COMPREHENSIVE AI SOLUTION FOR BREAST CANCER DETECTION USING DEEP LEARNING APPROACH

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APPROVAL

This Project titled **"Comprehensive AI Solution for Breast Cancer Detection using Deep Learning Approach"**, submitted by **Ieshita Nasrin Bithi** 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 **July, 2024**.

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We hereby declare that this project has been done by us under the supervision of **Ms. Israt Jahan, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The study utilizes deep learning, primarily transfer learning models, to enhance breast cancer diagnosis using ultrasound images. The Breast Ultrasound images (BUI) collection included 780 images classified as benign (487), malignant (210), and normal (133). The dataset was augmented to 5760 images to improve model training. Four pre-trained transfer learning models-VGG16, ResNet50, Xception, and a DenseNet201 were tested for their ability to classify breast cancer images. Before feeding image to the model this study employed several image pre-processing techniques like image resizing, gaussian filter, normalization, gamma correction to enhance the image quality. Xception achieved the best accuracy of 99%, outperforming the other models in this testing. The accuracy values for VGG16 were 96%, ResNet50 at 90%, and DenseNet201 at 93%. Despite its success, the study had limitations. The original dataset's size and variety are limited, which may have an influence on the model's applicability in real-world circumstances.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Breast cancer remains one of the most prevalent and challenging health concerns worldwide, affecting millions of individuals annually and exerting a significant toll on public health systems. Each year, an alarming half a million women succumb to the ravages of breast cancer [1] [2], solidifying its status as one of the foremost causes of female mortality. This insidious disease persists as a formidable global public health challenge, casting its shadow over the lives of countless women worldwide [3]. Notably, affluent nations bear the brunt of its burden, with incidence rates soaring to 74.1 new cases per 100,000 females, in stark contrast to 31.3 new cases per 100,000 in less developed regions [4]. The tally of breast cancer diagnoses surged from an estimated 1.67 million in 2012 [5], to 1.8 million in 2013 [6], escalating further to nearly 2.7 million in 2020, constituting approximately 12.5% of all reported cancer cases. Astonishingly, breast cancer has eclipsed lung cancer to claim the unenviable title of the most frequently diagnosed cancer worldwide [7] [8]. The World Health Organization (WHO) foresees a grim trajectory, projecting a staggering 19.3 million fresh cancer diagnoses by 2025 [9], a daunting surge to 27.5 million by 2040, accompanied by an estimated 16.3 million fatalities [10].

Early detection can prevent the fatality rate of the patient but the lack of medical experts, high cost for testing is the major obstacles and problems for early detection [11] [12] [13]. Currently, the early detection of malignant breast cancers relies on advanced medical imaging techniques such as mammography, MRI, and ultrasound [14] [15] [16]. Among these modalities, ultrasonography stands out as it surpasses mammography in sensitivity, particularly in identifying cancers nestled within dense breast tissue, and excels in distinguishing solid tumors from cysts [17]. Moreover, ultrasound technology presents a cost-effective alternative to mammography and holds promise in detecting anomalies that may elude traditional mammograms [18] [19] [20]. Radiologists possess the ability to promptly discern diverse breast tissues, with breast ultrasound image segmentation emerging as a pivotal technique for tumor localization and breast cancer diagnosis [21]. Nevertheless, the reliance on radiologists' clinical expertise introduces subjectivity and variability among observers, compounded by the time-intensive nature of manual analysis.

To address these challenges, the implementation of a computer-aided detection (CAD) system has been advocated, offering the potential to enhance the efficiency and reduce the labor associated with breast ultrasound image analysis [22] [23]. Such a system could also streamline the automated segregation of breast images [24]. Traditional CAD systems often relied on manually curated visual datasets, which may not seamlessly translate to ultrasound images acquired through diverse methodologies [25, 26, 27, 28, 29, 30]. Recent strides in artificial intelligence (AI) technology have paved the way for automated breast cancer screening using ultrasound images [31] [32] [33]. Convolutional neural networks (CNNs) have emerged as a cornerstone in medical image processing, offering distinct advantages in breast cancer diagnosis [34]. By leveraging hierarchical layers to extract information from image pixels, CNNs enable tasks such as image segmentation, disease diagnosis, and classification. The advent of deep learning technology holds immense promise in expediting ultrasound interpretation, facilitating the early identification of breast cancer.

This study aims to build a deep learning model-based CAD system that can detect Breast cancer in its benign, malignant, and normal stages in a very short time. The BUI dataset has been used for all the experiments in this study. The ultrasound images have a number of flaws, including artifacts and noise. After image processing and augmentation of dataset, this study feeds the preprocessed data into transfer learning model. Four transfer learning models have been employed to compare the performance. The model provides significant accuracy in detecting or classifying Breast cancer into different classes. This study's advanced CAD system has paved the way for more precise and personalized approaches to diagnosis and treatment, leading to improved patient care and outcomes.

1.2 Background and Present State

Breast cancer remains one of the most prevalent and challenging health concerns worldwide, affecting millions of individuals annually and exerting a significant toll on public health systems. To address these issues, computer-aided detection (CAD) systems have been proposed to enhance efficiency and reduce labor in breast ultrasound image analysis, facilitating automated image segregation. Traditional CAD systems, which often use manually curated visual datasets, may not be effective for ultrasound images from diverse methodologies. Recent advances in artificial intelligence (AI) have enabled automated breast cancer screening using ultrasound images. Convolutional neural networks (CNNs) have become essential in medical image processing, offering significant advantages in breast cancer diagnosis by extracting information from image pixels for tasks like segmentation, diagnosis, and classification. Deep learning technology shows great potential in expediting ultrasound interpretation and facilitating early breast cancer identification.

1.3 Problem Statement

Breast cancer remains a pervasive and complex global health challenge, impacting millions of lives each year and straining healthcare systems worldwide. Tragically, it claims the lives of approximately half a million women annually, making it a leading cause of female mortality. This disease persists as a significant public health concern, particularly burdening affluent nations with higher incidence rates compared to less developed regions. From the early 2010s to 2020, the number of breast cancer diagnoses has risen significantly, now constituting a substantial portion of all reported cancer cases globally and surpassing lung cancer as the most diagnosed cancer. The World Health Organization (WHO) predicts a troubling increase in new cancer cases and fatalities in the coming decades, underscoring the urgent need for effective prevention and treatment strategies. Early detection can significantly reduce patient fatality rates, but major obstacles include the lack of medical experts and high testing costs. Currently, early detection of malignant breast cancers relies on advanced medical imaging techniques such as mammography, MRI, and ultrasound. Among these, ultrasonography excels in sensitivity, particularly for detecting cancers in dense breast tissue, and effectively distinguishes solid tumors from cysts. It is also a cost-effective alternative to mammography and can detect anomalies missed by traditional mammograms. Radiologists can promptly interpret diverse breast tissues, with breast ultrasound image segmentation being crucial for tumor localization and breast cancer diagnosis. However, relying on radiologists introduces subjectivity and variability, and manual analysis is time intensive.

