CANCER SHIELD: AI-POWERED BREAST CANCER DETECTION

SITI AZALIA BINTI MEHAT

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

CANCER SHIELD: AI-POWERED BREAST CANCER DETECTION

SITI AZALIA BINTI MEHAT

This report is submittes in partial fulfilment of the requirements for the Bachelor of [Computer Science (Artificial Intelligence)] with Honours.

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

DECLARATION

I hereby declare that this project report entitled

CANCER SHIELD: AI-POWERED BREAST CANCER DETECTION

is written by me and is my own effort and no part has been plagiarized

without citations.

STUDENT: _______________*Aza*___________________________Date: 26/08/2024

(SITI AZALIA BINTI MEHAT)

I hereby declare that I have read this project report and found

this project report is sufficient in term of the scope and the quality for the award of

Bachelor of [Computer Science (Artificial Intelligence)] with Honours

SUPERVISOR: ____ Date: 30/8/2024

(PROFESSOR MADYA GS.DR. ASMALA BIN AHMAD)

DEDICATION

I would like to take this chance to congratulate whoever contributed directly or indirectly towards making the final year report a success. In particular I would like to dedicate this achievement to my family who have been so supportive since day one of my academic life. Honestly speaking, they have always believed in me hence they were very instrumental in bringing me thus far..

My supervisor Professor Madya Gs. Dr. Asmala bin Ahmad deserves eternal gratitude for showing me the way through other times when I felt lost amidst all academic confusion and pressure during my education program availed by the institution. Through all these years under his tutelage, he has taught me more than subject matter but also how to be successful student in general.

Furthermore, there are other people too whose contribution was significant for example lecturers at Universiti Teknikal Malaysia Melaka who instilled discipline in us while at school by imparting knowledge which is needed most if one is to achieve anything within their field of study or profession even future experts undertaking research before they can graduate as highly skilled professionals due to good information acquired throughout Secondary history teaching practice together with tutorial lessons going forth thereby enabling responding better when asked about subject matter related queries compared with those without idea about it.

In addition, I would like to express my gratitude to all my classmates and friends who encouraged me at every stage of this difficult journey. Their thought-provoking discussions opened my eyes, hard work and support made it possible for me to accomplish this dream.

ACKNOWLEDGEMENTS

First and foremost I would like to extend my thanks to my project supervisor; Professor Madya Gs. Dr. Asmala bin Ahmad for providing really great guidance, knowledge and support during this project. Moreover, their critical insights together with constructive feedback as well as moral encouragement towards the project were central pillars in shaping its outcomes.

My good friends and family members deserve my sincere appreciation for the continual backing which they have accorded me during my educational progress. Therefore, these people believed in me, encouraged me whenever I was down in the dumps and expressed love towards me thereby strengthening and motivating me.

Additionally, I wish to acknowledge the input of my classmates and colleagues whose cooperative spirit, intellectual discussions and constructive criticism have greatly enhanced this project. The collection of these different ideas guided the research by providing more information so as to take it deeper and better.

In conclusion I would also like to thank all those individuals, organizations as well as resources that supported this study from its beginning until now.

ABSTRACT

The breast cancer detection project report highlights the usage of mammogram images for medical diagnosis. This report tries to break the traditional method of tumor detection and classification. This study assesses the three models: VGG16, VGG16 (Fine-Tuning) and ResNet50 that help in tumor identification, and attempts to find out which model is most accurate in terms of detection.

A dataset called CBIS-DDSM comprised of 2,260 mammogram images has been used in this project that has been divided into training, testing and validation sets. The training dataset was used in training the models while accuracy, time taken, loss and precision are among evaluation metrics that were employed to measure their performance. Thus, these factors are important since they will be used for comparison purposes when it comes to breast tumours detection.

In this project, Breast Ultrasound Dataset consisting of 1,578 is utilized and categorized into three benign, malignant and normal classes. The inclusion of a normal class was important because it provides data for people diagnosed with normal breasts in the second phase of this project. With combination of machine learning techniques, this incorporation is crucial because it improves the model performance significantly resulting in improvements such as classification breast cancer segmentation and detection.

The results of this project enhance diagnostic medicine for better detection thereby leading to lesser inputs of diagnosticians who must do diagnoses for all within limited time ranges. For early diagnosis and prompt action, the efficient breast tumour detection model will be known from test results. The ResNet50 fine tuning model has the highest accuracy of 97%. It is followed by VGG16 fine tuning model with an accuracy of 92%. The other models in order of decreasing accuracy are ResNet50 (88%) and VGG16 (84%).

ABSTRAK

Laporan projek pengesanan kanser payudara ini menekankan penggunaan gambar mamogram untuk diagnosis perubatan. Laporan ini berusaha untuk memecahkan kaedah tradisional dalam pengesanan dan pengklasifikasian tumor. Kajian ini menilai tiga model: VGG16, VGG16 (Penalaan Halus), dan ResNet50 yang membantu dalam pengenalan tumor, dan cuba untuk mengetahui model mana yang paling tepat dari segi pengesanan.

Dataset yang digunakan dalam projek ini adalah CBIS-DDSM yang terdiri daripada 2,260 gambar mamogram dan telah dibahagikan kepada set latihan, ujian, dan pengesahan. Dataset latihan digunakan untuk melatih model-model tersebut sementara ketepatan, masa yang diambil, kerugian, dan ketepatan adalah antara metrik penilaian yang digunakan untuk mengukur prestasi mereka. Oleh itu, faktor-faktor ini adalah penting kerana ia akan digunakan untuk tujuan perbandingan dalam pengesanan tumor payudara.

Dalam projek ini, Dataset Ultrasound Payudara yang terdiri daripada 1,578 gambar digunakan dan dikategorikan kepada tiga kelas: benign, malignan, dan normal. Penggunaan kelas normal adalah penting kerana ia menyediakan data bagi individu yang didiagnosis dengan payudara normal pada fasa kedua projek ini. Dengan kombinasi teknik pembelajaran mesin, penggabungan ini adalah penting kerana ia meningkatkan prestasi model dengan ketara, menghasilkan peningkatan dalam klasifikasi, segmentasi, dan pengesanan kanser payudara.

Keputusan projek ini meningkatkan perubatan diagnostik untuk pengesanan yang lebih baik, seterusnya mengurangkan keperluan input dari diagnostik yang perlu membuat diagnosis dalam masa terhad. Untuk diagnosis awal dan tindakan cepat, model pengesanan tumor payudara yang cekap akan dikenal pasti berdasarkan hasil ujian. Model penalaan halus ResNet50 mempunyai ketepatan tertinggi sebanyak 97%. Ia diikuti oleh model penalaan halus VGG16 dengan ketepatan sebanyak 92%. Model-model lain dalam susunan ketepatan menurun adalah: ResNet50 (88%) dan VGG16 (84%).

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I: INTRODUCTION

1.1 Introduction

AI-powered systems for breast cancer detection are focused on in this paper, as it is a significant area of research meant to improve the accuracy and efficiency of mammogram analysis. Previous works such as those by the Malaysian Health Technology Assessment Section (MaHTAS), paved way for use of AI in analyzing mammogram pictures looking for cancerous disorders.

Ultimately, it aims at creating reliable technologies that can quickly and accurately identify breast cancer. As at now, existing diagnostic approaches are often time consuming and expensive therefore requiring automated kinds of systems that can perform speedy analysis with precision. Researchers are using AI models like VGG16, VGG16 with fine-tuning, ResNet50 and ResNet50 with fine tuning trained on datasets like CBIS-DDSM to achieve high sensitivity and specificity levels in detecting early stage breast cancers.

Some of the main problems are checking AI algorithms for clinical purposes and making sure they fit into the already existing health care systems. To create universal directions on how AI should be started to use in medicine, it is essential to co-operate with computer developers, doctor and representatives of the state authorities. In summary, despite tremendous strides in AI-enabled breast cancer diagnosis, persistent investigations seek to better the algorithms, make them easier to interpret and have them work with a more diverse range of data. The primary aim is to provide medical practitioners with sophisticated devices that will enhance their ability to diagnose correctly and thus lead to improvement in patient prognosis as far as the diagnosis and treatment of breast cancer is concerned not only in Malaysia but for all women around the world.

1.2 Problem Statement (PS)

The problem statement for this project is In Malaysia, this project's problem statement is that the constrained efficiency and accessibility of current breast cancer system result in prolonged time for breast cancer detection. Additionally, false positives and false negatives are a significant challenge that will lead to unnecessary medical treatment. Several issues related to access and acceptance by health professionals and patients in Malaysia include precision and awareness about advantages of artificial intelligence application to this field. Besides, today's methods of extracting features from mammogram pictures may not sufficiently detect minor but vital elements which point towards early stage breast cancer. Current methods might be inadequate for variation handling such as image quality, tissue density and noise - which are decisive factors for accurate diagnosis. The following problem statement could be that traditional techniques for detecting breast cancer depend on manual interpretation on a large scale which may result into delay or uncertainty in diagnosis. Thus, there is dire need for an automated AI-powered system that can effectively detect and classify mammogram images with high precision and sensitivity; hence facilitating early detection followed by timely intervention procedures. Finally, performance assessment of AI systems is another challenge faced in this area.

