A COMPARATIVE STUDY ON DEEP CONVOLUTIONAL NEURAL NETWORKS AND TRANSFER LEARNING FOR CHEST CANCER DETECTION

BY

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This Report Presented in Partial Fulfillment of the Requirements for
The Degree of Masters of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**A Comparative Study on Deep Convolutional Neural Networks and Transfer Learning for Chest Cancer Detection**", submitted by **Mst. Zannatul Maoya Mim**, ID No: **232-25-050** 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 M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 24 May 2025.

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DECLARATION

I hereby declare that this research has been done by me under the supervision of **Dr. Md Taimur Ahad, Associate 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 award of any degree or diploma.

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ABSTRACT

In this comprehensive study, highly effective advanced deep learning architectures are tested at detecting chest cancer from computed tomography (CT) scan images. The research is centered around six state of the art convolutional neural network (CNN) base models VGG19, ResNet152V2, DenseNet201, SE-ResNet152, Xception and InceptionV3 and evaluates the performance of these models in their original settings and after applying transfer learning techniques. The models' diagnostic accuracy and reliability for chest cancer diagnosis, a major global health problem of concern, is to be determined through automated image based analysis. In this study, a very rigorous methodological framework that includes dataset preparation, preprocessing and model training is applied, and transfer learning is used to improve the efficiency and generalization of learning. Also, with strong focus on test accuracy, each model's performance was assessed using key evaluation metrics. The experimental results show that DenseNet201, ResNet152V2, Xception and InceptionV3 are most accurate with an original accuracy of 97%. VGG19 dropped from 97% to 95% of accuracy under transfer learning. The results suggest that transfer learning tends to continue to support or enhance model effectiveness generally, although VGG19 is an example of an exception. This study in overall indicates the possibility of CNN based models like DenseNet201 and ResNet152V2 in development of accurate and scalable AI based solutions for early chest cancer detection from CT scans.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Chest cancer holds the status of the most dangerous form of cancer worldwide. The disease first appears in chest tissue, but its original sites may change, making it difficult to develop accurate diagnosis and treatment approaches. The survival rate of chest cancer patients depends on their diagnosis stage combined with cell type classification [1]. Patients need precise early diagnosis because the mortality rate can be lowered by accurately removing as much malignant tissue as feasible through timely and accurate identification.

The recent innovation of Computer-Aided Diagnosis (CAD) systems provides radiologists an advanced tool to achieve better outcomes in chest cancer detecting activities. These systems guide radiologists to improve segment detection as well as classification results while disregarding their level of experience. Deep CNNs provide better results than conventional CAD approaches to locate chest cancer inside chest regions [2]. Medical image recognition procedures advance most significantly through the replacement of regular shallow neural networks with Deep Convolutional Neural Networks according to [3]. CT scan images enable automated analysis because convolutional layers extract hierarchical features that allow cancerous area identification as well as segmentation.

The combination of manual physician examinations with chest cancer classification processes requires an extended duration that follows the time requirements of radiologists together with healthcare staff. Given the increasing medical imaging data volume healthcare organizations deeply require automated diagnostic systems for effective daily operations. The efficient operation of deep CNN allows successful classification and segmentation while reducing both time and work requirements [4]. Deep-learning models used for diagnosis help detect chest cancer early to generate better survival outcomes in patients.

In the field of CAD transferred learning boost model efficiency. Risk management in medical deep learning models faces challenges when applying extensive labeled medical information since such datasets need extensive sample collection without cost-efficiency in labeling. The data scarcity problem receives a solution through pre-trained models which enable effective fine-tuning operations with minimal datasets [5]. The algorithm allows model retraining using fine-tuning techniques to convert existing models for use in prediction as well as feature extraction tasks related to chest cancer datasets. Frequent deterioration of important characteristics occurs when extracting features to obtain optimal representations while saving processing time. Model performance becomes more stable with better capabilities toward newly available data when models use feature extraction methods to reduce computation time and building model duration. The collective operation of deep learning models based on their design elements facilitates more accurate classifications and performs in a steadier way.

In this research, six state-of-the-art convolutional neural networks (CNNs) and transfer learning techniques are investigated with chest cancer detection in following models: VGG19, ResNet152V2, DenseNet201, SE-ResNet152, Xception, and InceptionV3. We evaluate these models with respect to their effectiveness of classifying and segmenting chest cancer from the CT scan images. Analysis of their performance in comparison is made in order to learn the best strategy with deep learning of improving the chest cancer detection accuracy and CAD systems optimization for real life medical applications.

1.2 Motivation

The rising mortality rate of chest cancer needs early detection for chest cancer. It becomes essential because the disease displays increased frequency coupled with fatal outcomes. The diagnostic methods that utilize expertise from radiologists show susceptibility to human mistakes as well as professional judgment inconsistencies. Medical image analysis reaches high levels of automation because convolutional neural networks (CNNs) work with deep learning. It insufficiently assessed the performance levels of various CNN architectures when used for chest cancer screening tasks. It has been developed to evaluate CNN models together with transfer learning approaches which would improve both diagnostic accuracy and decrease computational needs for ultimately providing better diagnostic results.

1.3 Rationale of the Study

Current technology development in medical image analysis takes major gains from deep learning while CNN-based chest cancer detection techniques require further scientific work. Multiple deep learning models exist within medical diagnostics but the field needs standards describing which models achieve the best accuracy ratings combined with operational speed and generalization power. The research evaluates six advanced CNN models including VGG19, ResNet152V2, DenseNet201, SE-ResNet152, Xception and InceptionV3 to determine their ability in detecting chest cancer through CT scan imaging. The research evaluation of these models gives important information about their performance capabilities to enhance selection of appropriate clinical procedures in real-world diagnostic systems. The research findings will serve to establish a connection between theoretical knowledge and real-world CAD system development which supports the improvement of more precise early chest cancer detection systems.

1.4 Research Questions

- RQ1: What is the effectiveness level of various state-of-art CNN models when applied to CT scan identification of chest cancer?
- RQ2: Can transfer learning techniques enhance the ability to detect chest cancer?

1.5 Expected Output

- A comprehensive evaluation and comparison of the selected CNN architectures (VGG19, ResNet152V2, DenseNet201, SE-ResNet152, Xception, and InceptionV3) in terms of their accuracy, efficiency, and robustness in chest cancer detection.

- The study identifies which CNN model works best for both classifying and segmenting chest cancer through precision, recall, F1-score and computational efficiency benchmarks.
- The study reviews how transfer learning influences model success under restrictive medical imaging annotation conditions.
- The research includes a model comparison that evaluates strengths and weaknesses to guide next-step research while offering implementation guidance for medical imaging practice.
- The study recommendations provide clinical institutions with guidance to optimize their AI technology which advances early detection tools for chest cancers through artificial intelligence.

1.6 Project Management and Finance

The research work doesn’t get fund from any organization or individuals.

1.7 Report Layout

This study is composed of six chapters. Chapter 1 provides introduction, objectives and research question. Chapter 2 presents a literature review that summarizes the existing studies related to the chest cancer detection using deep learning and transfer learning. Chapter 3 was devoted to stating the methodology, with selecting the dataset, model architecture and evaluation metrics. In chapter 4 the experimental results are presented and analyzed, and different CNN models and transfer learning models are compared on the basis of its performance. In Chapter 5 explored sustainability, the societal and environmental impact, and ethical consideration. Finally, chapter 6 concluded the study with a summary of the main findings and a suggestion for future research.

CHAPTER 2
BACKGROUND

2.1 Preliminaries

There were many studies regarding convolutional neural networks (CNN) and transfer learning works in classifying and segmenting chest cancer from CT scans. Multiple of deep learning architectures are evaluated in terms of feature extraction capability and classification accuracy respectively. However, some challenges including limited data, the computational cost and model generalizability have been, despite some progress, remained, and it is time for comparative studies. This work compiles literature study by systematically assessing state-of-the-art CNN models and transfer learning model for their potential of disease detection and classification in chest cancer and use it to optimize AI-based diagnostic systems in medical applications.

2.2 Related works

This study proposed a model to classify the chest cancer types based on chest CT-scan images. In this application, they investigate the use of DenseNet121, combination of 2 data augmentation techniques such as, albumentations and mixup. The observation that one of DenseNet121 inputs, with Data augmentations are albumentations or the mixup, show a performance of 82.14%, 78.64% or 77.78% if only mixup or 77.78% or 58.69% without data augmentations was not quite bad [6].