1.4 Objectives

- Evaluate the performance of four state-of-the-art transfer learning models (VGG16, Xception, DenseNet201 and ResNet50) in accurately detecting breast cancer across three classes, aiming to identify the model with the highest accuracy and efficiency.
- Investigate the impact of various image pre-processing techniques, including image resizing, Gaussian filtering, Normalization, and Gamma Correction on enhancing the quality of medical images used for breast cancer detection by deep learning models.
- Compare the effectiveness and practical implications of utilizing deep learning models for breast cancer detection with traditional medical imaging techniques, assessing factors such as accuracy, scalability, computational resources, and potential deployment in resource-limited settings.
- Translate the research findings into actionable recommendations for improving early detection rates of breast cancer globally, with a focus on strategies to address the challenges of insufficient medical expertise and costly testing, especially in underserved communities.
- Investigate the generalizability and transferability of the developed deep learning model for breast cancer detection across diverse patient demographics, imaging modalities, and healthcare settings, aiming to assess its potential for widespread adoption and deployment in real-world clinical practice.

1.5 Scope and Limitations

The scope of the problem involves the challenges in the early detection of breast cancer, a prevalent and potentially fatal disease worldwide. These challenges include the need for frequent, invasive, and costly testing, and the limitations due to insufficient medical expertise, especially in resource-limited regions. The shortage of radiologists, high fees, and screening costs are major obstacles to early detection. Despite the benefits of early detection in reducing mortality rates, barriers such as limited access to screening facilities and skilled healthcare professionals lead to delayed diagnoses and poorer patient outcomes. The complexity of breast cancer diagnosis, which involves interpreting medical imaging data, highlights the necessity for innovative solutions to improve detection accuracy and efficiency. Thus, the scope of the problem extends to exploring the feasibility of using advanced technologies, such as deep learning models, to address these challenges and enhance early detection rates of breast cancer globally.

1.7 Report Organization

The report is organized into several chapters, each focusing on distinct aspects of the study:

Chapter 1: Introduction provides an overview of the research objectives and outlines the background, current state, problem statement, objectives, scope, limitations, and a summary of the study.

Chapter 2: Literature Review comprehensively reviews existing works in the field, compares them, identifies open issues, and summarizes the findings.

Chapter 3: Methodology/Requirement Analysis & Design Specification details the proposed methodology, system design, hardware and software requirements, project management strategies, and financial analysis.

Chapter 4: Implementation covers the development process, including model training, and evaluation.

Chapter 5: Result and Analysis presents experimental results, simulation outcomes, performance metrics, comparative analyses, and their implications.

Chapter 6: Impact on Society, Environment, and Sustainability explores the broader implications of the research on life, society, environment, ethical aspects, and includes a sustainability plan.

Chapter 7: Conclusion and Future Work summarizes the conclusions drawn from the study, suggests future research directions, and discusses limitations and potential conflicts of interest.

1.7 Summary

Breast cancer has a large worldwide effect, emphasizing the critical need for early identification due to high death rates and diagnostic problems. The potential of artificial intelligence (AI), particularly deep learning, to improve diagnostic accuracy and efficiency is underlined. This project intends to create a CAD system employing transfer learning models and image preprocessing techniques, with the goal of improving early identification and patient treatment, particularly in low-resource situations. The study covers background research, methodology, results analysis, social effect, and future prospects.

CHAPTER 2
BACKGROUND STUDY

2.1 Overview

These days, breast cancer is frequent. Many lives can be saved if breast cancer is detected early. Numerous relevant works exist on this subject. Numerous writers completed the same tasks. From their perspective, they completed their task. The primary objective of the researcher is to determine the optimal algorithms and accuracy for the prediction of breast cancer. In this section, detailed discussed about the previous study, that are published based on breast cancer detection. I select 10 best paper that are work with breast cancer to detect the cancer in the early stages.

2.2 Literature review

Bazazeh, D. et al. [34] The study contrasts three widely used machine learning methods for identifying breast cancer. SVMs perform best in terms of precision, specificity, and accuracy. The greatest likelihood of accurately diagnosing malignancies is seen in RFs. There are several forms of breast cancer, making it a heterogeneous illness. Large-scale data analysis and precise diagnosis are made easier with the use of ML methods. Machine learning methods for detecting breast cancer use supervised learning and classification models. To categorize breast cancers as normal or abnormal using the IRMA dataset, Nur Syahmi Ismail et al. [35] suggested a deep learning method employing the VGG16 and ResNet50 architectures. The outcomes showed that, with an accuracy of 94% as opposed to 91.7%, ResNet50 was outperformed by VGG16. Similar to this, Sharma, S. et al. [36] used Wisconsin Diagnosis Breast Cancer dataset as a training set in this paper's comparison of machine learning algorithms for breast cancer prediction, including Random Forest, kNN, and Naïve Bayes. The accuracy and precision levels displayed in the findings are competitive. Another research uses the WEKA software on a dataset of breast cancer patients to compare and contrast many methods, such as the kNN algorithm, the Pruned Tree, and the Bayes Network. 89.71% was the maximum accuracy attained using the Bayes Network method. The notions of supervised and unsupervised learning are also explained in the paper. Kumar, P. et al. [37] presents an enhanced CNN model. It highlights the high accuracy of the model, which has a true positive rate of 99%, precision of 99%, and overall accuracy of

97.20%. With its three basic layers and two activation functions, the model performs better than current CNN models, especially when applied to the CBIS-DDSM dataset. The suggested approach achieves better performance metrics, demonstrates notable progress in breast cancer identification, and offers physicians a useful second opinion. The work addresses a major global health problem for women by highlighting the potential of deep learning techniques to improve the accuracy of breast cancer screening. Additionally, Ahmed Iqbal Pritom et al. [38] investigated the use of many classification methods, including Support Vector Machine (SVM), C4.5 Decision Tree, and Naïve Bayes, with SVM demonstrating the most remarkable prediction accuracy of 75.75%. A UNET-based design was presented by Mirya Robin et al. [39] and was successful in segmenting tumour regions in histopathology pictures with a success rate of 94.2%. Image preprocessing, which emphasizes scaling for effective processing, comes after image acquisition via Kaggle. A U-Net model with a U-shaped architecture is used for accurate segmentation in feature extraction and image segmentation. The last step includes detection, when the model is validated on sample pictures and masks are created to show segmented sections. Furthermore, R. Almajalid et al. [40] outperformed previous techniques with a dice coefficient of 0.825 and a similarity rate of 0.698 while developing a novel segmentation framework based on U-net for breast ultrasound imaging. A nine-convolutional-layer modified U-Net model for breast cancer segmentation and classification was proposed by G. Jayandhi et al. [41]. This model creates a division map by combining six channels of RGB and HSV spaces. It has encoder and decoder blocks. The encoder blocks include a max pool, bilateral normalization, dilated convolution, and convolutional layer. With an F1 score of 93.5%, a dice coefficient of 94%, and an accuracy of 98.7%, the suggested technique achieves remarkable performance metrics. Meanwhile, Mohamed Bal-Ghaoui et al. [42] used transfer learning U-Net backbones for the automatic segmentation of breast ultrasound lesions, with DenseNet121 proving to be the best backbone. They achieved an average Dice coefficient of 0.7370 and a sensitivity of 0.7255. The Graph Neural Network (GNN) approach is essential for identifying and classifying breast cancer, especially when using multi-scale data from tissue architectures. [43] A unique Multimodal Graph Neural Network (MGNN) was presented by Jianliang Gao et al. [44] to forecast the prognosis of cancer patients. To clarify the underlying relationships between the two, the study first builds a bipartite graph utilizing either gene expression profiles or DNA copy number alteration (CNA) profiles. The embedding representation of every patient is then proposed to be obtained using a novel graph neural network. In the end, the output is categorized according to a preset threshold as either long-term or short-term survival. U-net and GNNs together may improve patient outcomes and lower death rates. Deep learning technique developments are expected to considerably improve breast cancer diagnosis and treatment approaches.