Table 1.1: Summary of Problem Statement

PS	Problem Statement
PS 1	Techniques currently employed for extraction of features from mammography images may fail to adequately account for minute yet important details that signify early stage breast cancer. The existing techniques may also not be capable of adapting to image-quality variations, noise and tissue density, which are fundamental aspects that affect precision in diagnosis.
PS 2	Conventional breast cancer detection methods rely heavily on manual interpretation, which could create possible delays and inconsistencies during diagnosis process. Hence, there is urgent need for an automated AI-based system that can effectively pinpoint and classify anomalies in mammogram images with good accuracy and sensitivity so as to allow early detection and intervention when necessary.
PS 3	Critical validation against a range of data sets and comparison with recognized diagnostic standards is needed to evaluate how well AI-supported detection systems for breast cancer perform. This involves contemplating on the correct measures of evaluation, making sure the technique works for people from various backgrounds or using all types of imaging and then ensuring that it is clinically useful as well as reliable in hospitals and clinics.

1.3 Project Objective (PO)

Table 1.2: Summary of Project Objectives

PO	Project Objective
PO 1	To extract relevant features from mammogram images for more accurate analysis.
PO 2	To develop an enhanced breast cancer detection technique based on Artificial Intelligence to improving early diagnosis.
PO 3	To evaluate the performance of the developed technique using metrics such as accuracy to ensure its reliability and effectiveness.

1.4 Project Scope

There are five project scope in this project. The scopes are:

1. Medical Imaging Data from Kaggle (Mammograms and Ultrasound Images)

   Reason: Breast cancer detection is dependent on mammograms which provide vital images for analysis purposes. This will ensure that the project deals with the primary source of diagnostic images. Another reason for using ultrasound images in the second phase of this project is because it has three different classes whereas mammograms only have two. Using two different sources of data can lead to better classification, detection and segmentation results in breast cancer.

2. Review and Analysis of Existing Literature:

   Reason: Researching recent literature, the research may build on the existing knowledge and identify areas looking for new ideas or gaps in the literature. It provides a context for the more recent developments in breast cancer detection including those in the processes of being developed.

3. Exploration of Advanced Medical Imaging Technologies:

   Reason: Studying new imaging technology ensures that the project remains relevant as far as development within the industry is concerned. This scope enables exploration of other possible approaches that can enhance accuracy of detection further than the standard mammography.

4. Exploration of Algorithms (Artificial Intelligence):

   Reason: To understand and process medical data and improve the results of treatment strategies, machine learning algorithms are useful. We can, therefore, improve the systems by employing computational methods in detecting breast cancer by the study of these approaches.

5. Software (Python, Visual Studio Code Google Colab and Draw.io):

   Reason: Python is a popular programming language that is easy to learn and understand. It provides a large selection of libraries and frameworks made especially for activities related to signal processing, machine learning, and data analysis—tasks that are frequently essential to detection techniques

1.5 Project Contribution (PC)

Table 1.3: Summary of Project Contribution

PS	PO	PC
PS 1) Techniques currently employed for extraction of features from mammography images may fail to adequately account for minute yet important details that signify early stage breast cancer. The existing techniques may also not be capable of adapting to image-quality variations, noise and tissue density, which are fundamental aspects that affect precision in diagnosis.	PO 1) To extract relevant features from mammogram images for more accurate analysis.	PC 1) The project deals with the improvement of feature extraction from the mammogram, the problem which the methods used at the moment face while not being able to show the dyer visible and at the same time critical situations leading to early stages of breast cancer. Through feature extraction enhancement means, the project makes it possible to perform a more precise and reliable study of mammography images.
PS 2) Conventional breast cancer detection methods rely heavily on manual interpretation, which could create possible delays and inconsistencies during diagnosis process. Hence, there is urgent need for an automated AI-based system that can effectively pinpoint and classify anomalies in mammogram images with good accuracy and sensitivity so as to allow early detection and intervention when necessary.	PO 2) To develop an enhanced breast cancer detection technique based on Artificial Intelligence to improving early diagnosis	PC 2) The project is aimed at developing an AI based advanced breast cancer detection technique. This technique is supposed to automate and improve the efficiency of detecting abnormalities in mammogram images allowing early diagnosis and intervention. A contribution here would be providing a robust AI driven system that can detect breast cancers with high accuracy and sensitivity levels.

PS 3) Critical validation against a range of data sets and comparison with recognized diagnostic standards is needed to evaluate how well AI-supported detection systems for breast cancer perform. This involves contemplating on the correct measures of evaluation, making sure the technique works for people from various backgrounds or using all types of imaging and then ensuring that it is clinically useful as well as reliable in hospitals and clinics. .	PO 3) To evaluate the performance of the developed technique using metrics such as accuracy to ensure its reliability and effectiveness	PC 3) The AI-based method had been subjected by project to an in-depth evaluation based on several established metrics including accuracy. This performed function is addressing the crucial question of how any given technique for AI can be evaluated properly in terms of efficiency and performance in real life medical setups. Such approaches may involve validation with several datasets as well as performance comparison with other methods that are currently used for diagnosis in practice; thus, its clinical relevance is proved.

1.6 Report Organization

Chapter 1: Introduction

This chapter discusses the project background, problem statement, objectives, scope, project contribution and about the detection of brain tumor.

Chapter 2: Literature Review

This chapter discusses a summary of the previous chapter that are relevant to the project. This chapter also discuss which models are appropriate for the project.

Chapter 3: Project Methodology

This chapter discusses the process of methodology for entire project.

Chapter 4: Design

This chapter discusses the design to solve the problem as well as the requirements of the project.

Chapter 5: Implementation

This chapter discusses the environment setup, including which software and the libraries will be used for this project.

Chapter 6: Testing

This chapter discusses the testing system and the results. The result will be compared and the best model will be chosen.

Chapter 7: Project Conclusion

This chapter summarizes the entire project and discusses the project limitations as well as future work.

1.7 Summary

In this chapter, In this section, I explain the goals, results I expect and why I think it’s important to improve breast cancer detection. Our main focus is to use sophisticated technology for a more accurate and quicker breast cancer diagnosis so that we can save lives as well as money spent on advanced-stage treatment. Therefore, we will evaluate our methods against certain standards in order to ascertain if they really work in medical practice or not. The principal goal behind our project is to improve the quality of diagnosis that is given to patients suffering from breast cancer. Subsequently, we would like to come up with a comprehensive framework that doctors can depend on for early identification and management as an iterative process built around feedback loops and benchmarking. This will simply involve looking through all previous work which exists in relation to breast cancer detection approaches through both classical and contemporary methods. Therefore, it gives us insight into how diagnostic procedures have evolved over time and what is happening at present with regard to AI based methods utilized for medical imaging. Subsequently, we will detail the methodology employed in our project including data collection, preprocessing techniques, model selection and evaluation criteria. On this basis combining literature information with the methodology of this project, we will attempt to create a good foundation for constructing and validating our breast cancer detection system based on artificial intelligence (AI).

CHAPTER II: LITERATURE REVIEW AND PROJECT METHODOLOGY

2.1 Introduction

Breast cancer, a common disease among women, is diagnosed in a medical field. When breast tissues multiply without control and an abnormal group of cells grows, this is what happens. Based on statistics provided by the World Health Organization (WHO), 2022 saw 2.3 million women diagnosed with breast cancer with 670,000 deaths worldwide. Malaysia had 8418 new cases of breast cancer and 3505 deaths due to this disease in 2022 alone. Among types of cancer occurring in women; breast cancers are the most prevalent. A woman from Malaysia stands at one in every 19 chances of developing breast cancer. As reported in the Malaysian National Cancer Report published on 2019, almost 47.9 percent cases were detected at late stage. Early detection leads to higher chances of cure for people suffering from breast carcinoma. It is possible to avoid advanced stages of the disease through early breast examinations or screening through mammography.

In this chapter, I will summarize all the algorithm, data and technique implemented that have been source from various online publications. The online publications will be include such as latest journals and research paper between 2018 until 2024. I read and compare each of the article to study and analyse their algorithm and techniques. To achieve the optimal result, I also conduct review of the references.

After documenting all the relevant research paper, I can conclude that there are variety of techniques were used to categorise if the breast have benign, malign cancer or it is normal. Different models have been applied because they are better suited to different situation. All the technique have gone through careful analysis to ensure better precision and effectiveness of the model.

2.2 Related work

The research covers the detection of breast cancer that has been performed by number of researchers using various methods. Detailed revies are as follows.

2.2.1 Early detection of breast cancer using machine learning techniques

Tahmooresi et al. (2018) developed a machine learning model for the early diagnosis for breast cancer by using hybrid model that combine several Machine Learning algorithms such as Support Vectore Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbour (KNN) and Decision tree. By using this model, earlu detection of cancer boosts the increase of survival chance to 98%. ANN is used to search for patterns among patients' healthcare and personal records to identify high-risk lesions. SVM in used to separate data until a hyperplane with high minimum distance is found. KNN is used to diagnose and classify cancer while Decision Tree (DT) is used for present classification or regression as a tree and the advantage of decision tree, it is not sensitive to noise. Random Forest Algorithm (RF) is used to assessing proximities among data points while AdaBoost Classifier is use to convert weak learners to strong by combining all weak leaner to a single strong rule but it sensitive to noise and quality of features. The last algorithm is Naïve Bayes (NB) classifier which use for distribute numeric attributes within each class. According to their findings, GMM was better than other algorithms which is 84%. For Chowdhary and Acharjya (2018) they are more focus on mammogram since it is cheaper and more efficient in detection. Their method shows 94% accuracy for detecting malignant breast lesions.