A deep learning based approach for multi classification in which the chest cancer was detected using the chest CT-Scan pictures from the dataset. To evaluate the effectiveness of three architectures, CNN, ResNet50 and DenseNet121 are considered. Different deep learning architectures are assessed in detail. However, they found that the DenseNet121 model outperforms the three other models that are suggested. Thus, ResNet50 shows 56.51% accuracy, while CNN shows 56.19% and the DenseNet121 model shows 71.74% accuracy [7].

Rani, R., & Gupta, S. have showed that the CNN model is taught and evaluated on a large dataset in the paper and images are classified into squamous cell carcinoma, adenocarcinoma, big cell carcinoma and normal tissues to classify chest cancer using CT scan images. The model was especially good at identifying squamous cell cancer and adenocarcinoma with excellent overall accuracy of 86%, good precision, recall and F1-scores [8].

Pal, J., Das, S., & Tripathy, J. is suggested CNN model to identify cancer nodules from the chest cancer dataset and to classify cancer as Adenocarcinoma, Large Cell Carcinoma and Squamous Cell Carcinoma. They used three deep learning case studies like VGG16, INCEPTIONV3 and RESNET50 that were used to diagnose chest cancer, they also discussed regarding various ways of evaluating the results [9].

Golkarieh, A., Bayrami, F., & Lashaki, R. A. propose the use of a BIR enhanced CNN model for classifying the severity of lung injury from CT images of the chest of the patients of chest cancer, evaluating the performance of different UNet backbone models (VGG16, ResNet50, Xception) and showing that VGG16 achieved the best performance with an accuracy of 98.36%, and their BIR enhanced CNN model with the same backbone (VGG16) reach classification accuracy of 97.83% [10].

Ezhilraja, K., & Shanmugavadivu, P. showed that deep transfer learning based pre-trained models are suitable to be used for diagnosis; convolutional neural networks as Dense Net121, ResNet50, InceptionV3, VGG16, Xception and VGG19 are used to show this. Amongst these models, VGG16 had the highest accuracy of 81.42% on the original dataset, after that 91.64% on the enhanced dataset [11].

Atiya et. al. proposed dual state transfer learning to build up a efficient training model, that is, innovate a training model with reduced variance and prevent over fitting. Pre trained models like the DCNN, VGG16, Inceptionv3 and RestNet50 were used by them. Using dual state transfer learning, the ResNet50 model achieves an accuracy of 94% on training (see Table (a)), while validation and test accuracy is 92.57 and 96.12 respectively [12].

Montaha et.al. used Artificial Intelligence (AI) and Machine Learning (ML) algorithms and they combine CNN model for classifying chest cancer. With a knowledge driven feature learning combined with the deep learning classification algorithm RestNet50, 98% accuracy is achieved [13].

Y. Jiang et. al. compared 21 models of deep learning: 10 3D and 11 2D for chest cancer risk prediction by using CT scans. The best 3D model had AUROC 0.86, which was better than 2D AUROC of 0.59, and 3D AUROC of 0.75. Interestingly, it did not seem to help pre-training on radiological datasets compared to the general purpose datasets [14].

Ozdemir et. al. propose a hybrid deep learning model using the combination of CNNs and Vision Transformers with grid and block attention mechanisms applied to the InceptionNeXt blocks for lung cancer classification using CT scans. The model was evaluated on Chest CT and IQ-OTH/NCCD respectively with 98.41% and 99.54% accuracy respectively. With 18.1M parameters, the lightweight model surpassed existing CNN and ViT based approaches in term of both accuracy and efficiency [15].

Choudhry et. al. proposed an enhanced deep learning-based strategy for classifying chest X-ray images using pre-trained models like RetinaNet, EfficientNet, and Faster-R-CNN through transfer learning. The dual-check system integrates AI-driven diagnostics with human validation, improving diagnostic precision and reducing errors in Cloud and Fog-based smart healthcare systems. The model outperformed traditional techniques and highlighted the need for further research to enhance AI system effectiveness in medical diagnostics [16].

Gayap et. al. reviewed deep learning techniques for lung cancer detection, emphasizing models such as 2D/3D CNNs, dual-path networks, and vision transformers (ViT) applied to datasets like LIDC, LUNA16, and JSRT. Their findings indicate deep learning consistently outperforms traditional methods in accuracy, sensitivity, and specificity for lung cancer detection in CT scans. Despite its potential, challenges such as data dependence, generalization, and interpretability must be addressed for clinical adoption [17].

Said M.M. et. al. proposed a Self-ONN-based deep learning approach for detecting lung and colon cancer in histopathology images from the LC25000 dataset, achieving outstanding results with 99.74% accuracy and specificity. The model outperformed five pre-trained CNN models, such as MobileNetV2-SelfMLP and DenseNet201-SelfMLP, highlighting the potential of AI in enhancing diagnostic precision. The study underscores the effectiveness of DL techniques, including transfer learning and lightweight architectures, in cancer diagnosis, achieving accuracy rates between 96.19% and 99.97% [18].

Asha and Bhavanishankar proposed an innovative lung nodule segmentation approach using the Segment Anything Model (SAM) combined with transfer learning, achieving a Dice Similarity Coefficient (DSC) of 97.08%, Intersection over Union (IoU) of 95.6%, and 96.71% accuracy. The method leveraged Bounding Box prompts and a vision transformer model to enhance segmentation performance, significantly improving Computer-Aided Detection (CAD) systems for lung cancer diagnosis. The results highlight the potential of SAM and transfer learning to advance early detection and improve patient care outcomes [19].

Shovon Hossain et. al. [20] proposed a robust model for lung cancer detection using the 2019 IQ-OTH/NCCD dataset, incorporating multichannel techniques and a residual connection into a convolutional neural network. The model, based on InceptionResNetV2, outperformed state-of-the-art (SOTA) models, achieving 89.95% accuracy, 91.42% precision, and 95.98% specificity. The use of multichannel features and residual connections enhanced feature extraction and training efficiency, significantly improving detection performance and reducing patient cost and time [20].

Yadlapalli et. al. employed deep transfer learning algorithms, including VGG16, VGG19, MobileNet, and DenseNet169, to classify lung cancer in CT scan images, with a focus on squamous and adenocarcinoma types. The VGG16 model achieved the highest accuracy at 91.28%, outperforming the other architectures in terms of classification accuracy. The study highlights the effectiveness of VGG16 in maximizing classification accuracy for lung cancer detection and emphasizes the potential of deep learning for improving medical imaging diagnosis [21].

Regmi et. al. evaluated CNNs and transformer-based models, including Vision Transformer (ViT), for medical image analysis across different datasets, including Chest X-ray and Kvasir. The ViT model outperformed state-of-the-art CNN models, achieving the highest F1 scores and ROC-AUC scores of 0.9532 and 0.97 for Chest X-ray and 0.9436 and 0.97 for Kvasir. The study highlights the superior performance of transformer models in classifying medical abnormalities, suggesting their potential as a new benchmark in medical image analysis [22].

Bishnoi et. al. proposed a novel Color-based Dilated Convolutional Neural Network (CD-CNN) for multi-class classification of lung cancer from histopathological whole slide images, emphasizing the impact of color space transformations. The CD-CNN model, using the HSV color space, achieved superior results with accuracy ranging from 0.97 to 0.99 and an AUC value of 0.97 to 0.984 across three datasets. The proposed model outperformed existing pre-trained models, demonstrating improved diagnostic performance and efficiency for lung cancer classification [23].

H. Malik et. al. introduced four novel convolutional neural network (CNN) models for classifying nine chest disorders, including COVID-19 and lung cancer, using chest X-rays (CXR), CT scans, and cough sound images (CSI). The proposed model achieved an impressive accuracy of 99.01%, outperforming baseline models like Vgg-19 and ResNet-50, and state-of-the-art classifiers. This demonstrates the model's potential to support radiologists and medical professionals in diagnosing chest diseases with high precision [24].

Bhosale and Patnaik proposed a novel deep learning-based approach for COVID-19 case classification using graph and capsule networks applied to CT and ultrasound images. The Capsule network achieved remarkable results with 99.2% accuracy and 98.93% AUC for CT scans, while the graph network performed well on ultrasound with 97.26%

accuracy and 96.93% AUC. This method demonstrates the potential for accurate multi-disorder diagnosis, including COVID-19, using a single network framework [25].

Xiao H. Liu Q. and L. Li introduced MFMANet, a multi-feature multi-attention network designed for subtype classification of non-small cell lung cancer (NSCLC) in CT images. Incorporating MSAM and MFGLA modules, the model captures spatial and scale-sensitive features to enhance small lesion detection. MFMANet outperformed existing models, achieving up to 99.06% accuracy in classifying adenocarcinoma and squamous cell carcinoma [26].