2.3 Comparison between existing works

Table 2.1: Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy
1.	Bazazeh, D. et al. [34]	Support Vector Machine (SVM), Random Forest (RF) and Bayesian Networks (BN)	97%
2.	Nur Syahmi Ismail et al. [35]	VGG16 and ResNet50	94%
3.	Sharma, S. et al. [36]	Random Forest, kNN, and Naïve Bayes	89.71%
4	Kumar, P. et al. [37]	CNN models	97.20%
5	Ahmed Iqbal Pritom et al. [38]	Support Vector Machine (SVM), C4.5 Decision Tree, and Naïve Bayes	75.75%
6	Mirya Robin et al. [39]	U-Net model with a U-shaped architecture	94.2%
7	R. Almajalid et al. [40]	Deep Learning Architecture U-Net	Not Specified
8	G. Jayandhi et al. [41]	U-Net model	98.7%
9	Mohamed Bal-Ghaoui et al. [42]	VGG16, VGG19, ResNet50, ResNeXt50, Se-ResNet50, Se-ResNeXt50, MobileNetV2, and DenseNet121	Not Specified
10	Jianliang Gao et al. [44]	Multimodal Graph Neural Network (MGNN)	Not Specified

2.4 Open Issue

Several open issues persist in the field of breast cancer detection using artificial intelligence and machine learning. First, there is a need to enhance the interoperability of deep learning models across different datasets and imaging modalities to ensure their applicability in diverse clinical settings. Second, integrating multi-modal data, such as combining histopathological images with genomic or clinical data, remains a challenge to improve diagnostic accuracy and predictive capabilities. Third, improving the robustness and interpretability of AI models is crucial for reliable clinical decision-making. Ethical considerations surrounding data privacy, patient consent, and fairness in algorithmic decisions also require careful attention. Furthermore, addressing practical deployment challenges, including regulatory approvals and cost-effectiveness, and establishing frameworks for long-term model monitoring and validation are essential for the successful adoption of AI-driven solutions in breast cancer diagnosis and treatment.

2.5 Summary

In summary, while strides have been made in employing AI and deep learning for breast cancer detection, continuous research and innovation are imperative to address the existing challenges. The integration of advanced technologies has the potential to enhance diagnostic accuracy and efficiency, reduce subjectivity, and make early detection more accessible and cost-effective. These efforts are essential for improving patient outcomes and reducing the global burden of breast cancer, particularly in resource-limited regions.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS

3.1 Overview

In this section, I discuss the proposed methodology and system design, detailing the hardware and software requirements necessary for implementation. The research management aspect covers the planning, execution, and monitoring of research activities to ensure timely and successful completion. Additionally, I provide a financial analysis to outline the budget, costs, and potential economic benefits of the research. Finally, I summarize the key points, emphasizing the importance of the proposed approach in enhancing breast cancer detection and the feasibility of deploying advanced technologies in clinical settings.

3.2 Proposed Methodology

Figure 3.1 shows the overall process of this study.

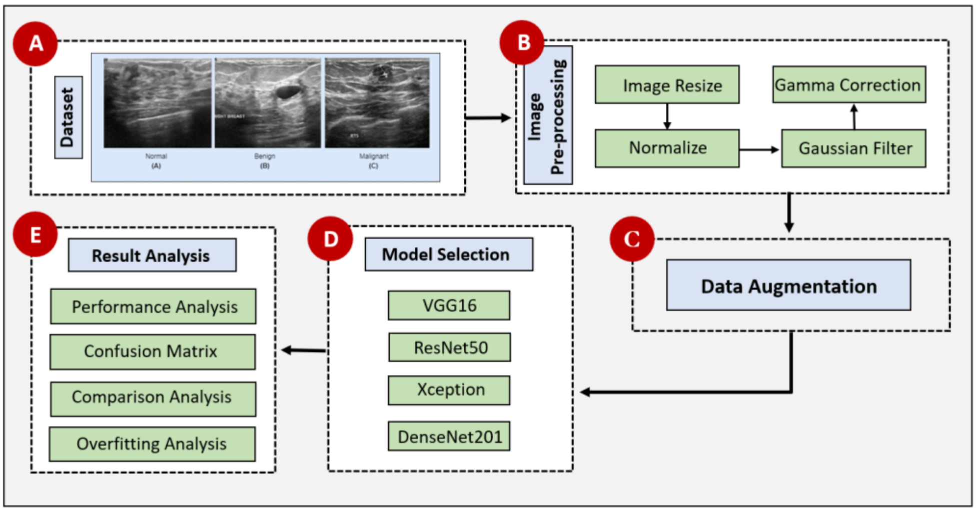

Figure 3.1: Overall methodology of the study.

The process is divided into five steps: Dataset Collection, Image Pre-processing, Data Augmentation, Model Selection, and Result Analysis. The steps are explained below:

A. Dataset: Three kinds of ultrasound images are included in the dataset: Normal, Benign, and Malignant.

B. Image Pre-processing: Standardize picture sizes, apply a Gaussian filter to increase features and minimize noise, adjust brightness for consistent settings, and scale pixel values to optimize model performance and training stability.

C. Data Augmentation: Enhance the variety of the dataset by doing data augmentation.

D. Model Selection: VGG16, ResNet50, Xception, and DenseNet201 are selected for implementing and training deep learning models.

E. Result Analysis: Evaluate and compare model performance to determine the best approach.

Dataset Description

The breast cancer dataset was collected from Kaggle. It consists of 3 classes with 780 images in total. The benign class has 487 images, while the Malignant and Normal classes have 210 and 133 images, respectively. All the images are in PNG format. Table 3.1 describe the dataset description and figure 3.2 depict the image overview.

Table 3.1: Dataset Description

Name	Description
Total Number of Images	780
Average Dimension	500 x 500
Color Grading	Grayscale
Data Format	PNG
Normal (a)	133
Benign (b)	487
Malignant (c)	210

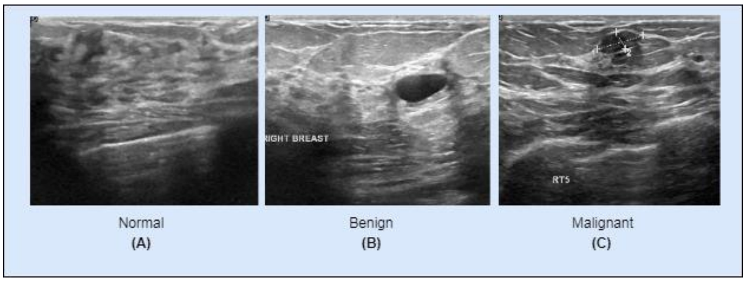

Figure 3.2: Shows the image overview with three classes.

Image pre-processing

Image preprocessing is the first and foremost step in feeding images into the deep learning model. This study utilized several image preprocessing techniques, such as image resizing, gaussian filter, normalization, and Adjust brightness and contrast to enhance the image quality and improve the model's outcomes. Image 3.3 shows the whole image processing techniques.

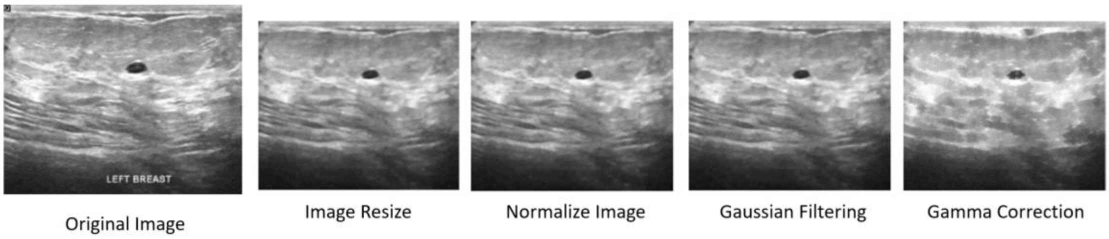

Figure 3.3: All steps of image preprocessing.