Table 2.1: Evaluation metrics Tahmooresi et al. (2018)

<table>
<tr><th>R</th><th>Methodology</th><th>Features</th><th>Data Base</th><th>Performance</th><th>Dataset</th></tr>
<tr><td>[17]</td><td>SVM</td><td>Variance, Range, Compactness</td><td>Mammogram</td><td>
<table>
<tr><th></th><th>MCC</th><th>Sensitivity</th><th>Specificity</th><th>Accuracy</th></tr>
<tr><td>Variance</td><td>83.2%,</td><td>95%,</td><td>88%</td><td>91.5%</td></tr>
<tr><td>Range</td><td>82.1%</td><td>94%</td><td>88%</td><td>90.5%</td></tr>
<tr><td>Compactness</td><td>70%</td><td>86%</td><td>84%</td><td>85%</td></tr>
</table>
</td><td>Digital Database for Screening Mammography (DDSM)</td></tr>
<tr><td>[18]</td><td>GMM
KNN</td><td>Tissue</td><td>Microwave Tomography Image</td><td>
<table>
<tr><th></th><th>MCC%</th><th>Sensitivity</th><th>Specificity</th><th>Precision</th><th>Accuracy</th></tr>
<tr><td>KNN</td><td>67%</td><td>87%,</td><td>84%</td><td>70%</td><td>80-90%</td></tr>
<tr><td>GMM</td><td>48%</td><td>67%</td><td>86%</td><td>70.8%</td><td>70-80%</td></tr>
</table>
</td><td>ETRI</td></tr>
<tr><td>[19]</td><td>SVM, KNN, RSDA</td><td>Fuzzy Histogram Hyperonization, Fuzzy C-mean, and Gray level dependence model</td><td>Mammogram</td><td>
<table>
<tr><th></th><th>Training set</th><th>Accuracy %</th></tr>
<tr><td>Normal</td><td>70</td><td>100</td></tr>
<tr><td>Benign</td><td>60</td><td>96.67</td></tr>
<tr><td>Malignant</td><td>50</td><td>94</td></tr>
</table>
</td><td>Mammographic Image Analysis Society (MIAS)</td></tr>
<tr><td>[20]</td><td>SVM, GMM</td><td>Contrast, Homogeneity, Mean, Correlation, Energy, Maximum</td><td>Mammography</td><td>
<table>
<tr><th></th><th>MCC</th><th>Sensitivity</th><th>Specificity</th></tr>
<tr><td>SVM</td><td>78.78%</td><td>82%</td><td>96%</td></tr>
<tr><td>GMM</td><td>72.06%</td><td>84%</td><td>86%</td></tr>
</table>
</td><td>DDSM
University of South Florida</td></tr>
<tr><td>[21]</td><td>LRC</td><td>Mitoses, Marginal-Adhesion, Normal Nucleoli, Clump Thickness, Bland Chromatin, Uniformity of cell shape, Single Epithelial cell size, Uniformity of cell size, Bare Nuclei</td><td>Standard Data</td><td>
<table>
<tr><th></th><th>Accuracy percentage</th></tr>
<tr><td>LRC</td><td>99.25</td></tr>
<tr><td>BFI</td><td>95.46</td></tr>
<tr><td>ID3</td><td>92.99</td></tr>
<tr><td>J48</td><td>98.14</td></tr>
<tr><td>SVM</td><td>96.40</td></tr>
</table>
</td><td>UCI</td></tr>
<tr><td>[22]</td><td>SVM, ANN, NB, Adaboost tree, PCA</td><td>WBC: Mitoses, Marginal-Adhesion, Normal Nucleoli, Clump Thickness, Bland Chromatin, Uniformity of cell shape, Single Epithelial cell size, Uniformity of cell size, Bare Nuclei
WDBC, Radius, Texture, Perimeter, Area, Smoothness, Compactness, Concavity, Concave Points Symmetry, Fractal Dimension</td><td>Standard Data</td><td>
<table>
<tr><th></th><th colspan="2">Accuracy percentage</th></tr>
<tr><th></th><th>WBC</th><th>WDBC</th></tr>
<tr><td>SVM</td><td>97.10</td><td>97.99</td></tr>
<tr><td>PCs-SVM</td><td>97.47</td><td>98.12</td></tr>
<tr><td>PCi-SVM</td><td>96.73</td><td>97.90</td></tr>
<tr><td>ANN</td><td>89.88</td><td>99.60</td></tr>
<tr><td>PCs-ANN</td><td>95.52</td><td>99.61</td></tr>
<tr><td>PCi-ANN</td><td>94.33</td><td>99.63</td></tr>
<tr><td>Naïve</td><td>96.21</td><td>93.32</td></tr>
<tr><td>PCs-Naïve</td><td>96.50</td><td>91.79</td></tr>
<tr><td>PCi-Naïve</td><td>96.16</td><td>91.72</td></tr>
<tr><td>Adaboost</td><td>95.84</td><td>97.19</td></tr>
<tr><td>PCs-Adaboost</td><td>96.24</td><td>96.73</td></tr>
<tr><td>PCi-AdaBoost</td><td>96.32</td><td>96.83</td></tr>
</table>
</td><td>Wisconsin Breast Cancer Database Original (WBC)

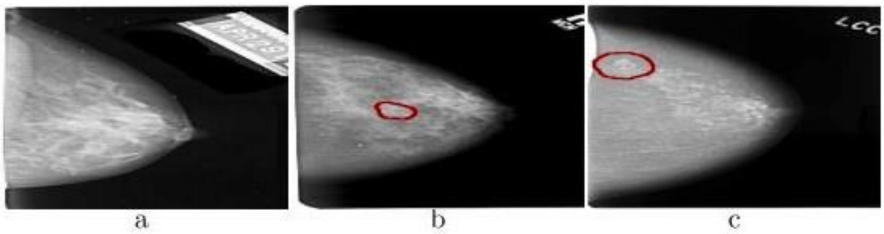
Wisconsin Diagnostic Breast Cancer Database (WDBC)</td></tr>
<tr><td>[23]</td><td>ANN,
SVM</td><td>Mitoses, Marginal-Adhesion, Normal Nucleoli, Clump Thickness, Bland Chromatin, Uniformity of cell shape and size, Single Epithelial cell size, Bare Nuclei</td><td>Standard Data</td><td>
<table>
<tr><th></th><th>Accuracy</th><th>Sensitivity</th><th>Specificity</th><th>AUC</th></tr>
<tr><td>SVM</td><td>99.51%</td><td>99.25%</td><td>100%</td><td>99.63%</td></tr>
<tr><td>ANN</td><td>98.54%</td><td>99.25%</td><td>97.22%</td><td>98.24%</td></tr>
</table>
</td><td>Wisconsin Breast Cancer Database (WBCD)</td></tr>
<tr><td>[24]</td><td>St-SVM,
PSVM,
LSVM,
NSVM,
LPSVM,
SSVM</td><td>Mitoses, Marginal-Adhesion, Normal Nucleoli, Clump Thickness, Bland Chromatin, Uniformity of cell shape and size, Single Epithelial cell size, Bare Nuclei</td><td>Mammography</td><td>
<table>
<tr><th></th><th>Accuracy</th><th>Sensitivity</th><th>Specificity</th><th>ROC</th></tr>
<tr><td>LPSVM</td><td>97.1429</td><td>98.2456</td><td>95.082</td><td>99.38</td></tr>
<tr><td>LSVM</td><td>95.4286</td><td>96.5217</td><td>93.3333</td><td>97.18</td></tr>
<tr><td>SSVM</td><td>96.5714</td><td>96.5812</td><td>96.5517</td><td>98.35</td></tr>
<tr><td>PSVM</td><td>96</td><td>97.3684</td><td>93.4426</td><td>97.75</td></tr>
<tr><td>NSVM</td><td>96.5714</td><td>96.5812</td><td>96.5517</td><td>98.35</td></tr>
<tr><td>ST-SVM</td><td>94.86</td><td>95.65</td><td>93.33</td><td>96.61</td></tr>
</table>
</td><td>WBCD</td></tr>
<tr><td>[25]</td><td>Weighted Hierarchical Adaptive Voting Ensemble (WHAVE) Disjunctive Normal Form (DNF) rule-based method, DT, NB, SVM</td><td>Mitoses, Marginal-Adhesion, Normal Nucleoli, Clump Thickness, Bland Chromatin, Uniformity of cell shape and size, Single Epithelial cell size, Bare Nuclei</td><td></td><td>
<table>
<tr><th>Method</th><th>Accuracy Percentage</th></tr>
<tr><td>DNF</td><td>65. 72</td></tr>
<tr><td>DT</td><td>94.74</td></tr>
<tr><td>NB</td><td>84.5</td></tr>
<tr><td>SVM</td><td>99.54</td></tr>
<tr><td>Hybrid</td><td>99.54</td></tr>
<tr><td>KNN</td><td>97.14</td></tr>
<tr><td>Quadratic Classifier</td><td>97.14</td></tr>
<tr><td>WHAVE</td><td>99.8</td></tr>
</table>
</td><td>WBCD</td></tr>
<tr><td>[26]</td><td>SVM
RBF kernel</td><td>Phylogenetic trees, Statistical Features, and Local Binary Patterns</td><td>DDSM</td><td>
<table>
<tr><th rowspan="3">Training</th><th rowspan="3">Testing (%)</th><th colspan="2">Model I
TIF %</th><th colspan="2">Model II
(LBP) %</th><th colspan="2">Model III
TIF and LBP %</th></tr>
<tr><th>Accuracy</th><th>Specificity</th><th>Accuracy</th><th>Specificity</th><th>Accuracy</th><th>Specificity</th></tr>
<tr></tr>
<tr><td>80</td><td>20</td><td>64</td><td>58</td><td>54</td><td>51</td><td>66</td><td>60</td></tr>
<tr><td>70</td><td>30</td><td>71</td><td>66</td><td>52</td><td>49</td><td>65</td><td>61</td></tr>
<tr><td>60</td><td>40</td><td>76</td><td>73</td><td>68</td><td>64</td><td>80</td><td>76</td></tr>
<tr><td>50</td><td>50</td><td>70</td><td>76</td><td>64</td><td>60</td><td>72</td><td>67</td></tr>
</table>
</td><td>MIAS</td></tr>
<tr><td>[27]</td><td>KNN</td><td>Mean, Standard Deviation</td><td>Thermogram</td><td>
<table>
<tr><th></th><th colspan="2">Accuracy</th></tr>
<tr><td rowspan="2">KNN</td><td>Normal</td><td>Abnormal</td></tr>
<tr><td>94.44%</td><td>88.88%</td></tr>
</table>
</td><td>Federal Fluminense University Hospital</td></tr>
</table>