Hermoza et. al. proposed a novel weakly-supervised approach to localize preclinical lung tumors in chest X-rays. The model leverages a censor-aware multi-class classifier and Grad-CAM for visual interpretability. Evaluated on the NLST dataset, the method achieved state-of-the-art C-index scores and effective weakly-supervised tumor localization, offering a pioneering direction for early lung cancer detection [27].

Humayun et. al. proposed a deep learning-based CAD system for accurate and non-invasive lung cancer detection, incorporating data augmentation, transfer learning, and localization techniques. VGG16, VGG19, and Xception models were evaluated, with VGG16 achieving the highest accuracy of 98.83% at 20 epochs [28].

Francisco Silva et. al. proposed a deep learning-based method using a Convolutional Autoencoder to predict EGFR mutation status from CT images of lung cancer patients and achieved 89 % accuracy and supports non-invasive genetic profiling and enhances precision oncology [29].

Vidhi Bishnoi & Nidhi Goel introduced a real-time transfer learning-based framework for classifying CT lung slices into benign and malignant without relying on manual nodule annotation. It uses K-means clustering for segmentation and a weighted VGG deep network (WVDN) for classification, achieving 93.2% accuracy [30].

2.3 Comparative Analysis

Here is a comparative analysis table summarizing the models, datasets, methods, and achieved accuracies:

Table 2.1: Comparative analysis of previous research works

Authors	**Models**	**Data Type**	**Methodology**	**Accuracy (%)**
Bumpenje & Abidin [6]	DenseNet121	CT-scan	Data augmentation (Albumentations, Mixup)	82.14
Hasan et al. [7]	CNN, ResNet50, DenseNet121	CT-scan	Comparative evaluation of CNN-based models	71.74 (Best)
Rani & Gupta [8]	CNN	CT-scan	Multi-class classification (4 classes)	86.00
Ezhilraja & Shanmugavadivu [11]	VGG16, VGG19, DenseNet121, InceptionV3, Xception, ResNet50	CT-scan	Pre-trained transfer learning model comparison	91.64 (Best)
Atiya et al. [12]	VGG16, InceptionV3, ResNet50	CT-scan	Dual-state transfer learning	96.12 (Test)
Jiang et al. [14]	3D CNNs, 2D CNNs	CT-scan	3D model AUROC	86
Our Study	VGG19, ResNet152V2, DenseNet201, SE-ResNet152, Xception, InceptionV3	CT-scan	Original CNN and Transfer Learning	97.00 (Best)

2.4 The Problem's Scope

A significant improvement in deep learning for medical image analysis has been seen, but the accurate and efficient way to detect chest cancer remains difficult. While existing research has proven successful applying D-CNNs and learning from transfer learned features, there has been no comprehensive comparison of state of the art CNN architectures in the task of chest cancer classification and segmentation. Additionally, the reliance on midterm large, labeled medical datasets is a limitation as obtaining annotated CT scan images is expensive and costly. While a considerable amount is known about the individual deep learning models, an open issue of research exists regarding which architecture achieves the best performance on the grounds of accuracy, computational as well or generalizability. In this regard, it is essential to increase the diagnostic accuracy and model efficiency, and determine the influence of transfer learning in medical image classification for an early detection and in making decision of chest cancer treatment.

2.5 Challenges

Challenges in deep learning and transfer learning applied to chest cancer detection include limitation of improving model performance and real world applicability. However, the first issue, which is still an issue nowadays when many excellent medical data do not exist with high quality and labels. CT scan images need expert radiologists to be annotated but the process is time consuming and expensive. When dealing with smaller datasets, this makes the challenge even worse due to over fitting and poor generalization of the model. Second, even transfer learning reduces the problem of insufficient data, but fine tuning of pre trained models for chest cancer detection is a tricky process that needs to be considered carefully about the model parameters and data preprocessing methods. Third, although there is a great potential of CNNs, training deep learning models on large datasets is a prohibitive computational cost and resource requirement for these CNNs, which are not scalable in clinical settings and creating a potential effect on the performance of the model and reproducibility. The challenges should be addressed to successfully integrate AI based diagnostic systems in clinical environments for more efficient and accurate chest cancer detection.

CHAPTER 3
RESEARCH METHOLOGY

3.1 Research Subject and Instrumentation

The primary objective of this study is the classification and early detection of chest cancer, a disease that is both highly lethal and hard to diagnose. The classification task requires enormous quantities of high-quality medical images to accurately distinguish between various stages and subtypes of chest cancer. To do this, I utilized publicly accessible datasets of kaggle, which contain annotated CT scan and chest X-ray images of non-diseased and various forms of cancers such as adenocarcinoma and squamous cell carcinoma. These images were collected from verified open medical imaging repositories for research studies. Python was utilized as the primary programming language, with libraries such as TensorFlow, Keras, NumPy, Pandas, and Matplotlib. Model training and testing were executed on Google Colab environment with the utilization of GPU and TPU acceleration to expedite the deep learning process. OpenCV and Scikit-learn libraries were employed on the Windows platform for data preprocessing, image normalization, and data augmentation.

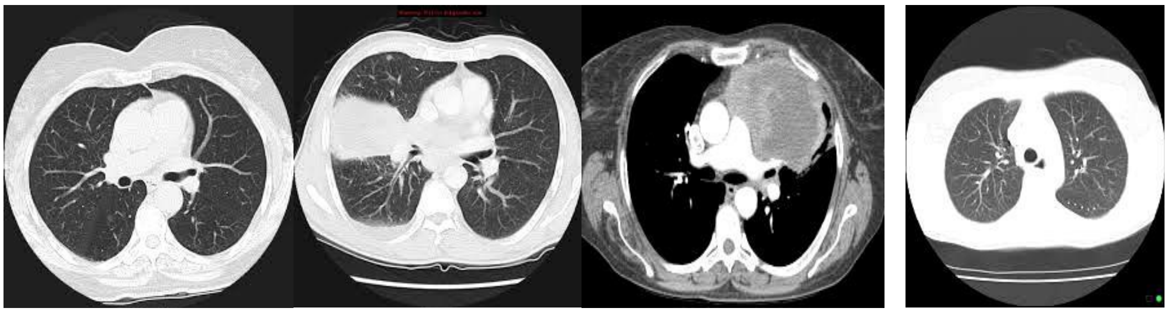
3.2 Data Collection Procedure

The dataset for the study was collected of chest cancer from Kaggle (Figure 3.1). The dataset had four classes: Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma and Normal (table 3.1). The images were captured using a microscope and stored as jpeg files.

Table 3.1: Name of classes and number of images

Classes Name	No. of images	After augmented
Adenocarcinoma	1236	1500
Large Cell Carcinoma	855	1500

Squamous Cell Carcinoma	1067	1500
Normal	1420	1500
	Total: 4778	Total: 6000



Adenocarcinoma Large Cell Carcinoma Squamous Cell Carcinoma Normal

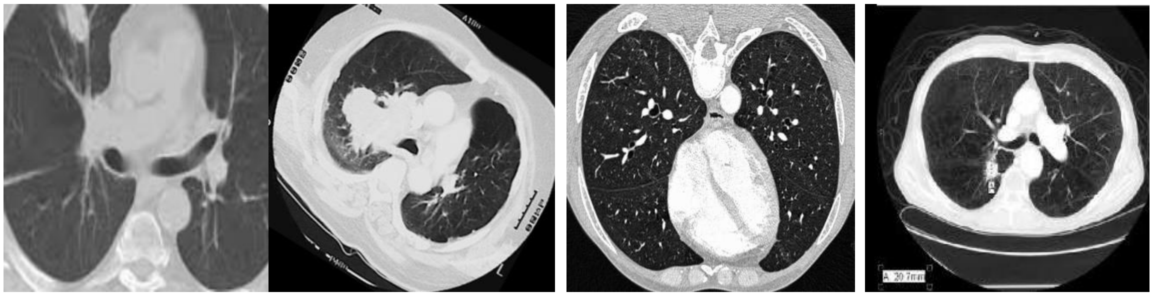
Figure 3.1: Samples of images used in the study

3.3 Image Pre-processing

In this step, the downloaded images from kaggle were checked manually to identify if those had a proper background. If disease symptoms such as spots, diseased colour, and diseased shape were not visible in an image, that image was removed from the dataset and processed data for coding implementation.