Image Resize

Image resizing is an important image processing technique that adjusts an image's dimensions, usually to fit a desired aspect ratio or specific dimensions, while maintaining or changing its visual quality. The images are resized into 224 x 224 from 500 x 500.

Normalize Image

The procedure known as normalization modifies the range of pixel intensity values. One should set the values in the picture matrix to zero if they are negative and to the maximum values if they are more than the maximum value. I can utilize higher learning rates or help models converge more quickly for a given learning rate since it helps stabilize the gradient descent step.

Gaussian Filter

Breast ultrasound image has a lot of speckle noise, before feed the deep transfer learning model, the images should be enhanced by removing the noise and artifact. The Gaussian filter is a widely used tool for image processing that distorts an image by convolving it with a Gaussian kernel, reducing high-frequency noise and enhancing image details [45].

Gamma Correction

The deep transfer learning model can extract more important feature when the images are more enhanced and clearer. Gamma correction is an image preprocessing technique that improves an image's contrast and brightness by using a nonlinear mapping function. It is especially helpful in remote sensing and medical imaging applications [46].

Data Augmentation

Dataset was small. There were 780 images in the original dataset. I enlarged it up to 5760 images using augmentation. Data augmentation techniques included horizontal and vertical flips, 90-degree clockwise and counterclockwise rotations, and 180-degree rotations. Data augmentation is beneficial because it artificially increases the quantity and variety of the training data without adding to the expenses associated with data collection. This reduces overfitting, improves generalization, and enhances model adaptability. Table 3.2 shows the description of augmented dataset.

Table 3.2: Augmented dataset description

Name	**Description**
Total Number of Images	5760
Average Dimension	224 x 224
Color Grading	Grayscale
Data Format	PNG
Normal (a)	2128
Benign (b)	3368
Malignant (c)	264

3.3 Hardware/ Software Requirement

Python programming language has been used for the implementation of this research-based project. This study employs enriched and robust pretrained transfer learning model using Google Colab. computer used Core-i5 processor, 16 GB RAM, 8 GB GPU.

3.4 Project Management and Financial Analysis

In terms of project management, my supervision guided and oversaw the development process, ensuring adherence to timelines and project goals. This included planning, organizing, and coordinating activities effectively to achieve the desired outcomes. As for financial analysis, this project did not involve financial aspects or considerations. The focus was primarily on methodological development and system design aimed at improving breast cancer detection using advanced technologies. Therefore, financial implications or budgetary considerations were not applicable to this study.

3.5 Summary

Here, I present a novel methodology aimed at tackling the challenges unique to breast cancer detection. This study integrates image preprocessing, a transfer learning model to improve accuracy and efficiency in detecting breast cancer across multiple classes. Figure-1 illustrates the overall process of my approach.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

In this chapter, I delve into the practical aspects of our research, focusing on the implementation and validation of our proposed methodology for breast cancer detection. I begin with an in-depth discussion on the design and training of our model, detailing the architecture, data preprocessing steps, and the rationale behind the choice of algorithms and parameters. Following this, I move on to system testing and model evaluation, where I outline the metrics and benchmarks used to assess the performance of our model, including accuracy, precision, recall, and specificity. Finally, I conclude with a summary that encapsulates the key findings and insights gained from the implementation and testing phases, providing a comprehensive overview of the efficacy and potential impact of our approach in the context of breast cancer detection.

4.2 Train Model

In my study on breast cancer diagnosis, I use Deep Learning approaches, including VGG16, ResNet50, Xception, and DenseNet201. These models were chosen because of their shown efficacy in image classification challenges and capacity to learn detailed elements from medical pictures.

- **Data preprocessing:** The collection includes ultrasound images classified as normal, benign, or malignant. To guarantee uniformity, all images are shrunk to a set dimension that corresponds to the input size of the chosen models (224 x 224). The images are then normalized, with pixel values ranging from 0 to 1. Furthermore, data augmentation techniques like as rotation, flipping, are used to broaden the training set and reduce overfitting.
- **Model Architecture:** Each architecture has distinct features. VGG16 uses a straightforward, deep stack of convolutional layers with narrow receptive fields. ResNet50 includes residual connections, which allows for the training of much deeper networks without the vanishing gradient issue. Xception uses depthwise separable convolutions, which makes it both efficient and strong. For all models, I change the last layer to produce probabilities for three classes: normal, benign, and malignant.

- **Training:** The models are trained with the categorical cross-entropy loss function and optimized with the Adam optimizer. I divided the dataset into training, validation, and test sets. Training is done in numerous epochs, with early stops to avoid overfitting depending on validation results. I use transfer learning to initialize the models with pre-trained weights from ImageNet, which accelerates convergence and improves performance.
- **Evaluation:** Models are evaluated based on accuracy, precision, recall, and F1-score. These metrics offer a complete visualization of the model's performance across classes.

Through accurate training and validation, my selected Deep Learning approaches exhibit strong performance in categorizing breast tissue types, indicating that they offer potential for improving early detection and diagnosis of breast cancer.

4.3 Model Evaluation

This research employs a detailed analysis with numerous indicators to ensure a clear grasp of the model's performance. Accuracy, precision, recall, and F1 score provide information on various features of the model's predictions, whilst the ROC curve and AUC curve provide a visual and quantitative evaluation of its discriminatory capacity. This thorough test validates the model's resilience and reliability in detecting breast cancer from medical images.

1. Data Preparation:

- **Load Data:** The test dataset, which contains pictures and labels, is loaded.
- **Preprocessing:** Images are preprocessed (resized, standardized, etc.) to meet the model's input requirements.

2. Model loading:

- **Load Trained Model:** The pre-trained model is loaded from the stored weights and switched to evaluation mode.

3. Prediction:

- **Generate Predictions:** The model is used to predict probabilities or classes for the test images.
- **Store Predictions:** The predicted values and true labels are stored for further analysis.

4. Evaluation metrics:

- **Accuracy:** The percentage of correct predicts out of all predictions.

$$\text{ACC} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

- **Precision:** The percentage of genuine positive predictions among all positive predictions produced by the model.

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

- **Recall:** Determines the percentage of genuine positive predictions among all real positive cases.

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

- **F1 Score:** The harmonic means of accuracy and recall, which strikes a balance between the two measurements.

$$\text{F} - 1\ \text{Score} = 2\,\frac{\text{precision}*\text{recall}}{\text{precision+recall}}$$

5. ROC Curve and AUC:

- **ROC Curve:** The ROC Curve is a depiction of the true positive rate (sensitivity) vs the false positive rate (1-specificity) at various threshold settings.
- **Area under the curve (AUC):** AUC measures the degree of separability; a higher AUC implies a better-performing model.

4.4 Summary

This study includes an exploration of trainable parameters through iterative adjustments to the model architecture and parameter tuning using training data. It aims to optimize neural network configurations, validate effectiveness, and ensure robust learning from data inputs.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

This chapter compares the performance of different pretrained transfer learning models in a categorization challenge. Four famous models- VGG16, ResNet50, Xception, and DenseNet201 are evaluated using accuracy, loss, ROC curves, and confusion matrices. In this chapter employed a number of measures to assess the transfer learning models, including precision, recall, F1-score, accuracy (ACC).

