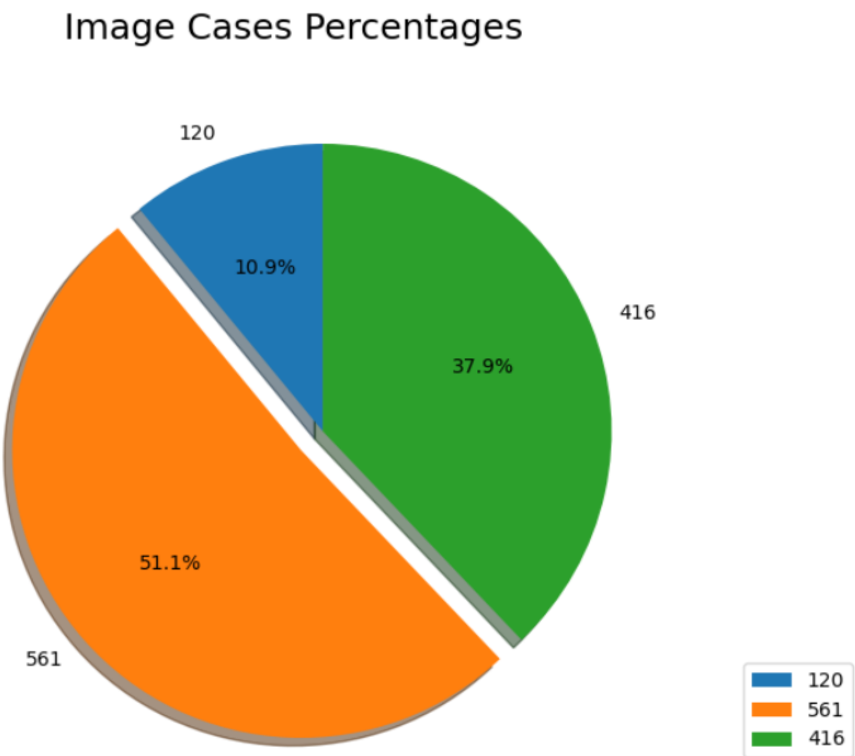


Figure 3: The pie chart shows the percentage of images in each class.

3.4 Data Augmentation

The effectiveness of a neural network in computer vision is typically contingent upon the presence of an ample quantity of labeled data. Collecting medical imaging data is a significant difficulty in the medical business. To address the lack of data, the training dataset is often augmented by applying various techniques such as rotation, flipping, affine transformations, cropping and padding, adding Gaussian noise, and adjusting linear contrast. This augmentation process enhances the model's ability to handle variations within the dataset. In this scenario, the augmentations are intended to transform the existing sample into a slightly modified version of itself. Below, the augmentation strategies are discussed in a sequential manner.

3.4.1 Rot90

The term "Rot90" denotes a rotation of 90 degrees, which is a widely employed data augmentation technique aimed at expanding the dataset by increasing the amount of data. The primary objective of this strategy is to artificially augment the quantity of photos in the collection. The "Rot90" enhancement technique includes rotating a picture by a 90-degree angle. Here, we utilize it in three distinct manners, namely by employing rotation angles 1, 2, and 3 in a random fashion. The "Rot90" augmenter rotates a picture by a specified angle. The mathematical expression for this two-dimensional clockwise transformation is:

$$R(\theta) = \begin{bmatrix} cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \quad (1)$$

To apply this rotation to an image for 90, 180, 270-degree formula is:

$$R(90°) = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix},\ R(180°) = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix},\ R(270°) = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad (2)$$

3.4.2 Fliplr

The technique known as "Fliplr" is commonly used to horizontally flip data for the purpose of data augmentation. Increasing the amount of pictures in the training dataset is an often used and targeted method. It enhances the model's ability to generalize and perform well on data that it has not been trained on. We employ these methods to reflect the picture effectively by randomly reversing it with a 50% chance. Let (x, y) represent the coordinates of the original picture. The horizontal flip operation involves negating the x-coordinate of each point.

$$x' = -x, \text{ and } y' = y \qquad (3)$$

3.4.3 Affine

An "Affine" transformation is a geometric operation that preserves straight lines and parallelism. In the context of data augmentation, "Affine" transformations are commonly employed to perform various sorts of transformations to a picture or a collection of data points. The transformations encompass translation, scaling, shearing, flipping, and rotation. However, in our dataset, we employ the "Affine" augmentation approach just for translation and scaling. The translation is selected between the range of -10 to -10 pixels, and the scaling factor is randomly determined between 0.9 and 1.1. The affine transformation encompasses both translation and scaling.

Translation:

$$x' = x + translate\_px \qquad (4)$$

$$y' = y + translate\_px \qquad (5)$$

Scaling:

$$x' = x * scale \qquad (6)$$

$$y' = y * scale \qquad (7)$$

Now, Here is the combined "Affine" transformation:

$$x' = (x + translate\_px) * scale \qquad (8)$$

$$y' = (y + translate\_px) * scale \qquad (9)$$

3.4.4 CropAndPad

The "CropAndPad" approach is a flexible tool for data augmentation that artificially enhances the variety of a picture collection. The process involves utilizing a mix of cropping and padding techniques on each image, while also carefully modifying the content and dimensions of the image. To implement this strategy, we opt to randomly crop or pad the image, and resize it by a pixel value randomly selected from the range of '-10' to '+10' pixels. This function randomly applies cropping and padding to the image, while adjusting the pixel values within the defined range.

Let I denote the original picture with dimensions H x W x C, where H represents the height, W represents the width, and C represents the number of channels.

Mathematically, the cropped image I_{crop} can be expressed as:

$I_{crop} = I\,[p_{top} : H - p_{bottom}, p_{left} \; : W - p_{right}, :]$

Mathematically, the padded image I_{pad} can be expressed as:

I_{pad} = pad (I_{crop}, pad_top, pad_bottom, pad_left, pad_right), where pad_top = max(0, $-p_{top}$), pad_bottom = max (0, = p_{bottom}), pad_left = max (0, $-p_{left}$), and pad_right = max (0, $-p_{right}$) (10)

3.4.5 AdditiveGaussianNoise

Additive Gaussian Noise, sometimes referred to as "AdditiveGaussianNoise," is a data augmentation technique frequently employed in deep learning and computer vision tasks. Data augmentation serves the objective of artificially enhancing the variety of the training dataset by doing a range of transformations on the current data. The process involves incorporating randomly generated values that follow a Gaussian distribution into the input data. This distribution is sometimes referred to as a normal distribution, which is characterized by a bell-shaped curve. Within the given context, it signifies that the additional noise levels are more prone to being around zero and less prone to being substantial. In our work on augmentation, the scale parameter regulates the magnitude of the noise, which is randomly selected from a range of '0' to '30' pixels. Let x represent the original image and x' represent the noisy image. To add random Gaussian noise to each pixel, we use the following mathematical terms:

$$x' = x + Gaussian\_noise \qquad (11)$$

$$y' = y + Gaussian\_noise \qquad (12)$$

3.4.6 LinearContrast

LinearContrast is a useful data augmentation tool that specifically modifies the contrast of photographs, thereby adjusting the brightness and darkness levels. This apparently straightforward strategy can have a huge impact on the training process and eventual performance of our model. In this study, we employ a randomly selected range of contrast factors, namely ranging from 0.9 to 1.1. Ultimately, the equation can be expressed as:

$$x' = contrast * (x - mean) + mean \quad (13)$$

$$y' = contrast * (y - mean) + mean \quad (14)$$

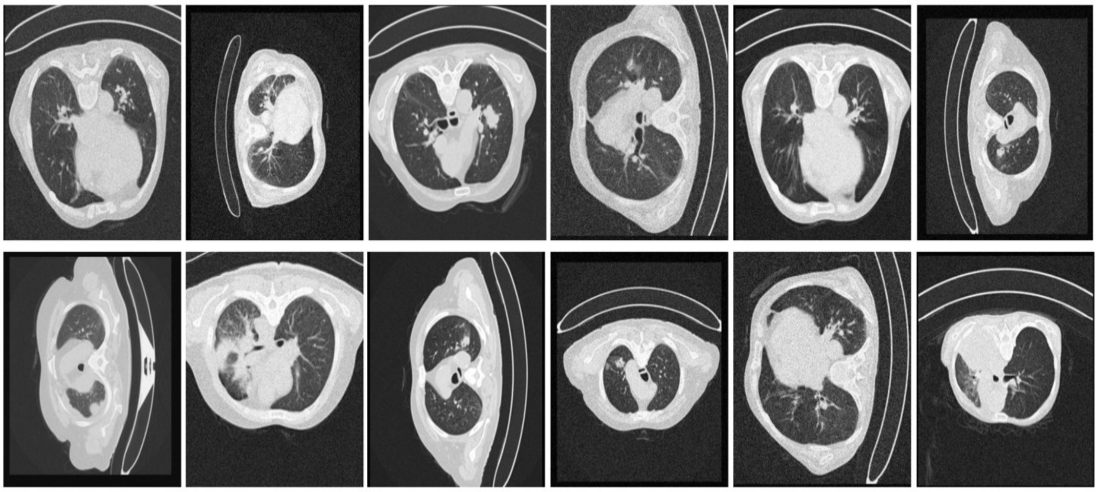


Figure 4: Some random sample of augmented images

3.5 Image Processing

Image processing is a multidisciplinary domain that encompasses the alteration of digital pictures to accomplish certain goals. Utilizing mathematical methods and computer approaches, image processing is crucial for activities such as analysis, augmentation, and information extraction. It is widely used in several disciplines such as medical imaging, computer vision, and scientific research. picture enhancement is a crucial feature that utilizes techniques such as filtering, smoothing, and sharpening to increase the quality of a picture. Moreover, image processing is essential in the study of pictures, as it enables the extraction of significant information from them. In order to optimize the results of our experiment, we carefully choose certain image filters and processing techniques to apply to our picture dataset for our proposed model. We select five picture filters from our image datasets, which are described below:

3.5.1 GaussianBlur

Gaussian blur is an image processing technique that utilizes a convolution operation with a gaussian filter to diminish noise and details by applying a weighted sum of adjacent pixels. This is a low-pass filter that applies blurring to a picture by convolving it with a bell curve function. The kernel assigns larger weights to pixels closer to the center and lower weights to pixels farther out. The mathematical expression for a gaussian blur is:

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{x^2 + y^2}{2\sigma^2}} \qquad (15)$$

3.5.2 Bit Plane Slicing

Bit-plane slicing is a method employed in image processing to partition a picture into its constituent bit planes. The pixel value is divided into several bit planes, with each plane representing a single bit. The highest-order bit is represented by the most significant bit (MSB) plane, while the lowest-order bit is represented by the least significant bit (LSB) plane. The MSB plane picture is created by extracting and utilizing only the most significant bit (MSB) of each pixel in the original image. The resulting image will exhibit reduced levels of detail compared to the original image, although it will retain the essential information pertaining to the image. The Most Significant Bit (MSB) plane picture is commonly employed for image compression due to its high storage efficiency. The mathematical expression for obtaining the most significant bit (MSB) plane of an image is provided by:

$$\text{MSB plane } = \frac{Image}{2^{bit\ depth-1}}, \quad \text{Bit Plane}_k = \left[\frac{Image}{2^{k-1}}\right] \%2 \qquad (16)$$

3.5.3 Adaptive Thresholding

Adaptive thresholding is an image processing approach that automatically adjusts the threshold value for each pixel dependent on its surrounding area, resulting in improved outcomes under different illumination situations. Contrary to global thresholding, local thresholding takes into account the intensity properties of neighboring pixels. The mathematical formula for adaptive thresholding entails the computation of a local threshold (T) for each pixel (I(x, y)) by considering the average or weighted average of the intensities of its nearby pixels. An often used technique is the adaptive mean thresholding:

$$T(x, y) = mean\ (I_{local}(x, y)) - C \qquad (17)$$

3.5.4 Image Negative

The image negative filter is a basic image processing operation that alters the pixel intensities of an image by subtracting each intensity value from the maximum feasible intensity value for the picture. This inversion leads to a complete reversal of the brightness levels, causing dark parts to become light and vice versa. As a consequence, an inverted or negative version of the original image is created. The image negative transformation for a grayscale image with pixel intensity values ranging from 0 to L-1, where L represents the greatest intensity level, may be expressed as:

$$I_{negative}(x, y) = L - 1\ (x, y) \qquad (18)$$

The below figure represents the all the filtered images that we use in our this project

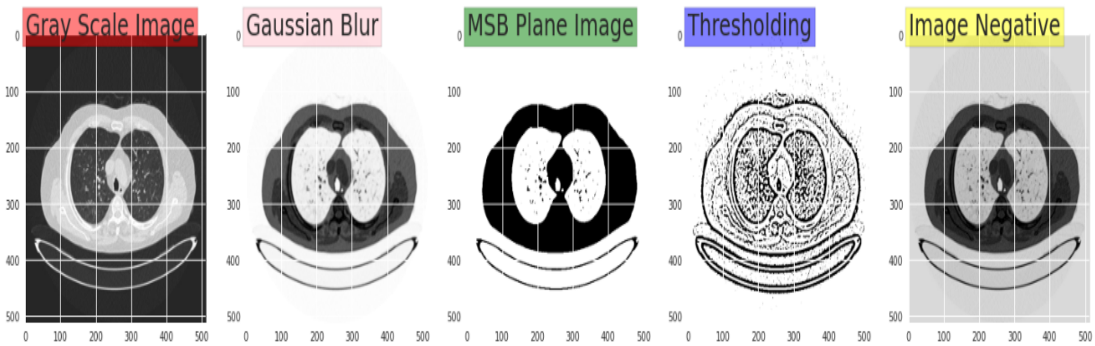


Figure 5: sample of image filter for each class.

3.6 Normalization

Picture normalization is a preprocessing method employed to normalize the pixel values of a picture, guaranteeing a constant scale and aiding improved convergence during deep learning tasks. The mathematical expression for image normalization is:

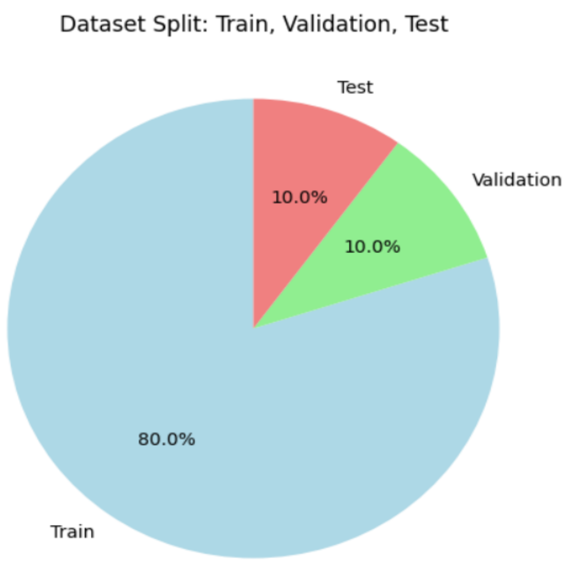
$$\text{Normalized Pixel Value} = \frac{Original\ Pixel\ Value - Mean}{Standard\ Deviation} \qquad (19)$$

The mean in the above formula indicates the arithmetic average of the pixel values in the image, while the standard deviation quantifies the extent to which the pixel values are spread out or dispersed. Normalizing pixel values mitigates the influence of diverse intensity ranges in pictures, hence enhancing the resilience and efficiency of deep learning models.

3.7 Dataset Split

To apply deep learning model in this experiment, we need to divide the dataset. So, for that reason we split the dataset into three part which is train, test and validation part. We choose to keep 80% data for train and 10% validation also choose 10% test data.