R	Methodology	Features	Data Base	Performance	Dataset
[28]	Bayes Net (BN), Multi-Class Classifier, DT, Radial Basis Function, RF	TP Rate, FP Rate, Precision, Recall, F-measure, ROC area	Blood Serum	| RF on TP rate | FP Rate | Precision | Recall | F | ROC | BN: 0.947, 0.035, 0.949, 0.947, 0.945, 0.995 Multi CC: 0.933, 0.043, 0.933, 0.933, 0.93, 0.987 DT: 0.87, 0.084, 0.878, 0.87, 0.868, 0.966 RBF: 0.774, 0.128, 0.722, 0.774, 0.739, 0.908 RF: **0.99**, **0.007**, **0.99**, **0.99**, **0.99**, **1**	Department of Biochemistry and Molecular Biology of Kasr Alainy
[29]	Logistic Regression (LR), DT, KNN, Cubic SVM (CSVM)	Radius, Texture, Perimeter, Area, Smoothness, Compactness, Concavity, Concave Points, Symmetry, Fractal, Dimension	Microscope Digital Image	Accuracy percentage **DT with 30 features**: 92.51 **KNN with 30 features**: 91.56 LR with 3 features: 96.27 LR with 6 features: **97.77** **LR with 30 features**: 95.65 LSVM with 3 features: 97.47 LSVM with 10 features: **97.87** **LSVM with 30 features**: 97.30 CSVM with 11 features: 97.98 SVM and CSVM: **98.56** **CSVM with 30 features**: 98 Stacking the Logistic, LSVM, and CSVM: 98.56	UCI
[30]	NSVC	BI-RADS, Age, Shape, Margin, Density, Severity	Mammography	Accuracy: 99%	UCI
[31]	RF-Recursive Feature Elimination (RF-RFE) method	ROI: Mean, Variance, Skewness, Kurtosis, Energy, Entropy ADC: Contrast, Entropy, ASM, Correlation	Diffusion-Weighted Magnetic Resonance Image (DW (Convert to ADC)-MRI)	| Accuracy | Sensitivity | Specificity | AUC | RF-RFE and RF: **77.05%**, **84.21%**, **65.21%**, **0.76** Histogram: 68.85%, 76.32%, 56.52%, 0.73 GLCM: 65.57%, 71.05%, 56.52%, 0.63 Histogram + GLCM: **77.05%**, **84.21%**, **65.21%**, **0.76**	Zhejiang Cancer Hospital
[32]	Fast Modular Artificial Neural Network (FM-ANN)	WBCD: f4, f8, f12, f14, f24, f27, f28 KDD: f22, f29, f47, f50, f60, f61, f62, f63, f64, f65, f71, f97f80, f98, f108,	X-Ray	| Feedforward % | MLP % | RBF % | MNN % | FM-ANN | WBCD 70:30: 98.45, 91.50, 93.75, 99.22, 99.80 WBCD 50:50: 94.91, 89.5, 90.65, 93.57, 95.71 **WBCD after training Accuracy**: **99.8** KDD 70:30: 94.91, 93.95, 98.45, 99.22, 99.96 KDD 50:50: 93.21, 92.95, 97.98, 98.22, 98.96 **KDD cup 2008 after training Accuracy**: **99.96**	WBCD, KDD Cup 2008
[33]	Optimized ANN	Size, Convexity, Solidity, Eccentricity, Aspect ratio, Circularity, the standard deviation value of the gray levels of images with and without MC in ROIs;	MRI	| High Accuracy | Average Accuracy | Sensitivity | Specificity | Optimized ANN: 100%, 89.77%, 89.08%, 90.46%	Radiologists of the University of Bari Aldo Moro

Based on the table of related work on different types of methodology, features and dataset. They conclude that mammogram images is the most famous type of data because it it quicker for detection than other type of data for detection and they also conclude that SVM is the most popular method because the accuracy already reach 99.8%.

2.2.2 Recent advancements in machine learning and deep learning-based breast cancer detection using mammograms

Sahu (2023) made research on recent advancement in Machine Learning (ML) and Deep Learning (DL) to detect breast cancer by using mammograms. Common factors that can cause breast cancer that can be controlled are obesity, consumption of alcohol and less physical activity while some factors that cannot be controlled are early menstruation, late menopause an genetics. Mammography was chosen because it is one of the best methods to diagnose breast cancer and it only use a low-dose of X-ray imaging so it will reduce the harm of the patient. Mammography will be performed to women that have asymptomatic symptom because we want to detect if they have probability of getting cancer.



CC view of mammogram images : (a) Normal (b) Bening (c) Malignant

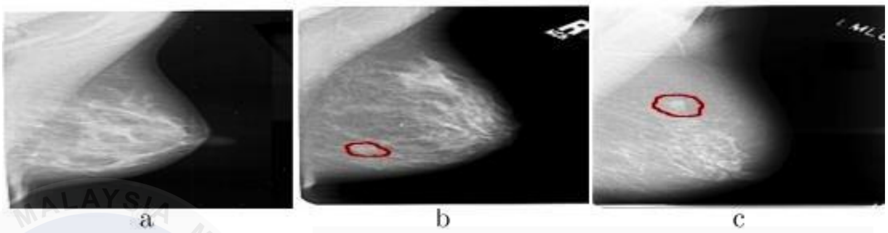


Figure 2.1: MLO view of mammogram images: (a) Normal (b) Bening (c) Malignant (Sahu, 2023)

Valdes-Santiago et al. (2023) employed a decision tree to identify appropriate ROI. Other than that, Deep Learning (DL) were also implemented. The segmentation methods increase the number of training parameters and also the cause. Shen et al. (2023) have design technique for simultaneous segmentation and classification. This research concludes that DL and ML based cancer detection have recent growth through out the years.

2.2.3 A novel breast cancer detection architecture based on a CNN-CBR system for mammogram classification

Bouzar-Benlabiod (2023) present a framework of new breast cancer detection architecture that based on Convolution Neural Network (CNN)- Case Based Reasoning (CBR) system by using mammogram classification. The first module involves data enhancement step that use Adaptive Histogram Equalization (CLAHE) and median filter. CLAHE is the variant of Adaptive Histogram Equalization (AHE) that use to improve image contrast. Akila et al. (2023) showed this method works to highlight masses, avoid dark and overly bright parts in an image. It uses T transformation to redistribute intensities of pixels. For Median Filter, Sukassini et al. (2023) compared multiple filter but median filter is the best to remove noise. It reduces noise by replacing every outlier pixel.

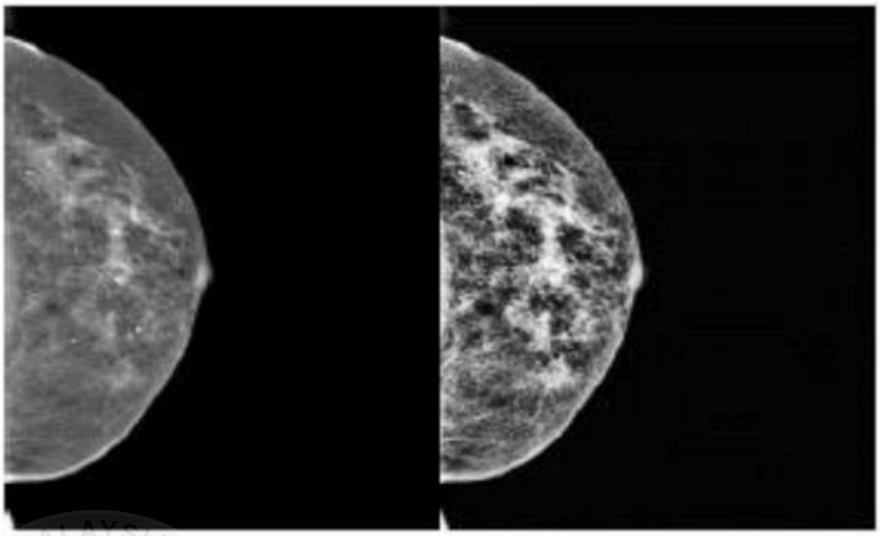


Figure 2.2: Left: Raw mammogram. Right: Mammogram after applying CLAHE and Median Filter (Bouzar Benlabiod, 2023)

For feature selection, this research using Wrapper Method. This method have best performance but it is time consuming. This method will find the combination that generate the best model performance. They also tested the feature combination on KNN technique with K=7 and ran the Wrapper algorithm. This set of attributes provide the best model precision with rate 84.25%. To conclude, CBR utilizes similarity algorithms to retrieve the most suitable solution for a given problem for its case based. CBR was chosen because it can be readily update by the experts and the entire process is easy to comprehend.