5.2 Experimental/ Simulation Result

In this section demonstrates the results of four pretrained transfer learning model.

The below table presents a comparison of four deep learning models- VGG16, ResNet50, Xception, and DenseNet201 highlighting their performance during training and testing. It shows Xception performing exceptionally well in both training and testing phases. VGG16 and DenseNet201 also perform well, while ResNet50 shows relatively lower training performance but decent testing results. This comparison provides insights into the generalization capabilities of each model.

Table 5.1: Train, and Model Accuracy for each model

Model's Name	**Training Accuracy**	**Model Accuracy**
VGG16	99.35%	96%
ResNet50	88.89%	90%
Xception	**99.57%**	**99%**
DenseNet201	100%	93%

1. Xception

Confusion Matrix: The confusion matrix shows the model's performance in classifying breast conditions: 24/27 accurate for breast_benign, 332/337 correct for breast_malignant, and 212/212 correct for breast_normal. Misclassifications occur mostly between breast_benign and breast_malignant. The model has great accuracy, particularly in predicting breast_malignant and breast_normal cases.

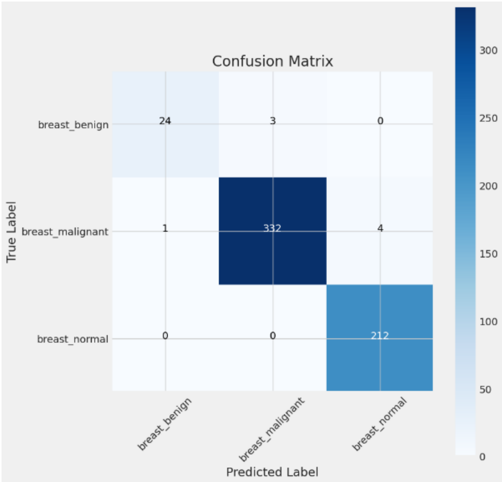

Figure 5.1: Shows the confusion matrix of Xception

Accuracy and Loss Curve: The loss curves demonstrate that both training and validation losses are reducing, suggesting good learning. The accuracy curves show high and steady accuracy for both training and validation, with optimal performance between the 4th and 5th epochs, indicating minimal overfitting and strong generalization.

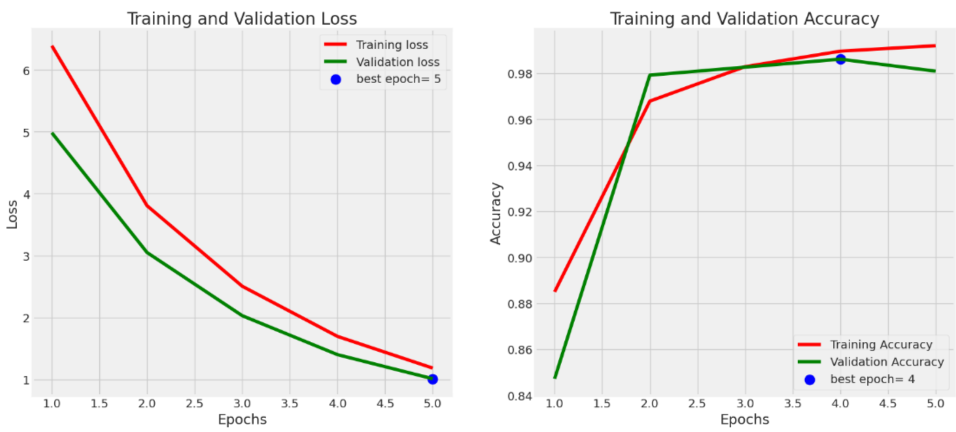

Figure 5.2: Shows the accuracy and loss curve of Xception

ROC Curve: The ROC curves show the performance in three classes. Class 2 has an AUC of 1.0000, which indicates excellent organization. Class 0 and 1 had AUC values of 0.9818 and 0.9957, respectively, showing good performance. The micro-average AUC of 0.9979 demonstrates the model's overall high accuracy and minimal false positives.

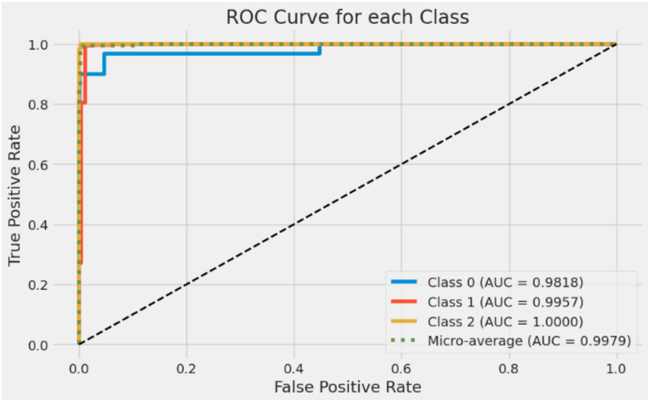

Figure 5.3: ROC curve of Xception

2. VGG16

Confusion Matrix: The confusion matrix shows the classification performance with 43 true positives (normal), 647 true positives (benign), and 416 true positives (malignant). Misclassifications include 9 normal as benign, 1 normal as malignant, 3 benign as normal, 24 benign as malignant, and 9 malignant as benign.

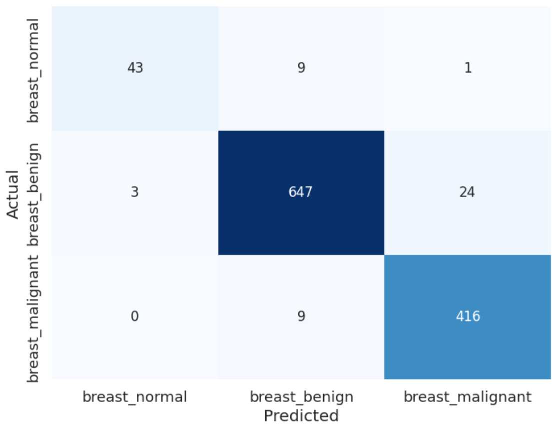

Figure 5.4: Shows the confusion matrix of VGG16

Accuracy and Loss Curve: The curves show high training accuracy and low training loss, indicating good model performance on the training data. However, the significant gap and fluctuation in validation accuracy and loss suggest that the model's performance on unseen data is unstable. To improve, techniques like regularization, dropout, and cross-validation should be considered.

Figure 5.5: Shows the accuracy and loss curve of VGG16

ROC Curve: The ROC curve shows the performance of a multi-class classifier with the AUC values indicating the effectiveness for each class: Class 0 (0.9649), Class 1 (0.9766), and Class 2 (0.9478), with a micro-average AUC of 0.9650. The curves above the diagonal line suggest a high overall classifier performance, especially for Class 1. The micro-average indicates strong overall discriminative ability across all classes.