Figure 6: The pie chart shows the percentage of split dataset into train, validation and test part.



3.8 Proposed Model

The model (CCNN) is designed as a sequential neural network with many layers. The initial layer consists of a 2D convolutional layer that employs 64 filters, each with a size of 3x3. This layer processes input data with a predetermined form. Subsequently, a rectified linear unit (ReLU) activation function and a 2x2 max pooling layer are used. The convolutional layer, activation layer, and pooling layer are repeated in the same sequence. Additionally, the second convolutional layer consists of 64 filters. Subsequently, a flattening layer is utilized to transform the 2D feature maps into a 1D vector. Following that, a densely connected layer with 16 units is inserted, and another densely connected layer with 3 units and a softmax activation function is appended to provide the ultimate output. The model summary presents details regarding the architecture, including the parameter count for each layer and the comprehensive structure of the neural network. The architecture of the model is given in figure-7.

3.8.1 Configuration of the model:

1. Batch size: 62,
2. Image size: 224 x 224,
3. loss='sparse_categorical_crossentropy'
4. Optimizer: 'Adam',
5. Activation function: 'Softmax'
6. Type of pooling layer: 'max_pool'
7. Amsgrad: False,
8. Decay: 0.0,
9. Beta_1: 0.9,
10. Beta_2: 0.999,
11. epsilon: 1e-07,
12. Learning_rate': 0. 001,
13. Epochs:100

3.8.2 Proposed Model Architecture:

Our suggested Convolutional Neural Network (CCNN) is defined by the given model. To capture spatial data and minimise dimensionality, the architecture consists of two convolutional layers with 64 filters each, followed by max-pooling and rectified linear unit (ReLU) activation layers. After flattening the output, the model adds non-linearity by joining it to a dense layer made up of 16 neurons. As the output layer for multi-class classification, the last dense layer with three neurons and a softmax activation function generates probability distributions over three classes. Its complexity and possible performance may be better understood by looking at the model summary, which provides information on layer kinds, output shapes, and the amount of trainable parameters.

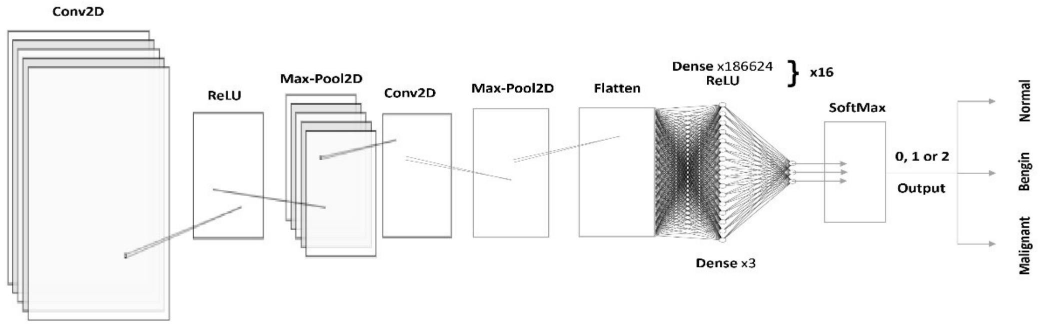


Figure 7: The figure represents the model architecture of our proposed CCNN model.

3.8.3 Ablation Study

We conducted ablation research on the underlying CCNN model by optimizing hyperparameters to get optimal performance. A total of four ablation studies were performed, such as optimizer, epoch, image size, batch size [20]. Upon conducting all ablation investigations, it has been determined that the suggested CCNN model possesses a more resilient architecture, resulting in enhanced classification accuracy and decreased processing time.

3.8.4 Training Strategy

For this experiment, we use seven deep learning model on “The IQ-OTHNCCD lung cancer dataset” and we keep same value in epoch, optimizer, batch size, image size, and learning rate for all models. Which is random epoch based on the callback function but we call 100 epoch for every model, optimizer = “Adam”, batch size = 62, image size = 224 x 224 and the learning rate is = 0.001 In multiclass cases, the default loss function is ‘categorical cross-entropy’. The 'Relu activation' function is employed to estimate the probability for each class. The dataset was divided into three parts: 80% for training, 10% for validation, and 10% for testing. To training the model we setup our device as CPU i5 8^{th} gen, 12GB RAM, 2GB GPU, and 512GB SSD storage. The explanation of those models is explained in below in part of 3.8.5:

3.8.5 Model Comparison

We use seven deep learning model and compare with our CCNN model in terms on accuracy, 224 x 224 image size, and training time.

CCNN: A Convolutional Neural Network (CNN) is a specialized network architecture specifically developed for deep learning methods that handle structured grid data, such as photographs. CNNs are sophisticated computational models used for complex tasks in computer vision, such as pattern recognition and picture categorization. However, our work solely focuses on conducting picture categorization tasks. The network incorporates a leveraging convolutional layer that autonomously and dynamically learns spatial hierarchies of features from the input data.

Our "Customized Convolutional Neural Network (CCNN)" model is composed of two convolutional layers with max-pooling, a flatten layer, and two dense layers. The initial convolutional layer is equipped with 64 filters, and the subsequent convolutional layer also employs 64 filters. The dense layer consists of 16 and 3 units, respectively, while the final layer employs a softmax activation function for the purpose of multi-class classification. The model has a total of 202,611 trainable parameters.

VGG16: [21] With sixteen weighted layers, VGG16 is a cutting-edge transfer learning model. The best five test results in the ImageNet dataset yielded highest accuracy for the model. Additionally, it was victorious in the Oxford Visual Geometry Group's Large-Scale Visual Recognition Challenge (ILSVRC) competition. Because the VGG model has more depth, it can aid the kernel in learning more complicated characteristics.

VGG19: The VGG19 model is a variation of the VGG model that consists of 19 weighted layers. Three more FC layers, totaling 4096, 4096, and 1000 neurons, are added to the VGG16 model. In addition, there is a Softmax classification layer and five maxpool layers. The convolutional layers make use of the ReLU activation function [22].

ResNet50: [23] Profound residual network With 48 convolutional layers, 1 MaxPool layer, and 1 average pool layer, ResNet-50 is a convolutional neural network with 50 layers. The number of layers in each of the many ResNet variants vary, but they all work on the same premise. Resnet50 is the name of the form that can function with 50 neural network layers.

ResNet101: [24] A convolutional neural network with 101 layers is known as ResNet-101. A previously trained variant of the network, trained on over a million photos from the ImageNet collection, is available for download. Images of 1000 different object categories, including a keyboard, mouse, pencil, and numerous animals, can be classified by the previously trained network.

DenseNet201: A convolutional neural network with 201 layers is called DenseNet-201. A pretrained version of the network, trained on over a million photos from the ImageNet collection, is available for download [1]. Images of 1000 different item categories, including a keyboard, mouse, pencil, and several animals, can be classified by the pretrained network. Consequently, a vast array of picture rich feature representations have been trained by the network. The network can handle 224 × 224 picture input sizes [25].

EfficientNetB4: Three dense layers of a convolutional neural network with batch normalization and dropout were implemented using the EfficientNetB4 architecture. By averaging the final projected progression probabilities from the most successful individual PET and CT models, ensemble models were created [26].

MobileNetV2: With the exception of using inverted residual blocks with bottlenecking characteristics, MobileNetV2 and the original MobileNet are fairly similar. Compared to the original MobileNet, its parameter count is significantly reduced. Any input size bigger than 32 by 32 can be used with mobile nets; higher picture sizes result in better performance [27].