3.3.1 Image Augmentation

This study used position augmentation such as scaling, cropping, flipping, and rotation, and colour augmentation such as brightness, contrast, and saturation was deployed. Random rotation from −15 to 15 degrees, rotations of multiple of 90 degrees at random, random distortion, shear transformation, vertical flip, horizontal flip, skewing, and intensity transformation were also used in the data augmentation process. This way, augmented images from every original image have been created. Figure 2 displays the samples of data augmentations of the images used in the study.



Center crop Rotated Flipped Vertical Shifted

Figure 3.2: Samples of data augmentations of the images used in the study.

3.4 Statistical Analysis

Standard statistical metrics evaluated the proposed deep learning models which performed chest cancer classification. The performance assessment includes accuracy and precision together with recall (sensitivity) and specificity along with F1-score and Area under the Receiver Operating Characteristic Curve (AUC-ROC). Each model produced confusion matrices for analyzing its true positive and negative results alongside false positives and negatives. The dataset was divided into training, validation, and testing sets. Performance evaluation was conducted for each class: Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma, and Normal. The model achieved higher accuracy and recall levels on each class while dealing with unbalanced data distributions. A robustness analysis of models utilized k-fold cross-validation with k=5 along with reporting averaged performance from all tested folds. The statistical tools allow multi-class models to demonstrate complete generalization outcomes through their classification operations.

3.5 Applied Mechanism

In this step original CNN models and transfer learning models Vgg19, Resnet152v2 , Densenet201,Seresnet152, Xception, InceptionV3 were used to automatically detect chest cancer. They were chosen as a classification tool due to its well-known technique of being a successful classifier for many real applications. For original CNN after the training model, the evaluation model was built for chest cancer detection based on the highest probability of occurrence as well as for transfer learning. Then, the images were classified into different disease classes and detect disease.

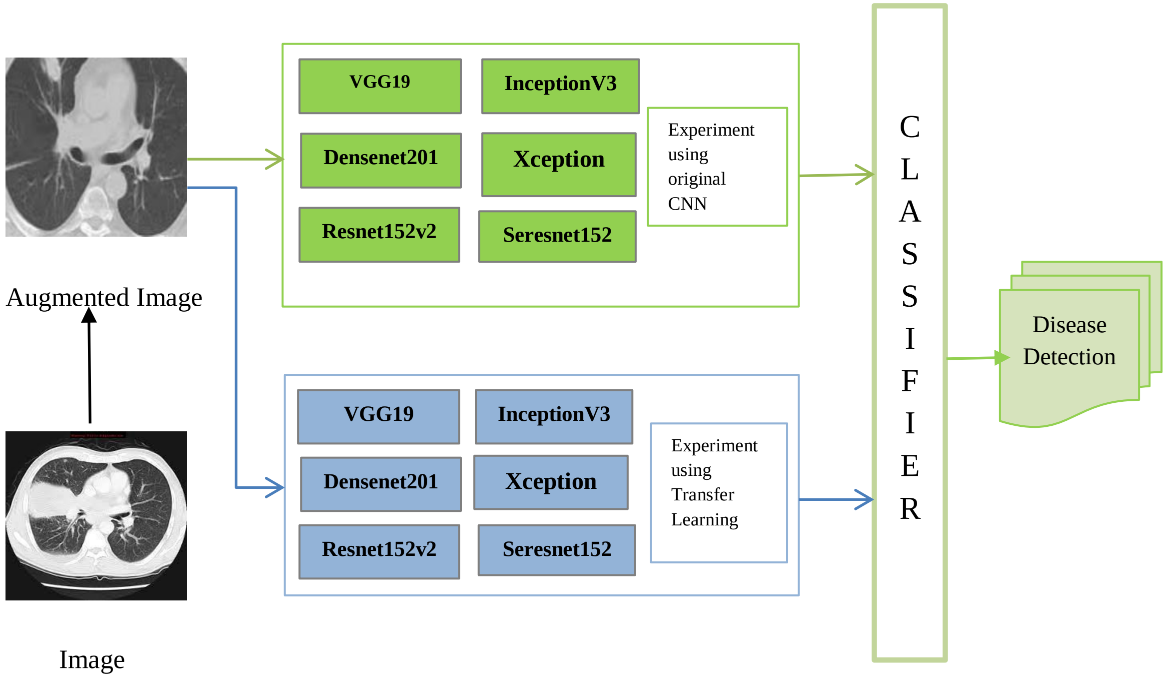


Figure 3.3: Diagram of the Experiment.

3.5.1 Deep Learning

Deep learning, specifically Convolutional Neural Networks (CNNs) was utilized to automatically learn hierarchical feature representations from chest CT and X-ray images. This allowed an effective classification of lung cancer types by capturing complex spatial patterns without the use of manual feature engineering.

3.5.1.1 VGG19

VGG19 is a classical CNN architecture that came from the Visual Geometry Group at Oxford. It has 19 layers, 16 convolutional and 3 fully connected layers. It applies fixed-size 3×3 convolutional filters with stride and padding; therefore, the architecture is simple and uniform. VGG19 is famous for its depth and homogeneity, which improves hierarchical feature being captured. Nevertheless, it has a significant number of parameters where the computation is quite computationally expensive. For this study, both original and transfer learning variants of VGG19 were used. For transfer learning, the top layers were substituted by custom dense layers for 4-class classification.

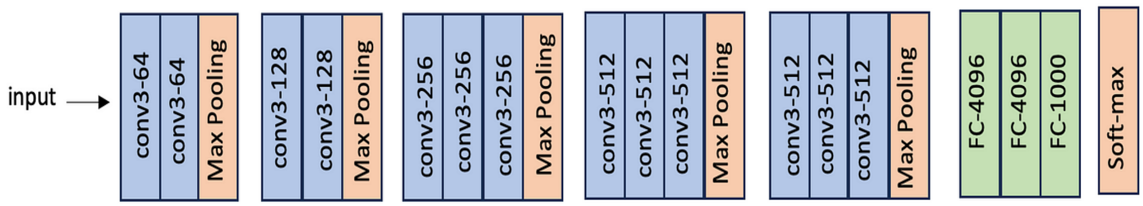


Figure 3.4: Architecture of VGG19

3.5.1.2 ResNet152V2

ResNet introduces shortcut or residual connections since vanishing gradients has almost become an unavoidable aspect especially in deep architectures to correct this issue. In a newer version ResNet152V2 is deeper this time with 152 layers and also enhanced, uses pre-activation within residual blocks (Batch Normalization → ReLU → Convolution). With these residual connections, the gradients bounce directly back through the network as efficient deep deep networks can be trained. For our work, we have used the pretrained ResNet152V2 on ImageNet and have tuned the top layers for the classification of chest cancer.

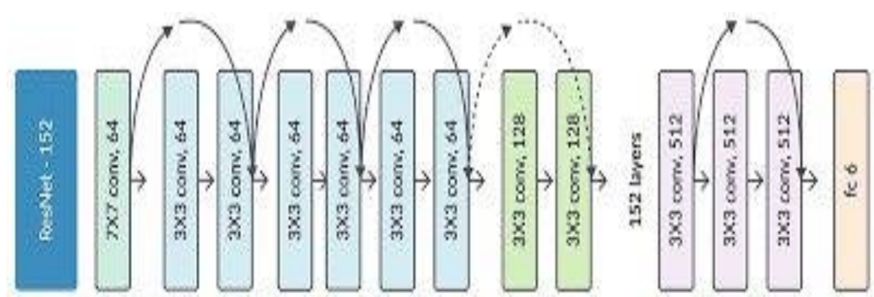


Figure 3.5: Architecture of ResNet152V2

3.5.1.3 DenseNet201

DenseNet (Densely Connected Convolutional Network) enhances information and gradient flow by forming connections between every layer to any other layer connecting each layer to every other layer in the network in the flow from front to the back. DenseNet201, using 201 layers, provides feature reuse and alleviates vanishing gradient while achieving parameters fewer than similar depth networks. The characteristics of each layer is getting inputs from all preceding layers, while the network must have the capability of learning high rich representation of features. We performed transfer learning with a pretrained DenseNet201 and retrained a classification head for our dataset.