2.2.4 Enhanced mammogram classification with convolutional neural network: An improved algorithm for automated breast cancer detection

Basha et al. (2023) made research on enhance mammogram classification using Convolution Neural Network (CNN). Based on this research, there were previous study that combine Deep Learning (DL) with Support Vector Machine (SVM) as an automated method to detect breast cancer in mammogram images. Another study uses image processing and similarity index techniques form Convolutional Neural Network (CNN) to identify masses and density of the breast tissue based in mammogram picture.

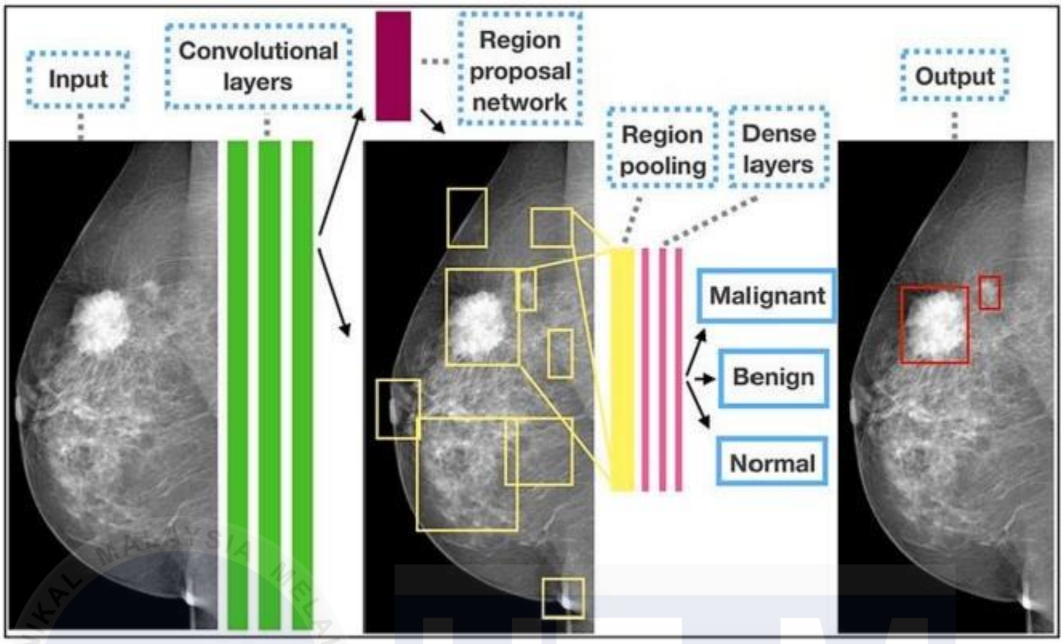


Figure 2.3: CNN Model based on tumour diagnosis (Basha et al. 2023)

For techniques, this research uses Non Local Means (NLM) and Adaptive Histogram Equalization (AHE) approach for image processing. They use NL to remove noise and then it uses contrast-limited (AHE) to improve brightness so that it will be easier to spot, segment and classify tumour. NLM is also use to leverages the redundancy in the given breast image to remove noise. It compares grey levels at single point and geometrical patterns in adjacent pixels. AHE only applies to a tiny portion of image. The only usage of AHE is to remove induced borders. This research also uses KNN classification procedure which it will analyse each unidentified pattern, calculate Euclidean distance and it will assess each class Ci of level K's confidence.

2.2.5 Artificial Intelligence for breast cancer detection: Technology, challenges, and prospects

Diaz (2024) in their research focus on technology, challenges and prospects that are faces in breast cancer screening. This paper focus on Deep Learning techniques because it enhances the breast detection performance of radiologist. The algorithm itself come in many forms depending on the architecture such as Deep Neural Network (DNN), recurrent Neural Network (RNN), deep belief networks (DBN) and convolutional Neural Network (CNN). The use of AI algorithms is to extract patterns and features that will be eventually used to provide outcomes. Based on this research, they can conclude that Deep Learning based AI systems have shown significant improvements in breast cancer detection because it can enhance screening outcomes, reduce false negatives and positive and it also can detect subtle abnormalities that missed by human observers.

2.2.6 Breast cancer detection and classification in mammogram using a three-stage deep learning framework based on Probabilistic Anchor Assignment (PAA) algorithm

Jiang (2022) in their research they focused on the framework by using PAA algorithm. Based on Kim et al. (2023) PAA differing from the anchor-based detector like faster R-CNN and YOLO. It separated set of anchors into positive and negative samples for ground-truth. PAA is an improved version of RetinaNet that consists of three modules which are backbone, feature pyramid network (FPN) and detection heads. FPN is proposed to handle multi-scale changes into objection detection. They modified FPN architecture of original PAA by removing the highest resolution level P7 and change the lowest level form P3 to P2. They also use Threshold adaptive post-processing of deep learning algorithm that use to reject redundant bounding boxes.

2.2.7 High accuracy hybrid CNN classifiers for breast cancer detection using mammogram and ultrasound datasets

Sahu (2023) study abour high accuracy hybrid by using CNN classifier for breast cancer detection. In this research they use mammogram and ultrasound. This study proposes five different hybrid CNN models and here there are two efficient deep CNN networks that hybridized together to improve the performance. 5-fold cross-validation has been carried out and there are six standard performance measures have been evaluated. Objective of this study is to achieve more precise performance with better computational efficiency.

To conclude, for this article five efficient hybrid deep learning frameworks have been developed. The proposed ShuffleNet-ResNet hybrid network, Hybrid 5, outperforms others. ShuffleNet and ResNet are hybridized for detecting breast cancer efficiently. From the experimental result, the scheme achieves best accuracy of 99.17% and 98.00% abnormality and malignancy detection. For the first dataset, it achieves accuracy of 93.18% malignancy detection while second dataset achieves 98.13% accuracy.

2.2.8 CNN-FS-IFuzzy: A new enhanced learning model enabled by adaptive tumour segmentation for breast cancer diagnosis using 3D mammogram images

Thippaluru (2024) study about enhanced learning model enabled by adaptive tumour segmentation for breast cancer detection by using 3D mammogram images. In this research to evaluate tumour detection it compares Adaptive Thresholding with Region Growing Fusion Model (AT-RGFM) with CNN-FS-IFuzzy learning model. It focusses on 3D mammography because it helps discover abnormalities easily. The 3D reconstruction was offered for a superior understanding of tumour expansion and visualization. It utilizes through Maximum Intensity Projection, a direct volume rendering method, Marching Cubes and indirect rendering method. Initially it will go to a rough evaluation of mass bounding through adaptive region growing method. In this research they use Gaussian Mixture model. Vijayarajeswari (2019) design a new mammogram classification by extract feature using Hough transform. Navid et al. (2023_ develop a novel optimization algorithm called World Cup Optimization (WCO) to detect breast cancer at the initial state while Sasikala et al. (2023) suggested the Binary BAT Algorithm (BBA) and Optimum Path Forest (OPF) classifier to improve performance to detect breast cancer.

In this research, they also enhanced the model by apply median filtering and image scaling to reduce false positives. After that C-RSOA is utilized to increase segmentation efficiency in terms of optimizing constraints of region growing. After that the segmented tumor images are forwarded to CNN-FS-IFuzzy learning model. Main scope of CNN-FS-IFuzzy method is to improve the accuracy of the suggested model.