3.9 Implementation Requirements

This research aims to construct a deep learning model based on Convolutional Neural Network (CNN) to accurately identify and classify lung cancer from CT scans. The study topics pertain to the accuracy, relevance, speed of processing, effectiveness, feature acquisition, comprehensibility, data improvement, model robustness, incorporation into clinical workflows, and possible medical significance. The anticipated results consist of a refined CNN model that exhibits improved computational speed, interpretability, and adaptability to various datasets and clinical environments. Project management entails employing a methodical strategy to tackle budgetary considerations, timeframes, and resource allocation. The scope of this study focuses on the use of deep learning techniques for the purpose of diagnosing lung cancer. The obstacles that arise in this context include constraints on available data, the capacity to comprehend the models, and ethical issues. The experimental configuration employs a computer device with precise hardware specs, Kaggle's Jupyter Notebook environment, and TensorFlow/Keras for implementing the model. The implementation requirements encompass the tasks of data preparation, model creation, and ethical concerns. The project's primary objective is to enhance lung cancer diagnosis by utilizing sophisticated deep learning techniques.

CHAPTER 4

EXPREMENTAL RESULT AND DISCUSSION

4.1 Experimental Setup

The lung cancer diagnosis and classification study was done using a personal computer device that has an Intel Core i5 8th generation CPU, 12 GB of RAM, and a dedicated GPU with 2 GB of video memory. The system's storage was comprised of a 512 GB SSD, guaranteeing rapid data access and retrieval. The whole experimental process occurred within the Jupiter Notebook environment, which was hosted on Kaggle. This allowed for effortless data exploration, model construction, and assessment due to the collaborative and cloud-based nature of the platform. The selection of Jupyter Notebook on Kaggle offers a user-friendly platform for Python programming, data visualization, and seamless interaction with widely-used deep learning frameworks like TensorFlow and PyTorch.

The experimental dataset used for training and assessment was processed in the Kaggle environment. The CT images associated with lung cancer were preprocessed and enhanced when required. The dataset, which contains vital information for the model's learning, was structured into training, validation, and test sets to enable efficient model training and assessment.

The lung cancer detection model utilized a convolutional neural network (CNN) architecture, which was constructed using TensorFlow and Keras within the Jupyter Notebook. The CNN architecture included of several layers, such as convolutional layers, max-pooling layers, and densely linked layers, with meticulously chosen hyperparameters to provide the best possible performance of the model. The training parameters of the model, including the batch size, learning rate, and optimizer (Adam), were set to achieve a trade-off between efficiency and accuracy throughout the training phase.

The model's performance was evaluated using conventional evaluation metrics including accuracy, precision, recall, and F1 score. The evaluation findings were then visualized using accuracy curves, loss curves, and confusion matrices. The experimental configuration also took into account ethical issues, guaranteeing adherence to data protection and consent regulations, specifically in the management of medical imaging data. Kaggle's collaborative platform enables the exchange of code, results, and ideas throughout the data science community, promoting transparency and cooperation in the field of medical image analysis.

4.2 Experimental Results & Analysis

We mention all the models with their accuracy including number of params in the model, number of epochs, total training time, time per epoch, optimizer, batch size, image size and learning rate. In this section, we will analysis the performance of each model based on the accuracy by analyzing the classification report and confusion matrix. So, we will analyze VGG16, VGG19, ResNet50, ResNet101, DenseNet201, EfficeintNetB4, MobileNetV2 and our proposed CCNN model.

4.2.1 Evolution Matrix

For the evolution matrix we use confusion matrix [29, 30] is commonly employed in machine learning to assess and illustrate the performance of models in supervised classification scenarios [31]. A square matrix is used to depict the relationship between the real class and the predicted class of instances. The rows correspond to the actual class, while the columns correspond to the expected class. For a binary classification job, the confusion matrix is a 2 × 2 matrix that provides the counts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) as follows:

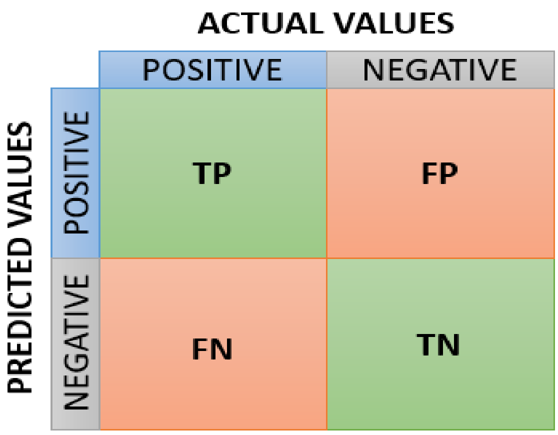


Figure 8: The Confusion matrix diagram.

This matrix encompasses all the unprocessed data on the forecasts made by a classification model on a certain dataset. In order to assess the overall accuracy of a model's predictions, it is customary to employ a separate testing dataset that was not utilized throughout the model's training phase.

A plethora of synthetic one-dimensional performance indicators may be derived from a confusion matrix. Examples of performance indicators include precision, recall, and F-score. By considering that different types of mistakes have unequal significance, cost-sensitive performance indicators may be calculated from the confusion matrix when combined with a 2x2 cost matrix. The selection of the appropriate performance indicator is closely correlated with the goal of the learning challenge [28].

4.2.2 Classification Report

A Classification report is employed to evaluate the accuracy of predictions generated by a classification algorithm. How many forecasts are True and how many are False. To be more precise, the metrics of a categorization report, as seen below, are determined by the values of True Positives, False Positives, True Negatives, and False Negatives.

Precision: Precision is a metric that quantifies the accuracy of a classifier. The class-specific definition of the metric is the quotient of the number of correctly identified positive instances and the sum of correctly identified positive instances and incorrectly identified positive instances. To put it otherwise, "what percentage of positive classifications were accurate!"

$$\textbf{\textit{Precision:}}\ \frac{TruePositive}{TruePositive + FalsePositive} \qquad (20)$$

Recall: Recall is a metric that quantifies the extent to which a classifier is able to accurately identify all positive examples, therefore reflecting its completeness. The class-specific definition of this metric is the quotient obtained by dividing the number of true positives by the total of true positives and false negatives. To put it another, "what is the percentage of correctly classified instances among all the instances that were actually positive!"

$$\textit{Recall:}\ \frac{TruePositive}{TruePositive + FalseNegative} \qquad (21)$$

F1-score: The F1 score is calculated as the weighted harmonic mean of accuracy and recall, with a perfect score of 1.0 and a lowest score of 0.0. In general, F1 scores tend to be lower than accuracy measurements since they use both precision and recall in their calculation. It is often recommended to use the weighted average of F1 scores instead of global accuracy when comparing classifier models.

$$\textit{F1-Score:}\ \frac{2*Precision*Recall}{Precision + Recall} \qquad (22)$$

Support: Support refers to the frequency of the class appearing in the given dataset. The presence of imbalanced support in the training data may suggest that there are underlying problems in the reported scores of the classifier. This situation may call for the implementation of stratified sampling or rebalancing techniques. Support is consistent across models, focusing on diagnosing the evaluation process rather than altering it.

$$\textit{Support Score:}\ \frac{Accuracy * Total\ Sample}{100} \qquad (23)$$

Accuracy: Accuracy is a quantitative assessment of a model's overall accuracy, determined by dividing the sum of true positives and true negatives by the total number of predictions. The metric calculates the accuracy of a model by determining the ratio of properly categorized examples to the total number of predictions. It gives a thorough evaluation of the model's performance across all classes. The formula accounts for both positive and negative predictions, rendering it a commonly employed statistic for assessing categorization models.

$$\textit{Accuracy:}\ \frac{TruePositive + TrueNegative}{TP\ TN+FP+FN} \qquad (24)$$

So, the classification report (precision, recall, f1-score, support and accuracy) for all the models is given below in table-3 based on the above formula and here 0 (zero) refers to the Benign class, 1 (one) refers to the Malignant class, and 2 (two) refers to the Normal class.