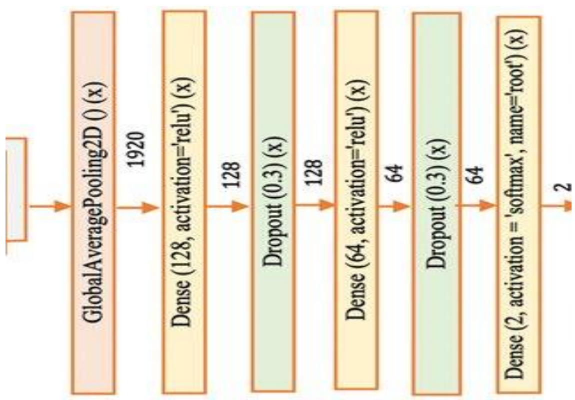


Figure 3.6: Architecture of DenseNet201

3.5.1.4 SE-ResNet152

Squeeze-and-Excitation ResNet152 is a deep residual learning of SE blocks based on ResNet. Such blocks are able to adaptively recalibrate the channel-wise feature response by modeling the relationships between channels. This enhances the network's vulnerability to informative features. The SE blocks are organized into three stages; Squeeze (Global Average POOLing), Excitation (Fully connected layer with non-linearity) and Scale (channel wise multiplication).The addition with the SE blocks does not bring high computational cost but improves the model accuracy strongly. We have used a pre-trained-SE-ResNet152 model with fine-tuned layers for the specific task of classification.

3.5.1.5 Xception

Xception (Extreme Inception) is built on principle of depthwise separable convolution. Rather than use standard convolutions, it decomposes them into depthwise and pointwise convolutions which greatly reduce the computational overhead with performance and little feature loss. Xception keeps the concept of Inception about capturing multi scale features but in a more efficient and scalable way. The model has entry flow, middle flow (repeated, and exit flow) and has skip connections similar to the ResNet. We tuned the Xception model (previously trained) on our dataset for our experiment.

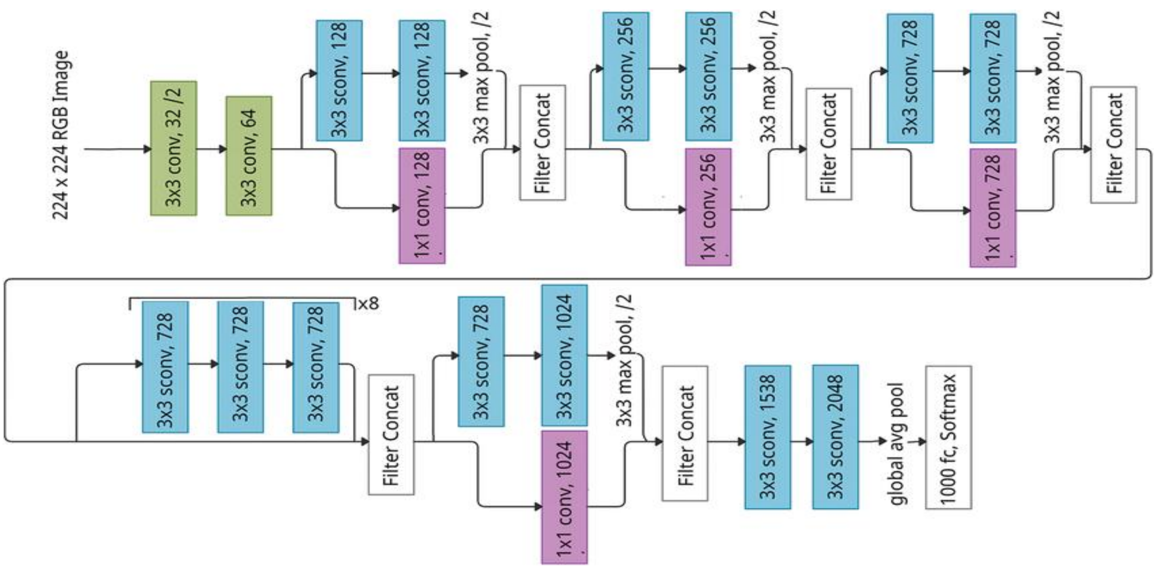


Figure 3.7: Architecture of Xception

3.5.1.6 InceptionV3

InceptionV3 is an updated version of original inception architecture with added factorized convolutions, asymmetric convolutions and secondary classifiers for accuracy and avoid overfitting. It also adds label smoothing, RMSProp optimizer and batch normalization to further boost effectiveness. InceptionV3 is a well-known network by reason of its depth, width and computational efficiency. We utilized a pre-trained InceptionV3 model for transfer learning and modified its classification layer to four classes output.

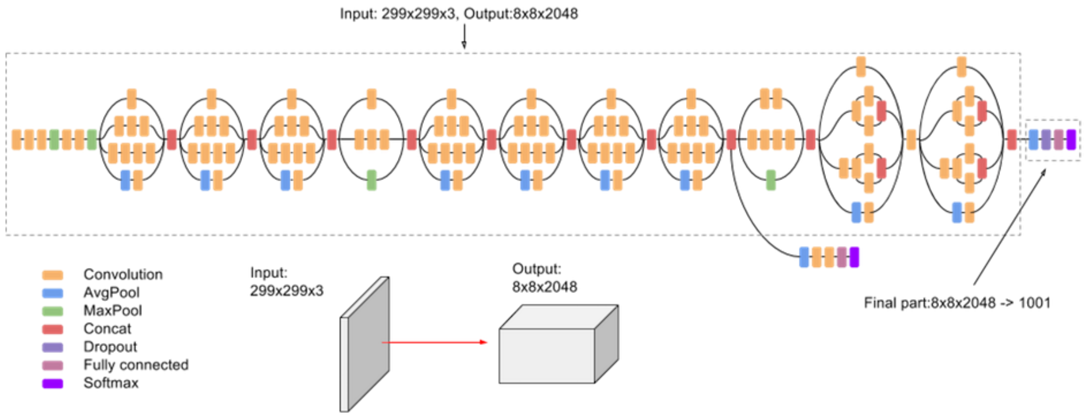


Figure 3.8: Architecture of InceptionV3

3.5.2 Transfer Learning

Transfer learning has an important role in this study mainly because of limited availability of labeled medical imaging data and computational intricacies involved in training deep neural networks from scratch. Transfer learning enables the use of the knowledge learnt from large scale datasets such as ImageNet and their application in the medical imaging domain, an area that is volumetrically short of data. Prior to fine-tuning, all models were driven by pretrained ImageNet weights. First, the convolutional base was frozen during training, and gradually unfrozen after training for fine-tuning. Global average pooling layer, followed by dense layers, and final softmax output, were added to the models to be more appropriate for the four-class classification.

3.6 Implementation Requirements

Applying deep learning and transfer learning models for classification of various diseases based on scientific premises involves immense computational power. Intel Core i5 10th generation processor, 1 TB hard drive, and 8 GB RAM are included in the hardware setup of the model. Development tools like Python, Pandas, NumPy, Matplotlib, Seaborn, and Scikit-Learn are included in the software setup. This entire setup provides a powerful and efficient tool for multi-disease classification within the chest cancer dataset.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

In this chapter we discuss our classification and chest cancer detection result by using deep CNN and transfer learning models and highlighting the comparative performance and effectiveness of each architecture in accurately identifying various chest cancer types

4.2 Evolution Methods

The results of the experiments are measured using the following machine learning classification model performance metrics like, accuracy, precision, recall, and F1 score. True positive (TP) values are true in reality. False positives (FP) occur when false results are mislabeled. The third form, false negative (FN), occurs when a correct value is misinterpreted as negative. The forth true negative (TN) is a positive value misidentified as negative.

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

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

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

$$F1\ Score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{4}$$

Data loss curves and confusion matrices have also been used to measure the performance of the models.

4.3 Experimental Results & Analysis

This section contains an extensive assessment of model performance using multiple criteria to examine and compare the performance of the original and transfer learning based CNN architectures in the case of chest cancer classification.

4.3.1 Performance of Original Deep CNN network

The performances of the six original individual CNN networks Vgg19, Resnet152v2 , Densenet201,Seresnet152, Xception, InceptionV3 are presented in this section. Among them, the Densenet201, Vgg19, Resnet152v2, Xception, and InceptionV3 models had the accuracy of 97 %, while the Seresnet152 model had the slightly lower accuracy of 96%.