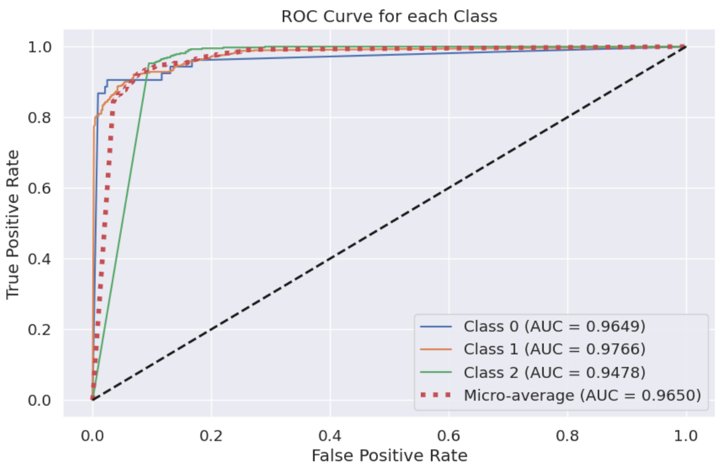

Figure 5.6: ROC Curve of VGG16

3. DenseNet201

Confusion Matrix: The confusion matrix shows that the classifier performs well for class 1 (426 correct) and class 3 (616 correct) but struggles with class 2 (33 correct, with misclassifications into classes 1 and 3). This indicates high accuracy for classes 1 and 3 and lower accuracy for class 2, suggesting a need for targeted improvements for class 2 predictions.

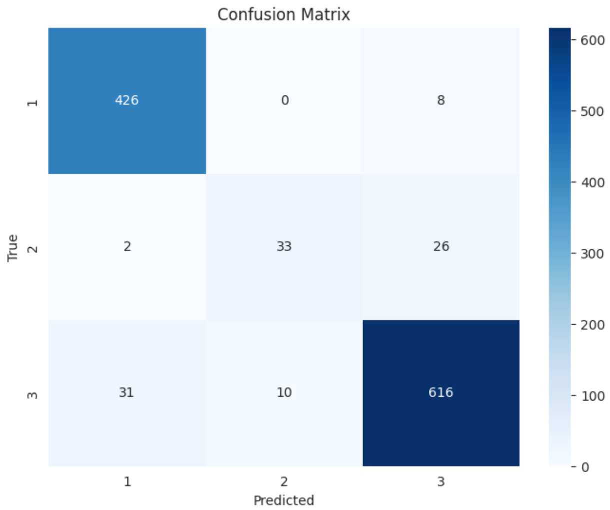

Figure 5.7: Shows the confusion matrix of DenseNet201

Accuracy and Loss Curve: The training curves show consistently low loss and high accuracy, indicating good learning on the training data. However, the validation curves display higher, fluctuating loss and lower accuracy, suggesting less effective generalization to the validation data.

Figure 5.8: Shows the accuracy and loss curve of DenseNet201

4. ResNet50

Accuracy and Loss Curve: The training and validation loss curves both decrease steadily, indicating that the model's performance is improving over time. The accuracy curves for both training and validation data increase and converge, reaching around 90%, demonstrating consistent improvement in model accuracy across epochs.

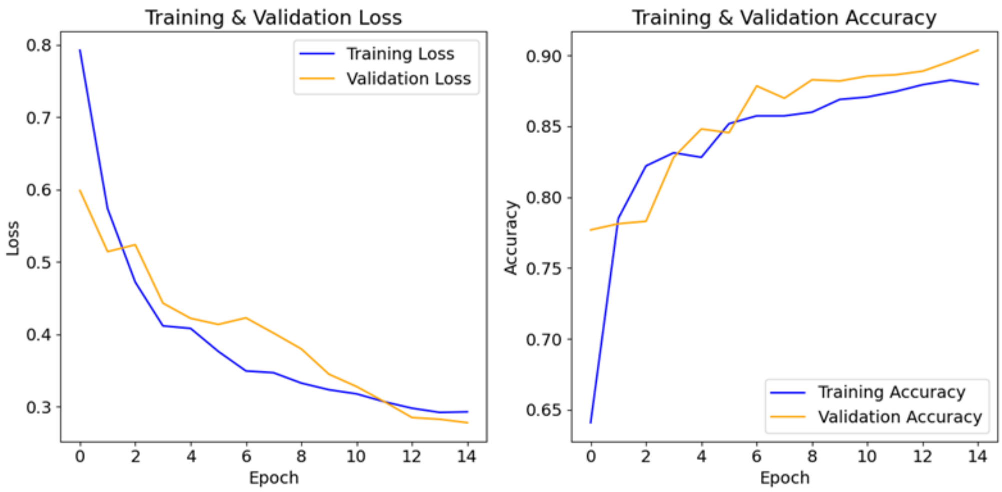

Figure 5.9: Shows the accuracy and loss curve of ResNet50

5.3 Performance Analysis

In this section demonstrates the various performance analysis matrices results like accuracy, F1 score, precision, recall of the proposed model.

Table 5.2: Shows the results of various performance matrices

Model	Accuracy	Macro Avg			Weighted Avg		
		Precision	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**
Vgg16	96%	0.93	0.90	0.92	0.96	0.96	0.96
ResNet50	90%	88.98	88.75	88.58	0.90	0.90	0.90
Xception	99%	0.98	0.95	0.96	0.99	0.99	0.99
DenseNet 201	93%	0.88	0.82	0.84	0.93	0.93	0.93

In table 5.2 shows various performance matrices that verify the model robustness, effectiveness, resilience. It demonstrated that the accuracy and other values are outperformed all previous work.

Comparison Between Four Transfer Learning Model

The chart compares the model accuracies of four pretrained transfer learning models: VGG16, ResNet50, Xception, and DenseNet201. The y-axis represents the accuracy percentage, while the x-axis lists the models. This bar chart clearly illustrates the performance disparities among these models, highlighting Xception as the best-performing model with an accuracy close to 99%.

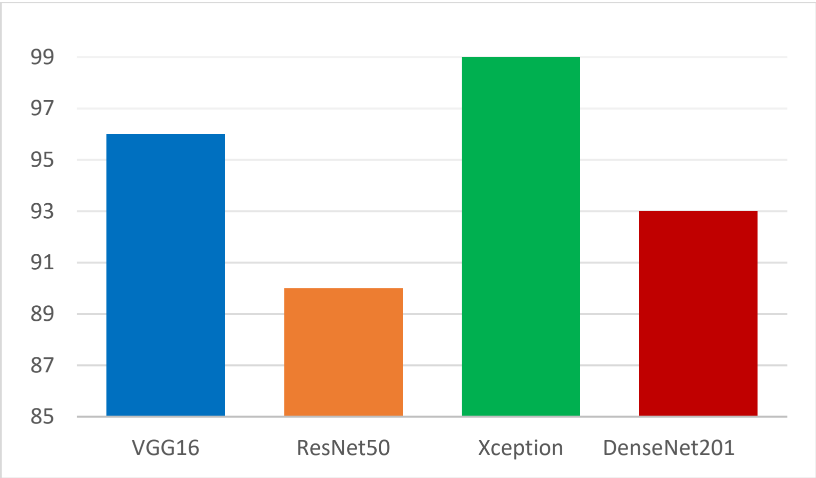

Figure 5.10: Accuracy Comparison Chart

5.5 Summary

Here, I discuss accuracy of our model and compare it with other state-of-the-art transfer learning models. This study highlights how my approach achieves competitive performance metrics, demonstrating its effectiveness in enhancing breast cancer detection compared to existing methodologies.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

This research paper has the potential to profoundly impact lives by revolutionizing the early detection of breast cancer through advanced deep learning techniques. By employing state-of-the-art transfer learning models like Xception and optimizing them with rigorous preprocessing and hyperparameter tuning, the study aims to significantly enhance the accuracy and efficiency of breast cancer diagnosis. This improved diagnostic capability could lead to earlier detection of tumors, enabling timely intervention and treatment that can drastically improve patient outcomes and reduce mortality rates. Moreover, by leveraging artificial intelligence to overcome the barriers of limited medical expertise and costly testing, the research seeks to make early breast cancer detection more accessible and cost-effective on a global scale. Ultimately, the impact of this research lies in potentially saving lives, improving quality of life for patients, and advancing the field of medical imaging and AI-driven healthcare solutions.