4.2.3 Result of Ablation study

The ablation investigations on the CCNN model encompassed deliberate modifications in crucial hyperparameters, such as the number of epochs, learning rate, optimizer, picture size, and batch size. The Adam optimizer with a learning rate of 0.001 attained the maximum accuracy of 98.18%. This discovery emphasizes the significance of selecting the right optimizer for improving model performance, with adaptive optimizers such as Adam demonstrating notable effectiveness. By maintaining a uniform picture size of 224 * 224 and a consistent batch size of 64 across all tests, we enable an equitable comparison between various combinations of optimizers and learning rates. Regardless of the differences in optimizer and learning rate, the total accuracy consistently maintained at a high level, ranging from 97% to 98.18%. This indicates a strong and resilient structure for the CCNN model, which has the ability to effectively adapt to the specific job at hand. Additional factors to consider include testing the model using supplementary metrics, such as accuracy and recall, and considering the practical implications of training time. These findings offer useful knowledge on the hyperparameter settings that enhance the performance of the CCNN model for the given classification problem.

Table 3: The table shows the ablation study based on learning size and optimizer.

Epoch	**Learning rate**	**Optimizer**	**Image Size**	**Batch Size**	**Accuracy**
100	0.01	SGD	224 * 224	64	97%
100	0.001	Adam	224 * 224	64	98.18%
100	0.001	Nadam	224 * 224	64	98%
100	0.001	RMSprop	224 * 224	64	97%

4.2.4 Performance Analysis of Proposed model:

Now, here is overall accuracy chart for our all-experimental models that we use in this research work. Firstly, we got 68.07% accuracy from VGG16 and VGG19 provide 69.28% accuracy. ResNet50 and ResNet101 provides second and third highest score 95.18% and 92.77%. In fourth MobileNetV2 provides 89.16% in lowest 48.80% achieved by EfficientNetB4 and DenseNet201 model achieved 92.27%. Lastly, our proposed model provides highest accuracy 98.18% compare to other models. All the achieve accuracy is shown in given figure-9 in bar chart:

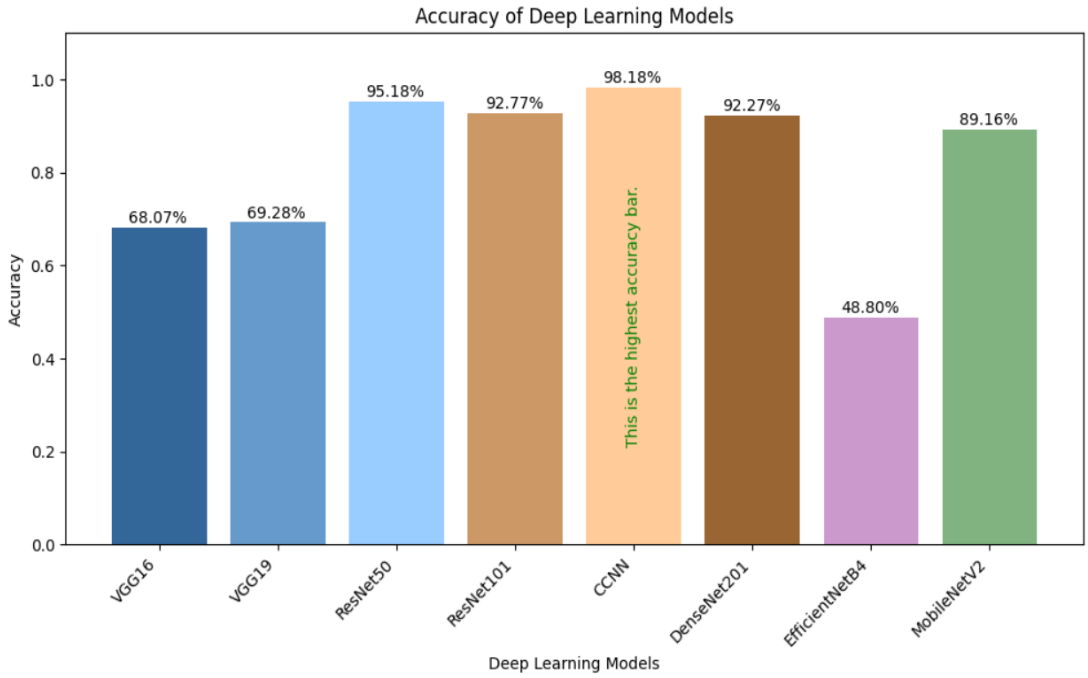


Figure 9: The accuracy chart of all deep learning models.

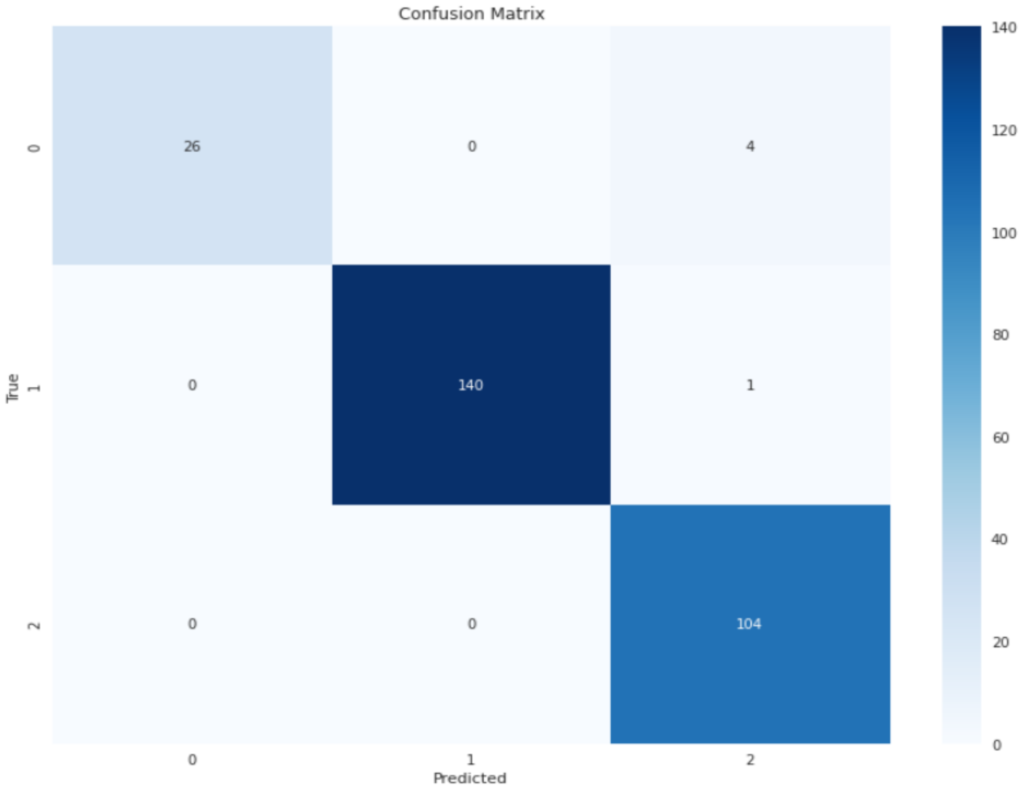


Figure 10: The Confusion matrix diagram of our proposed model.