Table 4.1: Classification report of deep CNN

		Adenocarcinoma	**Large_cell_carcinoma**	**Normal**	**Squamous_Cell_Carcinoma**	**Model Accuracy**
Vgg19	Precision	100%	88%	100%	100%	96.651%
	Recall	100%	100%	100%	86%	
	F1-score	100%	94%	100%	93%	
	Support (N)	448	449	448	447	
Resnet152v2	Precision	100%	88%	100%	100%	96.60%
	Recall	100%	100%	100%	86%	
	F1-score	100%	94%	100%	93%	
	Support (N)	449	446	448	449	
Densenet201	Precision	100%	88%	100%	100%	96.652%
	Recall	100%	100%	100%	86%	
	F1-score	100%	94%	100%	93%	
	Support (N)	447	450	459	446	
	Precision	100%	88%	100%	100%	

Seresnet152	Recall	100%	100%	100%	86%	96.42%
	F1-score	100%	93%	100%	93%	
	Support (N)	447	448	448	449	
Xception	Precision	100%	88%	100%	100%	96.60%
	Recall	100%	100%	100%	87%	
	F1-score	100%	94%	100%	93%	
	Support (N)	450	447	448	447	
InceptionV3	Precision	100%	88%	100%	100%	96.54%
	Recall	100%	100%	100%	86%	
	F1-score	100%	94%	100%	93%	
	Support (N)	449	447	447	449	

Table 4.1 shows the Accuracy, precision, recall, f1, and support (n) result of original CNN networks for chest cancer. The precision values of each architecture are considered. Here all the models performed the mentionable lowest precision value of 88% for identifying the Large_cell_carcinoma.

The confusion matrix of the original CNN is presented in Figure 4.1. Following Table 4.1, Densenet201, Vgg19, Resnet152v2, Xception, and InceptionV3 provides a better result, as expected.

Here,

ADC=Adenocarcinoma LCC=Large_cell_carcinoma NOR=Normal;

SCC=Squamous_Cell_Carcinoma

VGG19

	ADC	LCC	NOR	SCC
ADC	450	0	0	0
LCC	0	466	0	62
NOR	0	0	448	0
SCC	0	0	0	386

ResNet152v2

	ADC	LCC	NOR	SCC
ADC	446	0	0	0
LCC	0	448	0	61
NOR	0	0	448	0
SCC	0	0	0	389

InceptionV3

	ADC	LCC	NOR	SCC
ADC	448	0	0	0
LCC	0	448	0	62
NOR	0	0	447	0
SCC	0	0	0	387

Xception

	ADC	LCC	NOR	SCC
ADC	448	0	0	0
LCC	0	449	0	61
NOR	0	0	449	0
SCC	0	0	0	385

DenseNet201

	ADC	LCC	NOR	SCC
ADC	448	0	0	0
LCC	0	450	0	62
NOR	0	0	446	0
SCC	0	0	0	386

SeresNet152

	ADC	LCC	NOR	SCC
ADC	446	0	0	0
LCC	0	466	0	62
NOR	0	0	450	0
SCC	0	0	0	386

Figure 4.1: Six confusion matrices of deep CNNs

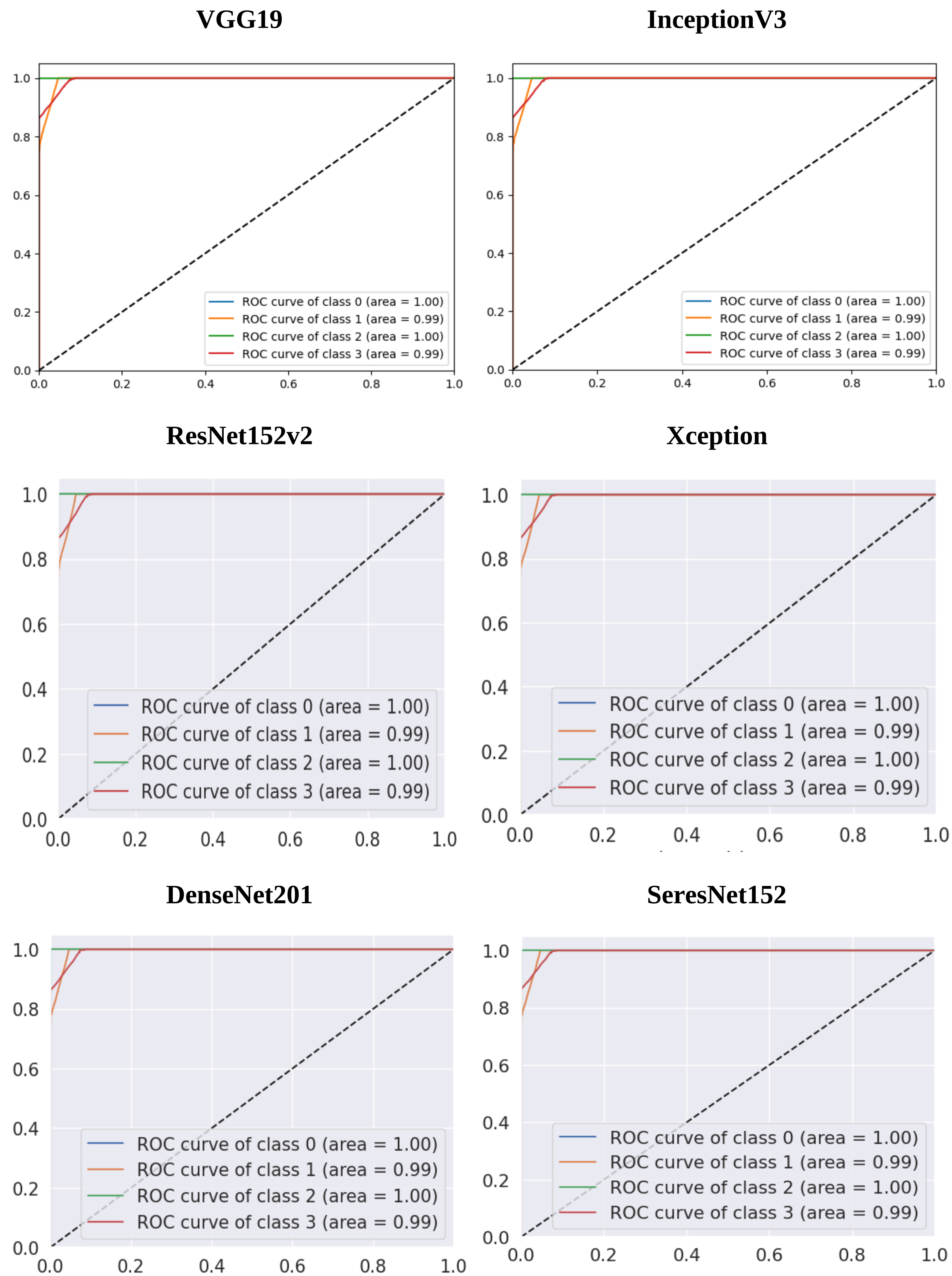


Figure 4.2: Deep CNNs' ROC curve

The ROC curves (Figure 4.2) provide insights into the performance of deep CNNs. The ROC curves suggest Densenet201, Vgg19, Resnet152v2, Xception, and InceptionV3 model curves are the closest to the top-left corner of the graph. This curve demonstrates a strong balance between sensitivity (true positive rate) and specificity (true negative rate). While Seresnet152 AUC value is slightly lower.

4.3.2 Performance of Transfer Learning

Six transfer learning CNN architectures' performance is presented in this section Densenet201, Resnet152v2 , Xception and InceptionV3 models all had high accuracy as shown in Table 4.2 with an accuracy of 97%, and the Seresnet152 was 96% and the Vgg19 model was the 95%. The accuracy decreases for Vgg19 than the original CNNs' is for transfer learning.

Table 4.2: Classification report of transfer learning

		Adenocarcinoma	**Large_cell_carcinoma**	**Normal**	**Squamous_Cell_Carcinoma**	**Model Accuracy**
Vgg19	Precision	96%	88%	100%	95%	94.08%
	Recall	99%	97%	96%	87%	
	F1-score	97%	92%	98%	91%	
	Support (N)	448	447	448	449	
Resnet152v2	Precision	100%	88%	100%	100%	96.65%
	Recall	100%	100%	100%	86%	
	F1-score	100%	94%	100%	93%	
	Support (N)	449	447	447	449	
	Precision	100%	88%	100%	100%	

Densenet201	Recall	100%	100%	100%	86%	96.65%
	F1-score	100%	94%	100%	93%	
	Support (N)	448	450	448	446	
Seresnet152	Precision	100%	88%	100%	100%	96.48%
	Recall	100%	100%	100%	86%	
	F1-score	100%	94%	100%	93%	
	Support (N)	447	447	450	448	
Xception	Precision	100%	88%	100%	100%	96.60%
	Recall	100%	100%	100%	87%	
	F1-score	100%	94%	100%	93%	
	Support (N)	450	447	448	447	
InceptionV3	Precision	100%	88%	100%	100%	96.09%
	Recall	100%	100%	100%	86%	
	F1-score	100%	94%	100%	93%	
	Support (N)	447	449	448	448	

Table 4.2 shows the Accuracy, precision, recall, f1, and support (n) result of transfer learning for chest cancer. The precision values of each architecture are considered. Here all the models performed the mentionable lowest precision value of 88% for identifying the Large_cell_carcinoma also precision value of Adenocarcinoma and Squamous_Cell_Carcinoma is low for the VGG19 model. The confusion matrix of the original CNN is presented in Figure 4.3. Following Table 4.2, Densenet201, Resnet152v2 , Xception and InceptionV3 provides a better result, as expected.