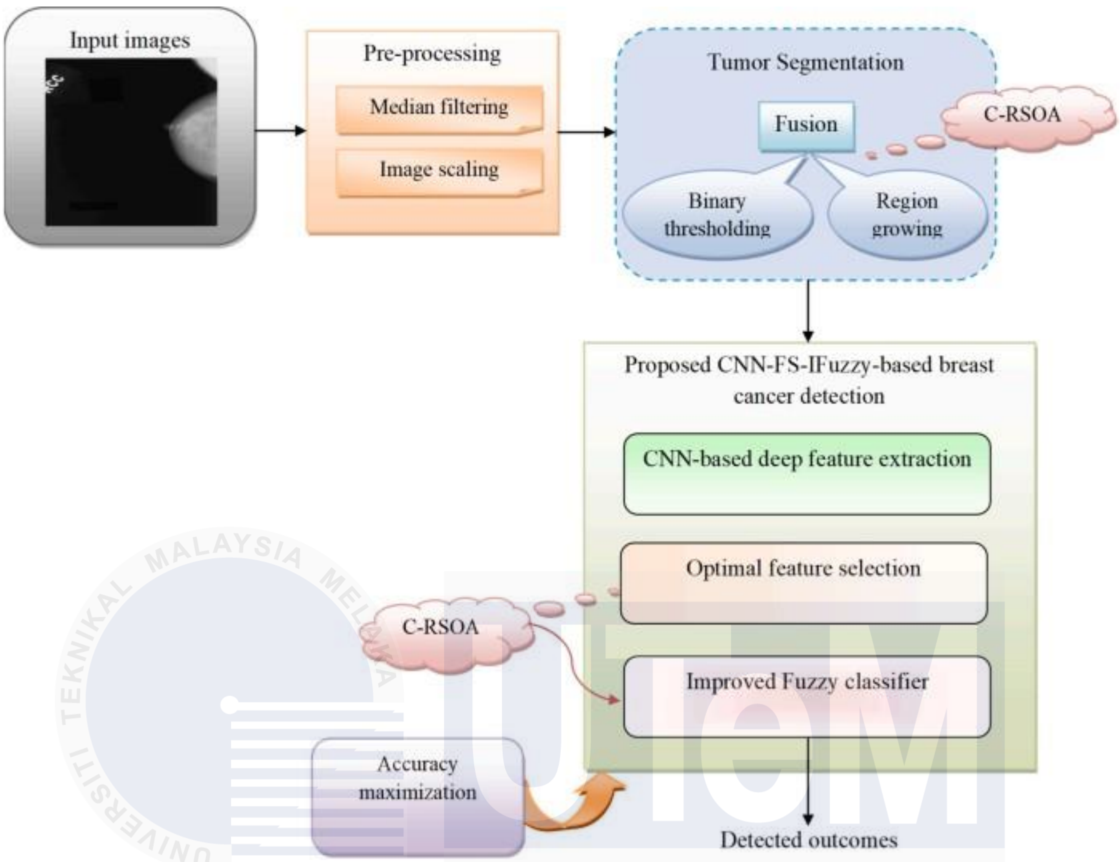


Figure 2.4: Adaptive tumour image segmentation to diagnose breast cancer using 3D mammogram images (Vijayarajeswari, 2023)

2.2.9 Unsupervised feature correlation model to predict breast abnormal variation maps in longitudinal mammograms

Bai (2024) proposed Unsupervised Feature Correlation Network (UFCN). It takes advantage of the deep U-shaped residual connected autoencoder reconstruction process to learn abnormal variation maps. UFCN is unsupervised CNN-based model that consist of identical parallel twin encoder and reconstruction decoder. In this research they use several modules such as Feature correlation module (FCM), Attention suppress gate module (ASG) , Breast Abnormality detection module (BAM) etc. Feature correlation module is used to learns multi-scaled feature correlation between current and prior mammograms to learn newly grown tumor while Breast abnormality detection module (BAM) is used to achieve an accurate binary mask indicating abnormal region. In this research paper, it uses two models which consist of Baseline and variant models. There are several blocks under this models which are U-Net, Attention U-Net, U-Net++, V-Net, etc.

Long et al. (2015) said that the function of U-Net is used to compare the performance of the proposed method while Myronenko(2019) said that SegResNet is for performance comparison. It is a deep neural network architecture design for segmantic segmentation task. It also enhance the performance of image segmentation.

Models' cancer and normal detection performance.

Model	Accuracy	Sensitivity	Precision	F1
U-Net	0.41	0.43	0.80	0.56
U-Net attention	0.42	0.43	0.80	0.56
U-Net++	0.40	0.42	0.79	0.55
SegResNet	0.47	0.46	0.78	0.58
V-Net	0.34	0.37	0.64	0.47
UFCN-T	0.43	0.43	0.73	0.54
UFCN-R	0.62	0.57	0.67	0.62
UFCN	**0.78**	**0.72**	**0.84**	**0.78**

Figure 2.5: Models cancer and normal detection performance (Bai, 2024)

2.2.10 An efficient deep learning scheme to detect breast cancer using mammogram and ultrasound breast images

Sahu (2024) in this research use several proposed methods which are Preprocessing, CNN Architecture, AlexNet, ResNet and MobileNetV2. For CNN architecture it is use for better prediction than each of base method. It will combine and the result is predicted by the majority of the votes to a single class by base classifier. Next is AlexNet, Krizhevsky et al. (2012) proposed AlexNet. It is transfer learning approache utilized in several application of computer vision. This structure has eight weighted layers which consists of five convolutional layers followed by three fully-connected layers. He et al. (2015) proposed ResNet. It is use in this research for skip connection or identity mapping that allow copy the input to next layer by giving substitute pathway for gradient flow.

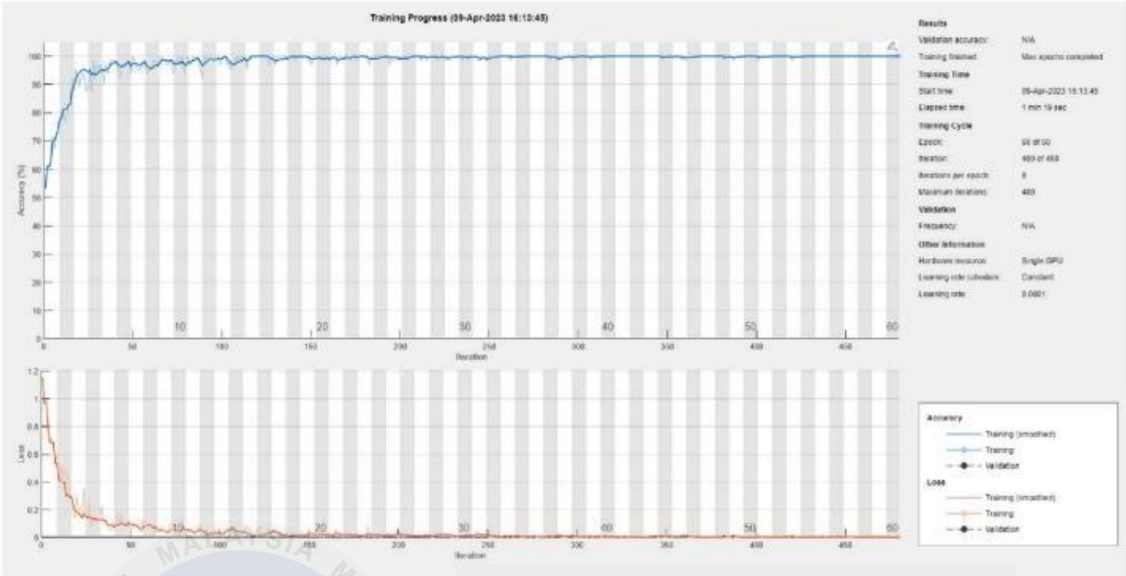


Figure 2.6: Accuracy and loss graph for AlexNet for abnormality identification on mini-DDSM dataset

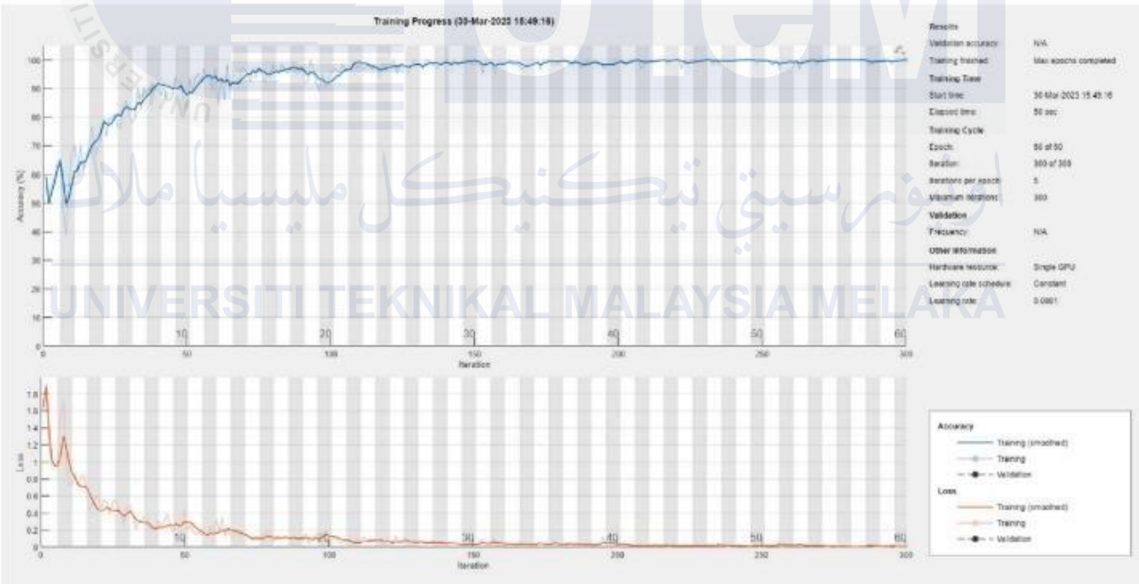


Figure 2.7: Accuracy and loss graph for AlexNet for malignancy identification on mini-DDSM dataset

For mini-DDSM dataset, the proposed method performing better than the others with 97.99% precision, 97.75% accuracy, 97.50% sensitivity, 98.00% specificity, 0.9774 F1 scores, and 0.9775 AUC. Based on all proposed method only three which are AlexNet, MobileNetV2 and ResNet can minimize false positive and false negative. The proposed technique exhibits higher classification performance across three different datasets, according to the experimental results. It obtains an accuracy of 99.17% for abnormality detection and 97.75% for malignancy detection in the mini-DDSM dataset.