4.2.5 Models Accuracy and Loss Curve diagram:

The CCNN (Convolutional Neural Networks) model demonstrates exceptional accuracy of 98.18% in the assessment of several deep learning models for the diagnosis and classification of lung cancer from CT images. The accuracy and loss graphs of the model for each epoch demonstrate its strong and consistent performance. Conversely, the renowned architectures such as VGG16 and VGG19 attained accuracies of 68.07% and 69.28% correspondingly, signifying relatively worse performance in this particular scenario. The ResNet50 model achieved a significant level of success, attaining an accuracy of 95.18%. This was accomplished by including an early stopping mechanism, which terminated the training process after 60 epochs if no progress was seen. Similarly, ResNet101 achieved an impressive accuracy of 92.77%. The DenseNet201 model, which was fitted with an early stopping callback, attained an acceptable level of accuracy, but the specific number is not provided, before ending after 50 epochs. The

EfficientNetB4 model, with early stopping, achieved an accuracy of 89.16%. However, training was terminated after 25 epochs. Conversely, MobileNetV2 had a reduced accuracy rate of 48.80%. In summary, the CCNN model shows great potential for accurately identifying lung cancer, surpassing many well-known designs in terms of accuracy. All the curve diagram is given below:

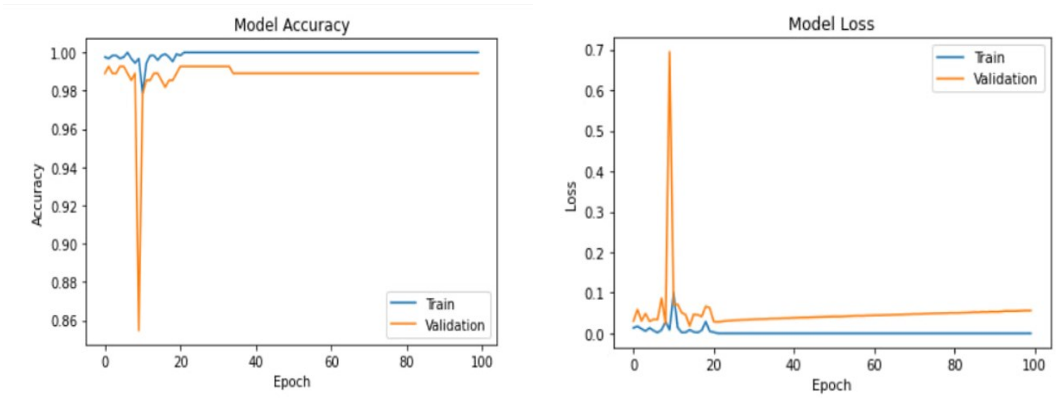


Figure 11: The model accuracy and model loss curve diagram of proposed CCNN model.

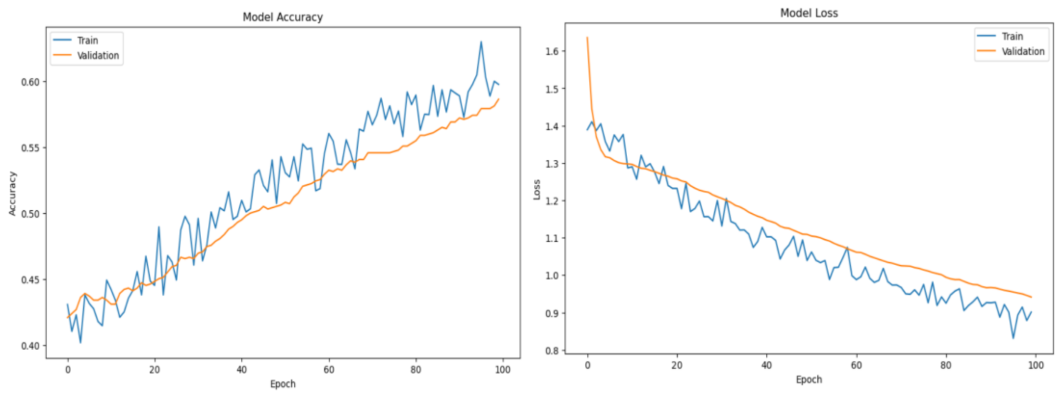


Figure 12: The model accuracy and model loss curve diagram of VGG16 model.

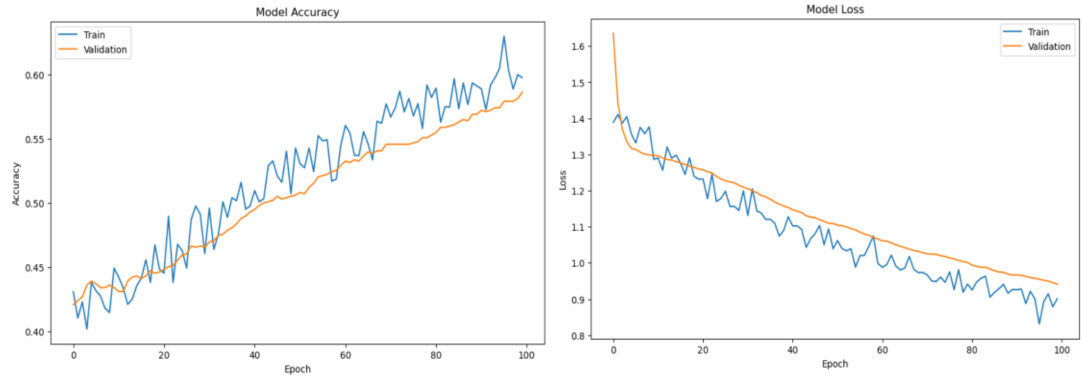


Figure 13: The model accuracy and model loss curve diagram of VGG19 model.

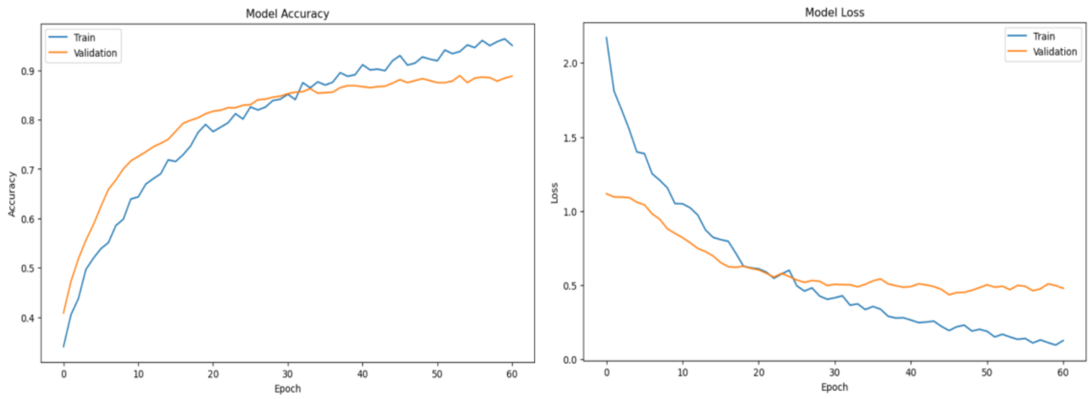


Figure 14: The model accuracy and model loss curve diagram of ResNet50 model.

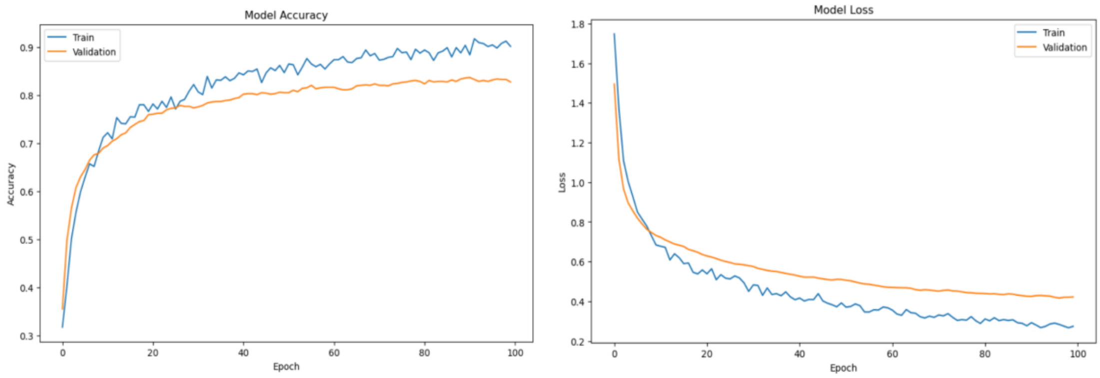


Figure 15: The model accuracy and model loss curve diagram of ResNet101 model.