VGG19

	ADC	LCC	NOR	SCC
ADC	442	0	19	0
LCC	0	433	0	57
NOR	0	0	428	0
SCC	6	14	1	392

ResNet152v2

	ADC	LCC	NOR	SCC
ADC	449	0	19	0
LCC	0	447	0	61
NOR	0	0	447	0
SCC	0	0	0	388

InceptionV3

	ADC	LCC	NOR	SCC
ADC	447	0	0	0
LCC	0	449	0	62
NOR	0	0	448	0
SCC	0	0	0	386

Xception

	ADC	LCC	NOR	SCC
ADC	448	0	0	0
LCC	0	449	0	61
NOR	0	0	449	0
SCC	0	0	0	385

DenseNet201

	ADC	LCC	NOR	SCC
ADC	448	0	0	0
LCC	0	450	0	62
NOR	0	0	448	0
SCC	0	0	0	386

SeresNet152

	ADC	LCC	NOR	SCC
ADC	447	0	0	0
LCC	0	447	0	62
NOR	0	0	450	0
SCC	0	0	0	386

Figure 4.3: Six confusion matrices of Transfer learning.

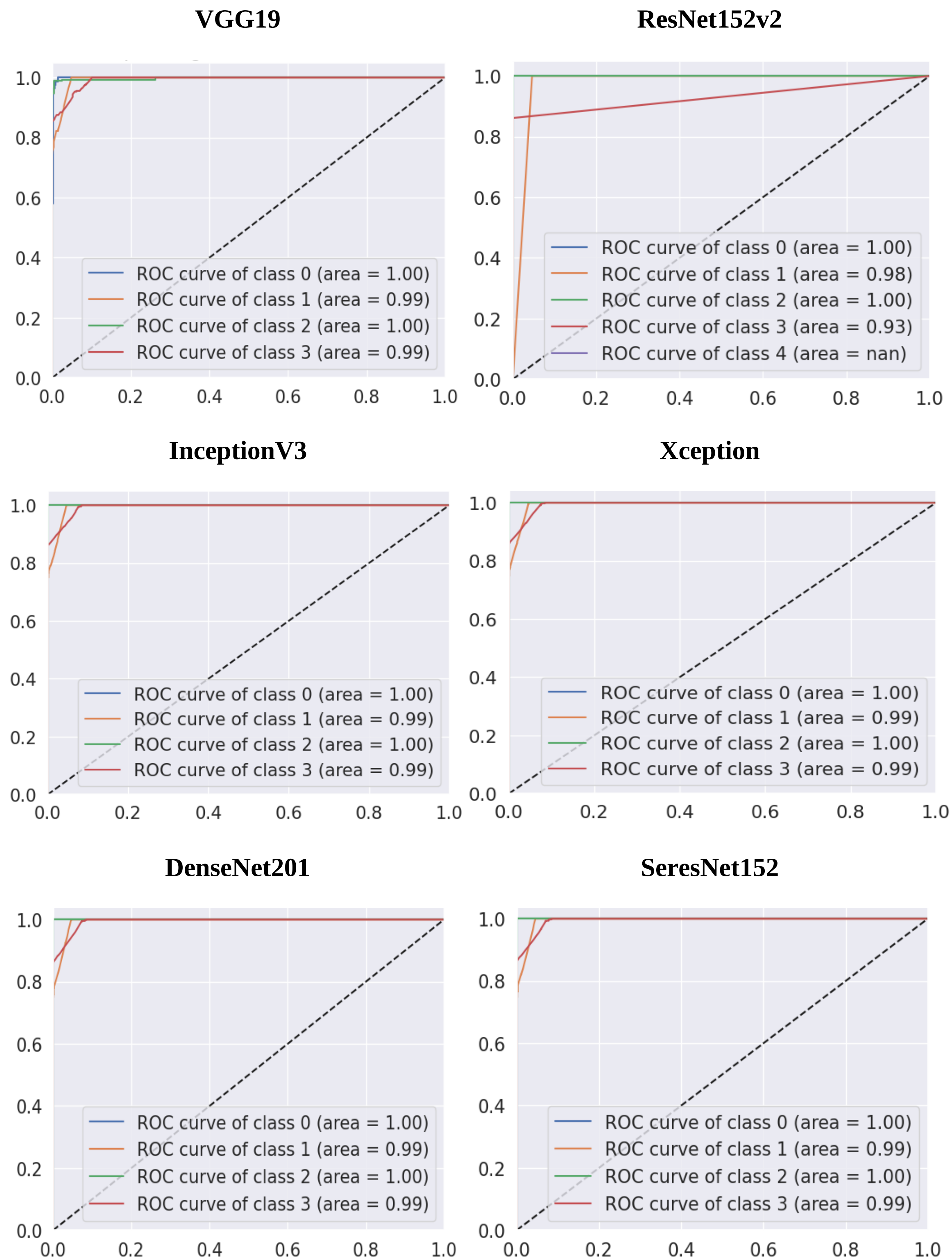


Figure 4.4: ROC curve of transfer learning

The ROC curves (Figure 4.4) provide insights into the performance of transfer learning. The ROC curves suggest Densenet201, Resnet152v2 , Xception and InceptionV3 model curves are the closest to the top-left corner of the graph. This curve demonstrates a strong balance between sensitivity (true positive rate) and specificity (true negative rate). While VGG19 AUC value is slightly lower.

4.4 Discussion

This study's results show that deep convolutional neural network (CNN) and the transfer learning technique achieved high accuracy in the chest cancer detection using CT scan images. Figure 4.5 shows that the six CNN models VGG19, ResNet152V2, DenseNet201, SE-ResNet152, Xception and InceptionV3 perform very well in classification task, here most models getting an accuracy of 97% except for SE-ResNet152, which has a slightly lower accuracy of 96 %. This suggests that deep CNN models are indeed learning hierarchical features from the medical imaging data and are therefore capable of automated cancer detection. Nevertheless, since they are quite accurate, training these models from scratch demands large labeled datasets and large computational resources in the real world.

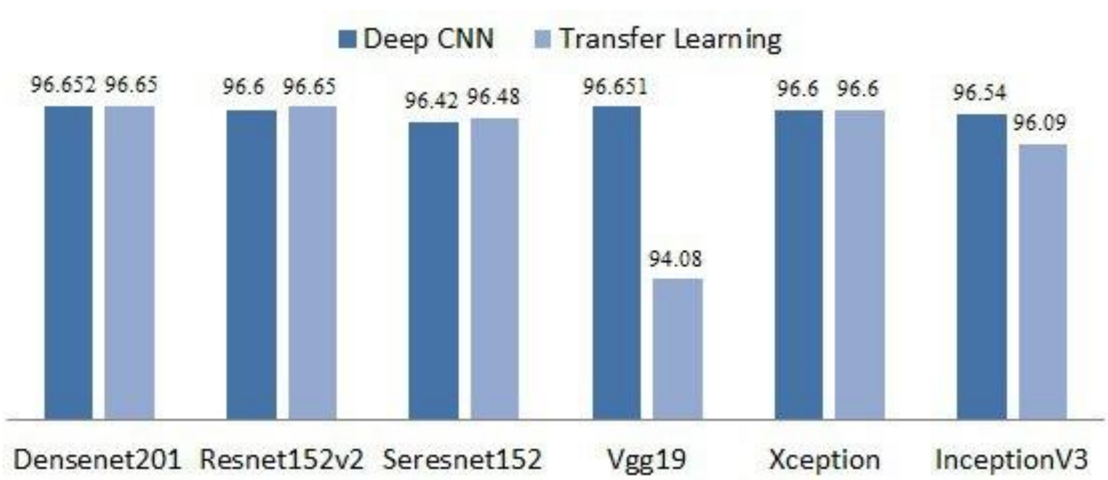


Figure 4.5: Comparison of model accuracy

Here, transfer learning was applied to the same CNN architectures to address these challenges. For the accuracy percentage results, DenseNet201, ResNet152V2, Xception, and InceptionV3 maintained a value of 97%, SE-ResNet152 did a value of 96% accuracy while VGG19 decreased slightly to 95%. The pre-trained models can utilize transfer learning to adapt to the new datasets with less training data thus alleviating the requirement of huge labeled medical datasets. Apart from efficiency, the training process is shortened and the high classification accuracy is preserved using this method. While VGG19 again has a lower accuracy compared to others, it implies that not all of the pre trained architectures are equally generalized when they are fine tuned for chest cancer detection. The successfulness of transfer learning relies on how much similar the pre-trained dataset is to the target dataset and how efficient the architecture are to trained a meaningful feature related to chest cancer.