6.2 Impact on Society and Environment

Impact on Society

The impact of addressing the challenges associated with breast cancer detection on society is multifaceted and far-reaching. Improved early detection rates resulting from advancements in technology and healthcare practices can lead to significant reductions in mortality rates and disease burden. By facilitating earlier diagnoses, individuals are afforded greater opportunities for timely treatment interventions, resulting in improved prognoses and enhanced quality of life. Moreover, the alleviation of barriers to access, such as limited healthcare resources and expertise, ensures that underserved communities receive equitable care and support in managing their health. Beyond individual health outcomes, the societal impact extends to economic benefits, as the prevention of advanced-stage breast cancer reduces healthcare costs associated with intensive treatments and long-term care. Additionally, heightened awareness and proactive screening efforts foster a culture of health promotion and empowerment, empowering individuals to take proactive steps towards their well-being. Ultimately, the collective impact of improved breast cancer detection transcends individual lives, contributing to healthier communities and a more resilient society.

Impact on the environment

While the impact of breast cancer detection on the environment may not be as direct as its impact on society or individual health, there are still several indirect ways in which advancements in detection methods can influence environmental sustainability.

- **Reduced Healthcare Waste:** Early detection methods, especially those that are less invasive and more accurate, can help minimize unnecessary medical procedures and reduce the generation of healthcare waste. This includes fewer biopsies and imaging tests that may be required when cancer is detected at later stages.
- **Efficient Resource Utilization:** Improved detection techniques may lead to more targeted and efficient use of healthcare resources, including medical equipment, consumables, and energy. By reducing the need for extensive diagnostic procedures, such as repeated imaging scans or exploratory surgeries, the overall environmental footprint of healthcare facilities can be reduced.
- **Decreased Use of Hazardous Substances:** Certain diagnostic tests and treatments for breast cancer may involve the use of hazardous chemicals or materials. By detecting cancer earlier and potentially avoiding the need for more aggressive treatments, there may be a decrease in the use and disposal of these substances, resulting in a positive environmental impact.
- **Promotion of Preventive Healthcare:** Early detection programs often emphasize lifestyle modifications and preventive measures, which can have broader implications for environmental sustainability. For example, promoting healthy diets and regular physical activity not only reduces the risk of developing breast cancer but also contributes to overall well-being and reduces the environmental impact associated with healthcare interventions for chronic diseases.
- **Research and Innovation:** Investments in research and innovation aimed at improving breast cancer detection can spur advancements in technology and medical practices that have wider applications beyond cancer care. These innovations may lead to the development of more eco-friendly medical devices,

imaging technologies, and treatment modalities that are less resource-intensive and more sustainable in the long term.

Overall, while the direct impact of breast cancer detection on the environment may be indirect, the broader implications of early detection for healthcare efficiency, resource utilization, and preventive healthcare can contribute to a more sustainable healthcare system and promote environmental stewardship.

6.3 Ethical Aspects

The ethical aspects surrounding breast cancer detection are multifaceted and require careful consideration to ensure that patient autonomy, privacy, and well-being are upheld throughout the process.

- **Informed Consent:** Patients undergoing breast cancer screening must be adequately informed about the benefits, risks, and limitations of the screening procedures. This includes providing clear explanations of potential false positives, false negatives, and the implications of test results on further diagnostic procedures and treatment decisions.
- **Privacy and Confidentiality:** The collection, storage, and sharing of sensitive medical data, including imaging scans and diagnostic reports, must adhere to strict privacy and confidentiality protocols. Healthcare providers and researchers have a responsibility to safeguard patient information and ensure that it is only accessed by authorized personnel for legitimate purposes.
- **Equitable Access:** Efforts to improve breast cancer detection should prioritize equitable access to screening programs and diagnostic technologies, particularly for underserved populations and marginalized communities. This requires addressing barriers such as financial constraints, geographical limitations, and cultural factors that may hinder access to healthcare services.
- **Minimizing Harm:** Screening procedures and diagnostic tests should be designed to minimize physical and psychological harm to patients. This includes ensuring that procedures are performed by trained healthcare professionals in a supportive and empathetic manner, and that appropriate support services are available to address the emotional and psychological needs of patients throughout the screening and diagnostic process.

- **Avoidance of Stigmatization:** Breast cancer screening and detection efforts should be conducted in a manner that avoids stigmatizing individuals based on their health status or risk factors. Healthcare providers and public health authorities have a responsibility to promote a non-judgmental and inclusive approach to breast cancer awareness and prevention, and to combat misconceptions and stereotypes that may contribute to stigma.
- **Research Ethics:** Ethical considerations also extend to research endeavors aimed at improving breast cancer detection methods. Researchers must adhere to established ethical guidelines for the conduct of clinical trials and studies involving human participants, including obtaining informed consent, minimizing risks, and ensuring the integrity and transparency of research findings.

Overall, navigating the ethical complexities of breast cancer detection requires a holistic approach that prioritizes patient autonomy, privacy, and well-being, while also addressing broader issues of equity, accessibility, and social justice in healthcare delivery.

6.4 Sustainability Plan

A sustainability plan for breast cancer detection initiatives encompasses strategies aimed at ensuring the long-term effectiveness, accessibility, and impact of screening programs and diagnostic technologies. Here's a comprehensive plan:

- **Resource Optimization:** Implement strategies to optimize the use of healthcare resources, including medical equipment, personnel, and facilities. This involves maximizing the efficiency of screening programs through streamlined processes, scheduling optimization, and resource-sharing arrangements among healthcare providers.
- **Capacity Building:** Invest in training and capacity-building initiatives to expand the pool of skilled healthcare professionals capable of conducting breast cancer screenings, interpreting diagnostic tests, and providing follow-up care. This includes training programs for radiologists, oncologists, nurses, and other healthcare workers involved in breast cancer detection and treatment.

- **Technology Integration:** Embrace advancements in technology, such as telemedicine and digital health platforms, to enhance the accessibility and reach of breast cancer screening programs, particularly in rural and underserved areas. Explore opportunities for mobile health units, community health centers, and outreach programs to provide convenient and cost-effective screening services to vulnerable populations.
- **Community Engagement:** Foster partnerships with community organizations, advocacy groups, and patient support networks to raise awareness about breast cancer detection, promote early screening, and reduce stigma associated with the disease. Empower community members to become advocates for their own health by providing education, resources, and support services tailored to their needs.
- **Research and Innovation:** Support ongoing research and innovation in breast cancer detection technologies, including the development of novel screening methods, diagnostic tools, and predictive models. Foster collaboration between academia, industry, and healthcare providers to accelerate the translation of scientific discoveries into clinical practice and improve patient outcomes.
- **Policy Advocacy:** Advocate for policies and regulations that support breast cancer detection efforts, including funding for screening programs, reimbursement policies for diagnostic tests, and mandates for insurance coverage of preventive services. Collaborate with policymakers, public health agencies, and advocacy groups to prioritize breast cancer prevention and early detection as key components of healthcare policy agendas.
- **Evaluation and Quality Assurance:** Establish mechanisms for ongoing monitoring, evaluation, and quality assurance to ensure the effectiveness and safety of breast cancer detection programs. Implement regular audits, performance assessments, and feedback mechanisms to identify areas for improvement and address any issues related to program implementation, service delivery, or patient outcomes.