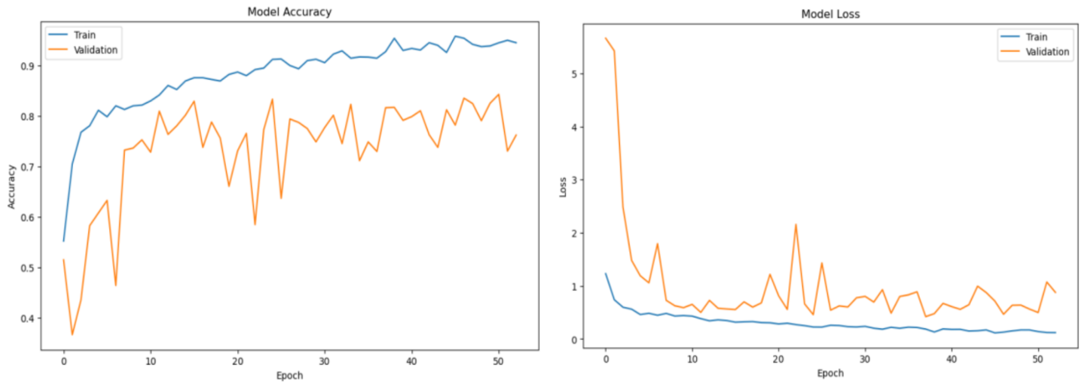


Figure 16: The model accuracy and model loss curve diagram of DenseNet201 model.

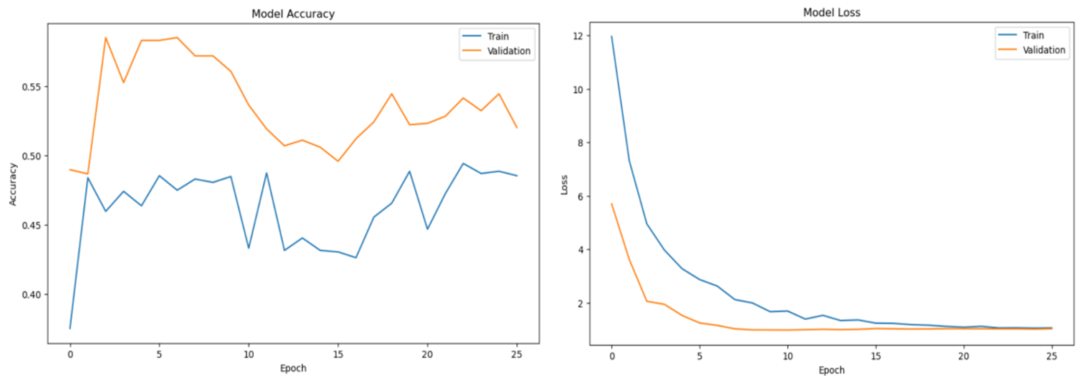


Figure 17: The model accuracy and model loss curve diagram of EfficientNetB4 model.

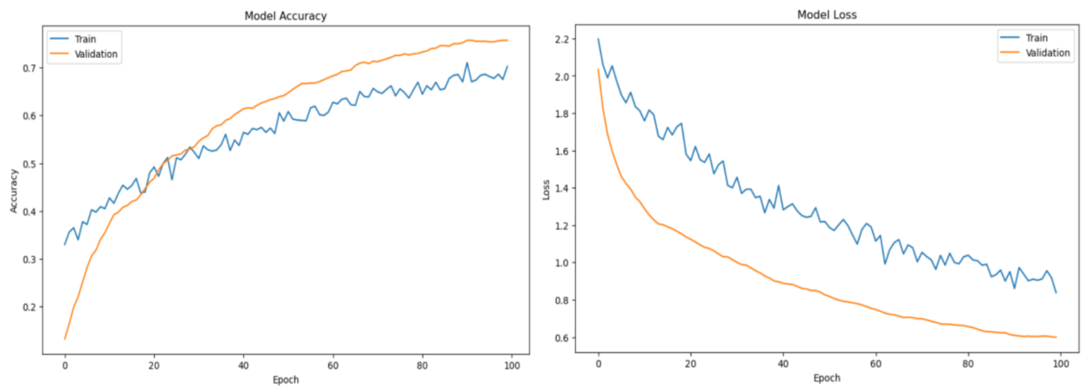


Figure 18: The model accuracy and model loss curve diagram of MobileNetV2 model.

4.2.6 Comparison with Pre-Trained Deep learning models:

We mentioned all the model that we use for this experiment. We got 68-69% accuracy from the VGG16 and VGG19 model including the larger number of parameters and longer training times 17-18 minutes and 10-11 second per epoch. Resnet%50 and ResNet101 striking a good balance between accuracy with almost 93 to 95% and the training time was 11-12 & 19-20 minutes including 11-12 second time per epoch, these models showcase good performance with moderate complexity. MobileNetV2 perform well in training time with 16-17 minutes total and 10-11 second per epoch and with the smallest number of parameters, but lower accuracy of 89% and suggests its suitability for applications prioritizing efficiency over absolute performance. Moreover, EfficientNetB4 offers the lowest accuracy from all those model, which is around 49% and total training time 5-6 second including per epoch time is 11-12 second. Moreover, The DenseNet201 model perform well with the almost 92% accuracy and total training time 9-10 minute including 11-12 second per epoch with the lowest number of epoch. Lastly, our proposed CCNN performs exceptionally well with an accuracy of 98.18% and this the highest accuracy from all models and the total 3-4 minute training time with 2-3 second per epoch time. From CCNN model we got less training time, less time per epoch with the highest accuracy. Now all the comparison based on all models, number of params per model including total time, and time per epoch are shown in the below table-2:

Table 4: The table shows the number of params, number of epochs, total training time, time per epoch, optimizer, batch size, image size and learning rate for each model.

Models	No. of Params	Epochs	Total Time (min)	Time per Epoch (sec)	Optimizer	Batch Size	Image Size	LR	Accuracy
CCNN	3,023,619	100	3-4	2-3	Adam	62	224	0. 001	98.18%
VGG16	14,718,275	100	17-18	10-11	Adam	62	224	0. 001	68.07%
VGG19	20,027,971	100	17-18	10-11	Adam	62	224	0. 001	69.28%
ResNet 50	23,602,051	60	11-12	11-12	Adam	62	224	0. 001	95.18%
ResNet 101	43,313,071	100	19-20	11-12	Adam	62	224	0. 001	92.77%

Mobile NetV2	2,266,947	100	16-17	10-11	Adam	62	224	0. 001	89.16%
Efficien tNetB4	28,390,307	25	5-6	11-12	Adam	62	224	0. 001	48.80%
DenseN et201	18,335,427	50	9-10	11-12	Adam	62	224	0. 001	92.27%

Table 5: The classification report of all models.

Models	**Class**	**Precision**	**Recall**	**F1-score**	**Support**	**Accuracy**
CCNN	0	0.97	0.97	0.97	30	**98.18%**
	1	1.00	0.99	0.99	141	
	2	0.98	1.00	0.99	104	
VGG16	0	0.17	0.17	0.17	06	**68.07%**
	1	0.51	0.42	0.46	61	
	2	0.38	0.48	0.43	45	
VGG19	0	0.16	0.17	0.16	05	**69.28%**
	1	0.51	0.39	0.44	62	
	2	0.44	0.57	0.50	52	
ResNet50	0	0.13	0.11	0.12	04	**95.18%**
	1	0.46	0.46	0.46	65	
	2	0.33	0.35	0.34	40	
ResNet101	0	0.27	0.17	0.21	07	**92.77%**
	1	0.53	0.52	0.52	74	
	2	0.33	0.38	0.36	40	
MobileNetV2	0	0.33	0.11	0.17	07	**89.16%**
	1	0.47	0.45	0.46	65	
	2	0.34	0.43	0.38	40	
	0	0.00	0.00	0.00	0	

EfficientNetB4	1	0.58	0.22	0.32	53	**48.80%**
	2	0.42	0.89	0.57	65	
DenseNet201	0	0.00	0.00	0.00	0	**92.27%**
	1	0.48	0.52	0.50	71	
	2	0.35	0.30	0.32	34	