2.2.11 Intellectual detection and validation of automated mammogram breast cancer images by multi-class SVM using deep learning classification

Kaur et al. (2019) in this research to remove speckle noise for the mammography image it uses filtering methods which are mean filter and median filter. It utilized to take away speckle sound of images. Other methods, which are Deep Learning technique it will fetch he raw image from database and it will apply to the seven layer of CNN. All the extracted features will be stored in a buffer for next phase where K-mean clustering and Decision Tree is applied to classify normal, benign and malignant classes of mammographic masses. Next, for classification this project use K-mean clustering and Multiclass Support Vector Machine (MSVM). This is unsupervised classification and it used ti underly structure to detect anomalies, locate features and gather insight into data. For classification and identification of similar features to make predictions about identified features. MSVM or Decision Tree is used to realize the classification result. Optimal hyper planes were defined to determine obtain value of membership function.

Measures	Manual/Automated		
	MLP (%)	J48 + K-mean Clustering (%)	Proposed DLTechnique (%)
Image Set NORMAL = 'mdb003.jpg'			
Accuracy	76	90	**92**
Specificity	74	88	**90**
Sensitivity	76	90	**93**
Precision	78	90	**90**
F-score	72	89	**96**
Recall	76	90	**93**

Figure 2.8: Quantitative result of proposed Deep Learning with base (Kaur et al, 2019)

2.2.12 Hybrid deep learning enabled breast cancer detection using mammogram images

Kumar P.J (2024) in this research introduced Quantum SpinalNet (Q-SpinalNet) for detecting breast cancer using mammogram images. They use Non-Local Means Filter (NLM) to pre-process the image then the segmentation will be carried out by using ET-SegNet that have integration of Edge-attention guidance Network (ET-Net) and Segmentation Network) (SegNet). To extract from the features they use Local Ternary Pattern (LTP), Fuzzy Local Bincary Patterns (FLBP), statistical features, Pyramid Histogram of Orientation Gradients (PHoG) and Median Binary Patterns. To detect the tumour, in this research they use Q-SpinalNet which is design by amalgamating Deep Quantum Neural Network (DQNN) with SpinalNet and the result obtained are 90.3% accuracy, 90.9% of True Negative Rate (TNR) and 90% of True Positive Rate (TPR).

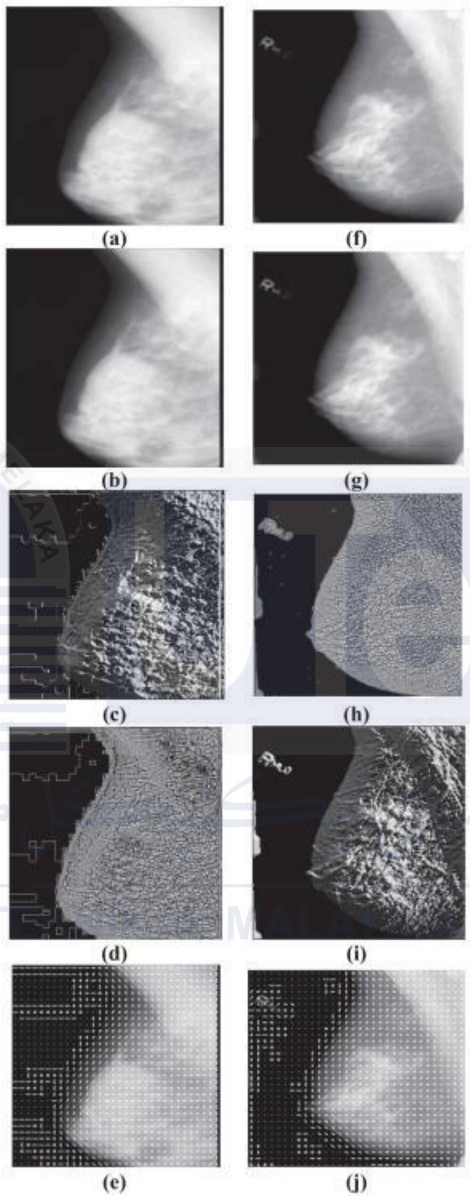


Figure 2.9: Experimental results (Satish Kumar P.J 2024) , a) Input image, b) Filtered image-1, c) LTP image-1, d) MBP image-1, e) PHoG image-1, f) input image-2, g) filtered image-2, h) LTP image-2, i) MBP image-2, j) PHoG image-2(Kumar P.J, 2024)

2.2.13 Deep learning enhancement on mammogram images for breast cancer detection

Singla (2022) in the use various techniques and datasets to make sure the enhancement process by using such techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and Deep Neural Network (DNN) based enhancement. In this paper the steps involve in OSTU Segmentation are first it will take an image that are being taken form Mammographic Image Analysis Society (MIAS) then it will construct an objective function with the help of

OSTU method. The OSTU method will be apply and the threshold value will be calculated. Lastly, they apply threshold value for image segmentation. Based on this research, they use two performance metrics which are Mean Square Error (MSE) and Peak signal-to-noise-ratio (PSNR). To conclude, based on this research, DNN-based process is the best way for MIAS images because it offers better performance for image segmentation.

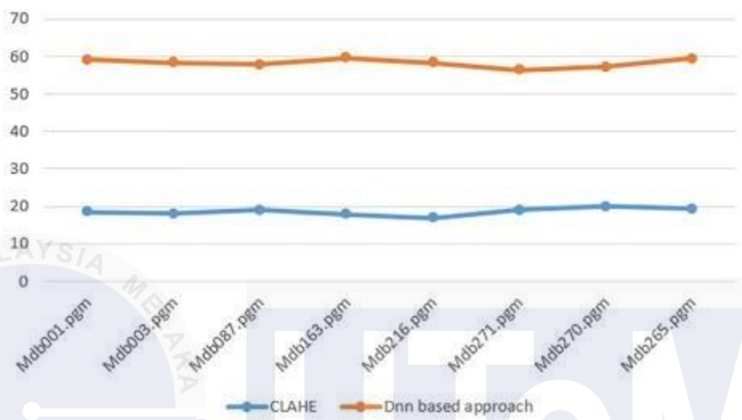


Figure 2.10: Analysis of Peak signal-to-noise-ratio (PSNR) values (Singla, 2022)

2.2.14 Revolutionizing breast cancer diagnosis with a comprehensive approach using a digital mammogram-based feature extraction and selection for early-stage identification

Thangavel (2024) in this research study about transformative approach to diagnose breast cancer. In this study, they combined ResNet expertise in hierarchical feature with U-Net segmentation prowess. With this combination it provides more accurate detection of breast abnormalities and it also create a dynamic feature pipeline for intricate pattern and the region-specific of the abnormalities. They also add neural network in the pipeline because it can refine the diagnostic process by analysing extracted feature, reduce false positive and increase specificity. This study performance is accuracy of 99%, precision of 98.6%, recall of 99.01% and specificity of 98.9%.

2.2.15 SRMADNeT: Swin ResUnet3+-based mammogram image segmentation and heuristic adopted multi-scale attention based DenseNet for breast cancer Detection

Ghuge (2024) in this research they want to improve the segmentation process in order to have correct diagnosis and early detection of the cancer. In this study they collected the mammogram pictures from traditional global datasets. Then the pictures will undergo the segmentation process by using Swin ResUnet3+ which represents voxel segmentation on medical images as a sequence-to-sequence prediction. After segmentation it will be forwarded to the identification stage where Adaptive Multi-Scale Atthention-based Densenet and Extreme

Learning Machine (AMAD-ELM) model is implemented. The parameter of AMAD-ELM is optimized through the suggested Position-based Improves invasive Weed and Crisscross Optimization (PIWCO). For the result, when considering the value of False Negative Rate (FNR), the develop model is reduce by 74.9% of African Vulture Optimization Algorithm (AVOA-AMAD-ELM), 74.1% of Lemurs Optimizer (LO-AMAD-ELM), 81.2% of EWO-AMAD-ELM, 81.2% of COA-AMAD-ELM accordingly. These findings showed that the developed model has better performance than the other traditional system.

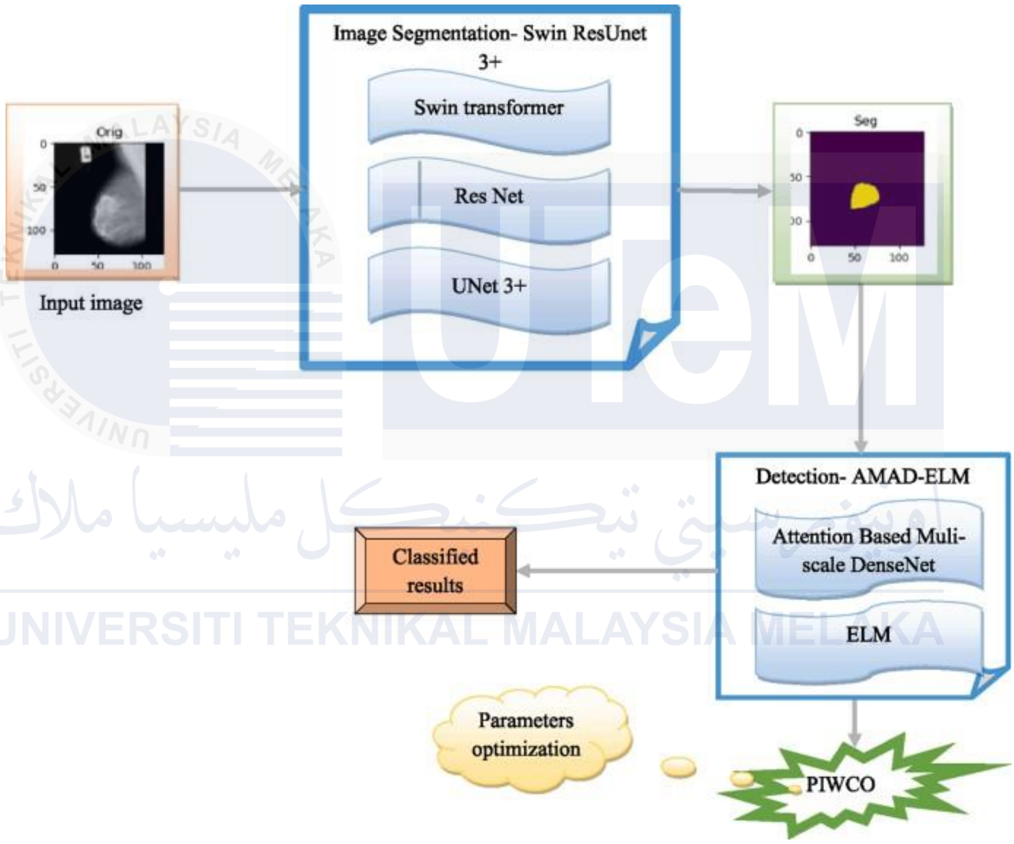


Figure 2.11: The architecture of the recommended breast cancer identification model