By implementing a comprehensive sustainability plan that addresses these key areas, breast cancer detection initiatives can enhance their long-term impact and contribute to the reduction of breast cancer mortality rates on a global scale.

6.5 Summary

This research paper aims to revolutionize early breast cancer detection using advanced deep learning models, enhancing diagnosis accuracy and accessibility, which can lead to timely treatment and reduced mortality rates. The societal impact includes reduced mortality, economic benefits, and equitable healthcare access. Environmentally, early detection minimizes medical waste, optimizes resource use, and promotes preventive healthcare. Ethical considerations focus on informed consent, privacy, equitable access, and minimizing harm. The sustainability plan emphasizes resource optimization, capacity building, technology integration, community engagement, research, policy advocacy, and quality assurance to ensure long-term effectiveness and impact.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusion

This study proposed a reliable computer aided design system that can identify and classify ultrasound images into different classes with higher accuracy. Four deep learning models were compared with each other after image preprocessing techniques. Radiologists and clinical experts can utilize the CAD system that depends on image preprocessing and DL algorithms as a potential and powerful screening tool to avoid or reduce needless cases and shorten the time it takes to early detection and diagnose breast cancer.

7.2 Further Suggested Works

1. Multi-Modal Fusion: Explore the integration of multiple imaging modalities, such as mammography, ultrasound, and MRI, to enhance the performance of breast cancer detection models. Fusion techniques could leverage the complementary information provided by each modality to improve overall accuracy and diagnostic confidence.

2. Transfer Learning Extensions: Investigate advanced transfer learning techniques, such as domain adaptation and fine-tuning strategies, to further improve the performance of deep learning models in breast cancer detection tasks. Fine-tuning pretrained models on domain-specific datasets could help tailor the models to the nuances of medical imaging data and improve their generalizability.

3. Clinical Decision Support Systems: Develop clinical decision support systems (CDSS) that integrate deep learning models for breast cancer detection into existing healthcare workflows. These systems could assist radiologists and clinicians in interpreting imaging data, providing real-time feedback and recommendations to support clinical decision-making.

4. Robustness and Adversarial Defense: Enhance the robustness and resilience of deep learning models against adversarial attacks and domain shifts that may occur in real-world clinical settings. Techniques such as adversarial training and domain adaptation could be explored to mitigate the impact of these challenges and improve the reliability of the models.

5. Global Accessibility: Promote the accessibility and affordability of deep learning-based breast cancer detection technologies, particularly in low-resource settings and underserved communities. This could involve developing lightweight models optimized for deployment on low-cost hardware platforms and designing user-friendly interfaces tailored to the needs of diverse healthcare settings.

7.3 Limitations

1. Limited Dataset Size: One of the limitations of this study could be the size and diversity of the original dataset used for training and evaluation. A larger and more diverse dataset may provide a better representation of real-world scenarios and improve the generalizability of the results.

2. Model Interpretability: While deep learning models like Xception achieve high accuracy in breast cancer detection, their black-box nature can make it challenging to interpret the underlying decision-making process. Future research could focus on developing methods to enhance model interpretability and provide insights into the features and patterns driving the predictions.

3. Clinical Validation: Although the deep learning models demonstrated promising results in this study, their clinical utility and effectiveness in real-world healthcare settings need to be validated through rigorous clinical trials and longitudinal studies. This would involve assessing factors such as sensitivity, specificity, and predictive value across different patient populations and healthcare contexts.

4. Computational Resources: Deep learning models, particularly those based on convolutional neural networks like Xception, require significant computational resources for training and inference. Addressing the computational burden associated with these models is essential for their practical deployment in resource-limited environments, where access to high-performance computing infrastructure may be limited.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
COMPREHENSIVE AI SOLUTION FOR BREAST CANCER DETECTION USING DEEP LEARNING APPROACH

Student ID: 201-15-3216

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**

CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References

1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project highlights foundational engineering **(K3)** concepts by using deep learning and data augmentation approaches to image processing. The study exhibits expert knowledge **(K4)** by using transfer learning techniques such as VGG16 and ResNet50, as well as Xception and DenseNet201, to improve the accuracy of breast cancer detection in ultrasound pictures, which is critical for computer-aided diagnosis.	**Page no:** [4] **Section:** [1.4]
				The research uses engineering practice and design **(K5)** through the figure of the process of experimentation. The project applies the Transfer Learning paradigm to engineering practice and technology **(K6)**.	**Page no:** [14-15] **Section:** [3.4]
				This effort contributes to **K8 (Research Literature)** by combining ideas from previous research to enhance breast cancer diagnosis using deep learning, demonstrating a thorough mastery of current approaches.	**Page no:** [7-9] **Section:** [2.1, 2.2]

2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This study addresses **EP-2** by acknowledging the challenges in breast cancer diagnosis, such as the limits of existing approaches and the difficulty of combining transfer learning with deep learning. It addresses issues in comprehending geographical distributions through comparison analysis, providing insights for the improvement of diagnostic methods.	**Page no:** [9-10] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	In order to improve breast cancer diagnosis among deep learning techniques, this research carefully compares experimental results to address **EP-3**. The results demonstrate that Transfer Learning is the most important answer.	**Page no:** [11-14] **Section:** [3.2, 3.3]
4.	**EP4: Familiarity of Issues**	Yes	CO8	The multidisciplinary nature of this research goes beyond computer science and engineering, influencing medical diagnoses in respiratory disorders such as breast cancer and advancing public health and healthcare practices **(EP-4).**	**Page no:** [14-15] **Section:** [3.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO5	The complete strategy of this project offers a holistic solution to complicated obstacles in medical diagnostics, assuring **EP-7**. It does this by combining numerous components across data collecting, statistical analysis, and recommended methodology. This approach tackles high-level problems.	**Page no:** [14-15] **Section:** [3.4]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	In order to assure systematic research and progress the field of pneumonia detection using deep learning and transfer learning, my study makes use of a variety of resources, including GPUs, annotated datasets, deep learning frameworks, and ethical concerns.	**Page no:** [16-18] **Section:** [4.2, 4.2, 4.3]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		By using efficient computational resources and abiding by ethical standards for patient data protection, this initiative improves healthcare and promotes environmental sustainability. It also makes a positive impact on society.	**Page no:** [26-30] **Section:** [6.1, 6.2, 6.3, 6.4]
5.	**EA-5: Familiarity**	Yes		By investigating a unique strategy in breast cancer diagnosis using transfer learning and deep learning-which is illustrated by early concepts and a thorough comparison analysis—this study builds on previous research and provides fresh perspectives in the area.	**Page no:** [11-14] **Section:** [3.1, 3.2]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	Through the integration of efficient project management and financial control, this project tackles **CO4** by guaranteeing careful planning, resource allocation, and budget estimate for the best possible resource utilization throughout the study lifetime.	**Page no:** [14-15] **Section:** [3.4]
2	CO9	Yes	By putting patient privacy first, getting informed consent, and openly recording the research process, the project demonstrates adherence to ethical principles. It also ensures responsible knowledge dissemination and societal well-being through the moral application of cutting-edge	**Page no:** [26-29] **Section:** [6.2, 6.3]

			healthcare technologies that abide by **CO9**.	
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's thorough data collection, rigorous statistical analysis, careful methodology development, and thorough experimental results and analysis all demonstrate a dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape. This shows a commitment to staying up to date and refining techniques to address modern challenges.	**Page no:** [19-25] **Section:** [5.2, 5.3]

Final Report Checking for Ieshita V2

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