4.3 Discussion

The presented project focuses on the development and evaluation of a Customized Convolutional Neural Network (CCNN) for the classification of lung cancer from CT images. Acknowledging the scarcity of labeled medical imaging data, the project employs data augmentation techniques, such as rotation, flipping, affine transformations, cropping, padding, Gaussian noise addition, and contrast adjustment, to enhance the model's ability to handle dataset variations. The CCNN model is meticulously designed, featuring two convolutional layers with max-pooling, a flattening layer, and two dense layers, culminating in a softmax activation function for multi-class classification. The project conducts an ablation study to optimize hyperparameters and compare the proposed model with popular transfer learning architectures, including VGG16, VGG19, ResNet50, ResNet101, DenseNet201, EfficientNetB4, and MobileNetV2. The evaluation includes a detailed classification report, accuracy chart, and curve diagrams for each model. The CCNN model emerges as the top performer, achieving an outstanding accuracy of 98.18%, surpassing all other models in terms of efficiency and accuracy. The comprehensive discussion encompasses not only the technical aspects of model architecture, hyperparameter tuning, and performance metrics but also emphasizes the practical implications of the proposed solution in the critical domain of medical image analysis. Overall, the project underscores the potential of custom-designed neural networks in addressing specific challenges in medical imaging, with the CCNN model exhibiting remarkable capabilities for accurate lung cancer classification.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society

- The proposed Customized Convolutional Neural Network (CCNN) significantly improves diagnostic accuracy by efficiently and accurately diagnosing lung cancer from CT images.
- The research utilizes data augmentation approaches to mitigate the issue of limited labelled medical imaging data, resulting in the creation of more resilient and adaptable models.
- The CCNN model's decreased training time, along with its better accuracy, enables faster and more dependable lung cancer diagnoses, possibly hastening treatment choices and enhancing patient outcomes.
- The project's focus on precise categorization enhances the possibility of promptly identifying lung cancer, a crucial element in enhancing survival rates and alleviating the total impact of the disease on society.
- The project's investigation of diverse architectures and augmentation techniques provides valuable insights into successful approaches for tackling obstacles in medical imaging. This research has the potential to impact the advancement of comparable solutions for a range of healthcare applications.

5.2 Impact on the Environment

- Optimizing medical image categorization decreases superfluous examinations, hence minimizing patients' radiation exposure.
- Specialized models, such as CCNN, enhance the efficiency of resource allocation, reducing the amount of computing power needed for diagnosing lung cancer.
- Precise categorization facilitates timely identification, hence possibly minimizing the requirement for expensive therapies and their corresponding ecological consequences.
- Data augmentation strategies decrease the need for large datasets, hence reducing the environmental impact of data collecting.

- Utilizing advanced neural networks can expedite diagnosis speed, hence improving the efficiency of healthcare operations and decreasing total resource utilization.

5.3 Ethical Aspect

It is of utmost importance to priorities ethical issues in the development and implementation of the proposed lung cancer classification model. First and foremost, it is imperative to strictly uphold privacy and consent, following stringent criteria for managing medical imaging data. Ensuring clear and open communication with patients and securing their informed permission for the utilization of data is essential in upholding ethical norms. Furthermore, it is crucial to undertake efforts to mitigate bias in order to prevent the reinforcement of current healthcare inequalities. To mitigate these problems, it is crucial to ensure equitable representation of all demographic groups in the training data and to consistently check for any biases. Furthermore, the importance of model interpretability cannot be overstated in establishing confidence within the medical field and verifying that the system's conclusions can be comprehended and verified by healthcare experts. Continual cooperation with medical professionals is crucial for incorporating their specialized knowledge, promoting a mutually beneficial partnership between artificial intelligence and human expertise. Consistently assessing the model's performance and making necessary adjustments using fresh data and insights is crucial to maintain ethical standards in the quickly progressing area of medical AI.

5.4 Sustainability

The overall sustainability of this project lies in its potential to revolutionize lung cancer diagnosis through the development and implementation of a Customized Convolutional Neural Network (CCNN). By employing efficient data augmentation techniques, the project addresses the challenge of limited medical imaging datasets, reducing the need for extensive data collection that might otherwise have environmental implications. The optimized models, including CCNN, contribute to sustainable healthcare by minimizing unnecessary tests through accurate medical image classification. Early detection facilitated by these models can lead to more targeted treatments, potentially reducing the environmental impact associated with extensive medical interventions.

Additionally, the use of advanced neural networks enhances diagnostic speed, fostering more efficient healthcare processes and reducing resource consumption. In summary, the project not only advances the field of medical image classification but also aligns with sustainability principles by promoting resource efficiency and minimizing the environmental footprint associated with traditional diagnostic approaches.

CHAPTER 6
Summary, Conclusion, Recommendation, and Implication for Research

6.1 Summary of the Study

This study primarily concentrated on creating and assessing a Customized Convolutional Neural Network (CCNN) to classify lung cancer based on CT data. To address the difficulties posed by a scarcity of medical imaging data, data augmentation methods were utilized. These methods included rotation, flipping, affine transformations, cropping, padding, Gaussian noise addition, and contrast adjustment. Their purpose was to improve the model's capacity to handle the diverse range of patterns present in the dataset. The CCNN model, which was suggested, exhibited higher performance in comparison to known transfer learning models, with an amazing accuracy rate of 98.18%. The CCNN model was evaluated extensively, using classification reports, confusion matrices, and training curves, demonstrating its strong performance and efficiency. The study furthermore incorporated a dataset that was divided into training, validation, and test sets, guaranteeing a methodical assessment. In addition, image processing methods including a range of filters, including Gaussian blur, bit-plane slicing, adaptive thresholding, image negative, and normalization, were employed to enhance the input data. The project's environmental effect stems from its capacity to improve diagnostic precision, minimise superfluous examinations, and provide more streamlined healthcare procedures, therefore fitting with the overarching objectives of sustainability in medical contexts.

6.2 Conclusions

The main theme of this study was to create a very effective deep learning model for accurately categorizing lung cancer based on CT data. The implementation of a tailored Convolutional Neural Network (CCNN) demonstrated exceptional efficacy, with a precision rate of 98.18% with the very less training time. This surpassed the performance of widely recognized transfer learning models like VGG16, VGG19, ResNet50, ResNet101, DenseNet201, EfficientNetB4, and MobileNetV2. The performed ablation tests further emphasized the strong design of the CCNN model while optimizing hyperparameters. The experiment also included a thorough examination of several image processing methods and data augmentation strategies to tackle the difficulties related to the scarcity of labelled medical imaging data. Comparing with transfer learning methods, the CCNN model outperformed in terms of accuracy, while also showing shorter training durations and reduced computing complexity. The comprehensive assessment, which involved the use of confusion matrices, classification reports, and accuracy curves, yielded a deep comprehension of the model's performance. In addition, the research examined the possible environmental consequences, highlighting the necessity for energy-efficient model designs in medical imaging applications. Future research could include investigating more sophisticated designs and integrating supplementary datasets to improve the generalization of the model. In summary, our experiment adds to the current endeavors in utilizing deep learning for precise and efficient lung cancer diagnosis, demonstrating the potential capabilities of the suggested CCNN model.

6.3 Implication for Future Study

- The study offers a basis for investigating sophisticated neural network structures for medical imaging assignments.
- The knowledge acquired can be used to different forms of cancer identification and many healthcare uses.
- Subsequent research endeavors may priorities the optimization of hyperparameters and the investigation of alternative data augmentation strategies.
- The exploration of integrating multi-modal data may be conducted to enhance the comprehensiveness of diagnoses.
- Investigating explainable AI techniques to improve the transparency and reliability of models is a promising research direction.
- The user did not provide any text. It is crucial to collaborate with medical experts to integrate their expertise and real-life clinical situations.
- There is a need for additional improvement and development of deep learning models to enhance the analysis and diagnosis of medical images.

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