One of the main reasons for the transfer learning witnessed in this study is its ability to make model robust, while the overfitting is reduced. Normally even the traditional deep CNN models that are trained from scratch are prone to overfitting if trained with the limited medical imaging datasets. Transfer learning addresses this issue by using knowledge learned from pre trained networks to retain essential feature representations learnt from very large scale image datasets. Furthermore, transfer learning imposes very little computational requirements, which significantly lessens the compute costs and thus makes it more deployable in the real world medical imaging applications where limited resources are available.

However, both deep CNNs and transfer learning are overall effective. As several models may perform better than others when fine tuned for medical tasks, the optimal architecture selection is extremely important in determining the performance. Moreover, hyper-parameter tune learning rates, batch size and some optimization strategies, that can generally drive the model accuracy and convergence speed significantly.

Also, image quality, patient demographics and scanning protocol can alter model performance. Most medical imaging datasets are inconsistent because of the differences in equipment and imaging conditions, and data collection procedures. In general, these factors can lead to potential biases in deep learning models and, thus, influence the generalization of deep learning models on a wider population base within the healthcare institutions. The future work should be carried out on domain adaptation techniques and data augmentation strategies to improve robustness and generalization of the model to the diverse clinical environment.

This study emphasizes the power of deep CNNs and transfer learning in the detection of chest cancer. Deep CNNs are extremely accurate, yet transfer learning has additional advantages of reducing dependence on data, expediting training, and allowing easier model generalizability. The findings stress the importance of selecting the best architecture, tuning the hyperparameters, and addressing difficulties related to interpretability and variability in the data. Future work should explore the integration of deep CNNs, transfer learning to further improve classification accuracy and enable more clinical use. These techniques can be further refined to boost early cancer detection and serve to better outcomes for patients in actual life clinical settings with AI driven CAD systems.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on society

Society is greatly benefited to improve the early diagnosis, improve patients' outcomes and provide health care accessibility by integrating deep learning, specifically CNNs and transfer learning, into the chest cancer detection. In this case, these AI driven models reduce the dependency on manual interpretation and reduces the influence of human errors, so that a proper timely diagnosis can be done more quickly and accurately. In resource starved areas without expert radiologist access, AI powered diagnostic tools that can be affordably and scaled offer a solution to deliver quality healthcare to reaches underserved populations. Further, the automation of the cancer detection leads to optimized hospital resources, lowering the workload of the medical professionals and reduces costs of the healthcare. But there are ethical issues to address such as data privacy and transparency, as well as AI bias, if such deployments are to be ethical. AI adoption in medical diagnostics growth has the potential to revolutionize the public's health strategies, increase cancer survival rates, and increase the overall efficiency of healthcare systems worldwide.

5.2 Impact on the environment

The impact of AI on chest cancer detection on the environment is indirect, but important because deep learning systems have such a low carbon footprint, their increasing efficiency contributes to reducing the carbon footprint of healthcare systems. These technologies can speed up and improve diagnoses, thereby avoiding unnecessary diagnostic tests or repeated imaging and thus save medical supply such as medical imaging supplies and energy. In addition, AI driven systems can be deployed away from a hospital's location, reducing the need of travel and enabling patients in remote areas to have access to healthcare services with no environmental cost of transportation. The computing resources for developing and training deep learning models are fairly and therefore potentially energy intensive as well as possibly wasteful if not handled carefully. With the increasing use of AI in healthcare, it is essential to combine the benefits of AI with strategies of minimizing the environmental footprint for such technologies.

5.3 Ethical Aspects

It is important to have an ethical understanding of using deep learning and transfer learning in chest cancer detection such that the technology is deployed responsibility and equitable. Empirical examples of this thesis include data privacy as one of the core ethical issues since medical images and a patient's information are very sensitive. Confidentiality of patients must be protected and the data must only be used for approved purposes. This must be done over very strict protocols to ensure that the data is safely stored and security of it is guaranteed. The concern is that AI models have the possibility for biasing in them, as the same AI models are trained on the database which is not representative. When AI systems are trained with poor data variations and the model lacks diversity, then AI system may work poorly for some demographic groups and may result in misdiagnosis or unequal healthcare outcome. Additionally, the results from these systems must be transparent in AI decision making so that patients trust the system. Making AI models accountable requires a vital component of clear explanations of how the AI models make decisions and the factors that the AI consider. Thirdly, AI can go a long way in augmenting diagnosis, yet human oversight is necessary to enable AI tools to complement rather than the wisdom of medical doctors. Care needs to be taken in this area in terms of the ethical considerations to make sure that the benefits of AI driven detection of chest cancer reaches a fair, just and transparent manner.

5.4 Sustainability Plan

The sustainability plan for integrating deep learning and transfer learning for chest cancer detection is directed at keeping these AI technologies sustainable in the long run, environmentally responsible and accessible. It is important to update models and retrain them with several datasets, regularly, in order to keep models accurate and evolving to things that happen in medical imaging. To make these systems available in developed and resource-limited areas as well as to approach equitable healthcare, we have to partner with healthcare providers, AI researchers and policy makers. Therefore, there must be efforts to develop energy efficient model in data centers. Additionally, ethical sustainability will be guaranteed by robust governance and regulatory frameworks, addressing how to ensure lots of privacy, no biases and transparency, building trust and maintaining that AI will continue to positively impact on cancer detection.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

This study was aimed towards enhancing the diagnostic accuracy of chest cancer detection with the application of deep CNNs and transfer learning and improving patient outcomes. Researches with diverse CNN architectures, VGG19, ResNet152V2, DenseNet201, SE-ResNet152, Xception, InceptionV3 have been used to determine their performance in recognizing chest cancer using medical imaging. In order to optimize accuracy and deal with issues of less data, transfer learning techniques were used to leverage pre trained models. The analysis of the results proved that the Densenet201, Vgg19, Resnet152v2, Xception, and InceptionV3 models were superior in original CNN and Densenet201, Resnet152v2 , Xception and InceptionV3 are superior in transfer learning models. However, the study emphasized the benefits of AI for the societal health, which are earlier detection, wider accessibility, less costly health care, and less resource consumption. The study is part of the growing field of AI-based chest cancer detection, indicating its potential to revolutionize diagnostics and enhance healthcare systems worldwide.

6.2 Conclusions

In conclusion, it was shown that deep convolutional neural networks (CNN) as well as transfer learning have a promising role in improving chest cancer detection accuracy and efficiency. The research shows how these technologies can be used to improve early diagnosis, decrease the costs of healthcare and increase access especially in a resource limited setting by having evaluated several state of the art CNN architectures and using transfer learning. Ultimately, this research is a contribution to current chest cancer diagnosis revolutionization by AI, and it points to its ability to reinvent healthcare systems by transforming them globally while encouraging ethical, equitable, and sustainable development.

6.3 Implication for Further Study

Extensive research possibilities exist in this field to improve present-day AI-based chest cancer detection research. AI model improvements in the future should involve training across extended and diverse datasets which encompass numerous medical demographics and imaging practices as well as potential patient conditions. AI system performance will improve across multiple populations when bias mitigation techniques are included. Additionally, exploring hybrid models that combine deep CNNs with other machine learning approaches, such as reinforcement learning or unsupervised learning, could result in more accurate and robust results. Research in model interpretability and explainability is also crucial, as it would allow healthcare professionals to understand and trust AI-driven decisions. Additionally, the integration of AI systems with real-time diagnostic software and creating a better workflow for radiologists could further streamline the process of cancer detection. Lastly, as technology underlying AI keeps evolving, studies that examine the long-term impact of AI on healthcare systems, the economic feasibility of broad implementation, and the ability of AI to reduce global health problem are essential to its responsible and equitable deployment.

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