(Ghuge, 2024)

2.2.16 MOB-CBAM: A dual-channel attention-based deep learning generalizable model for breast cancer molecular subtypes prediction using mammograms

Nissar (2024) in this research is about how deep learning model act as significant tools and solutions for cancer detection. In this study, the methods they use are deep learning model MOB-CBAM that utilizes the backbone of MobileNet-V3 architecture with Convolutional Attention Module. They use The Chinese Mammography Database (CMMD) to evaluate the model. In this research they use intelligent machine learning (ML) and deep learning (DL) algorithms. For filtering, they use median and wiener filter to remove noise from the image. Next, for image enhancement, this study uses Contrast Limited Adaptive Histogram Equalization (CLAHE) to increase the size of training data and to address imbalance in training data that are generated from minority class. The result for this research, the model proves with the accuracy of 98%. In this research they also use Mammographic Image analysis Society (MIAS) and Curated Breast Imaging Subset (CBIS-DDSM) dataset. For MIAS, the accuracy is 97% while for CBIS-DDSM, the accuracy is 98%.

2.2.17 Mammo-Light: A lightweight convolutional neural network for diagnosing breast cancer from mammography images

Raiaan et al. (2024) in this research they propose a computer-aided classification approach. For preprocessing strategies, they use photometric techniques to balance and increase the size of the dataset. Then, they apply the Convolutional Neural Network (CNN) to classify the breast cancer that available in the dataset which are Mammographic Image analysis Society (MIAS) and Curated Breast Imaging Subset (CBIS-DDSM) dataset. CBIS-DDSM is use to validate the performance of the proposed model while MIAS is use to assess the robustness of the model. The results are 99.17% and 98.42% respectively.

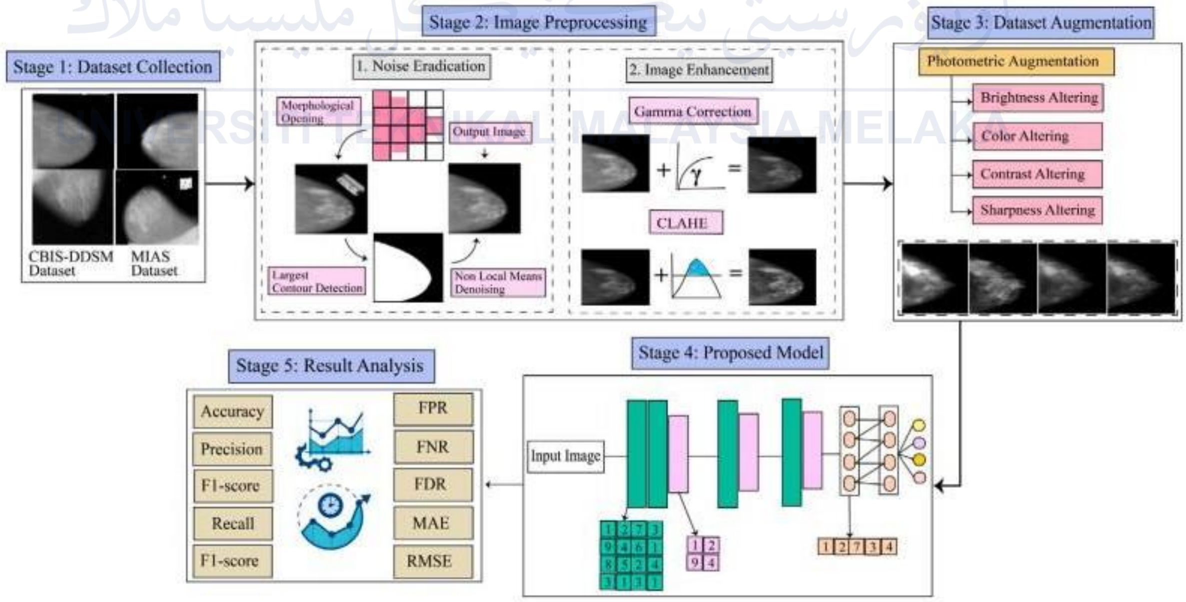


Figure 2.12: Pipeline of Mammo-Light (Raiaan et al, 2024)

The results in order to evaluate the model efficiency are recall, specificity, precision, F1 Score etc. The recall is 99.14%, the specificity is 99.72%, the precision is 99.16%, the F1-score is 99.15%, the NPV is 99.72%, the FPR is 0.27%, the FNR is 0.85%, and the FDR is 0.83%. Further, they have assessed their model on the MIAS dataset, and attained a recall of 98.37%, a specificity of 99.2%, a precision of 98.48%, an F1-score of 98.42%, an NPV of 99.24%, an FPR of 0.79%, an FNR of 1.62%, and an FDR of 1.51%.

2.2.18 Breast cancer detection and diagnosis using hybrid deep learning architecture

Raaj (2023) in this journal propose hybrid Convolutional Neural Network (CNN) architecture. The data are classified into three different cases which are normal, benign and malignant. The dataset that being used in this article are Mammographic Image analysis Society (MIAS) and Curated Breast Imaging Subset (CBIS-DDSM) dataset. The process flow of the detected region is the they will use the scanner device then they will have acquisition of the mammogram images. The images will undergo pre-processing and Computer Aided Methods (CAM) will identify the presence of cancer in breast tissue sample. Next, it will do the region segmentation.

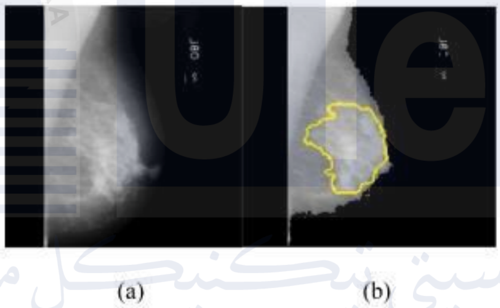


Figure 2.13: Segmentation output (Raaj, 2023)

2.2.19 Artificial intelligence for breast cancer detection in screening mammography in Sweden: a prospective, population-based, paired-reader, non-inferiority study

In this research, Dembrower (2023) named ScreenTrustCAD was a non-inferiority trial undertaken on the population at Capio Sankt Goran Hospital, Stockholm, Sweden where 40 and 74 years old women that did not have breast implants participated in population based breast cancer screening.The primary goal was to evaluate the effectiveness of double reading by one radiologist plus AI with respect to the standard double reading done by two doctors with an intention of assessing whether or not this approach could lead to a decrease in breast cancer diagnosis by 15%. AI only single readings and triple readings by two radiologists with AI were secondary analyses.58,344 women underwent mammograms between April 1, 2021 and June 9, 2022.

Out of these, 55,581 individuals were included in the study.269 (0.5%) women were diagnosed with breast carcinoma due to screening according to results.Non-inferiority (95% CI 1.00-1.09) was shown when it was found that the rate of cancer detection for double reading done by one doctor plus AI was 1.04 times larger compared to that of double reading done by two physicians (261 as opposed to 250 cases).In addition triple readings with AI done by two doctors (269 compared to 250 instances relative proportion 1.08 95% CI 1.04-1.11) and single readings exclusively through AI (246 against the 250 instances their relative proportion being 0.98 95% CI 0.93 1) were present among the secondary analyses as well respectively.

2.2.20 Efficient breast cancer detection via cascade deep learning network

Asadi (2023) conducted this research using an advanced cascade network model, which is capable of identifying concentrations of calcium in breast tissue which would be helpful in early detection of the disease. In order to differentiate between benign and malignant tumors, the methodology includes preprocessing of images, followed by segmentation and classification. For segmentation purposes, a UNet architecture with a ResNet backbone is used to isolate the tumor from the image as a mask. Notably, the segmentation model achieved an F1-score of 97.30%. Classification is done using ResNet50 for feature extraction while an 8 layer neural network makes a decision. The F1-score (98.41%) and high accuracy (98.61%) recorded by this classification model further attests its performance Comparison of comprehensive experimental results provides additional supporting evidence for effective delivery of this approach.

2.2.21 Breast cancer diagnosis system using hybrid support vector machine-artificial neural network

Tze Sheng Lim (2021) suggests a hybrid breast cancer diagnosis system based on the combination of support vector machine (SVM) and artificial neural network (ANN) in this article. A set of 160 mammograms obtained from mini-MIAS database was utilized for data training phase. Accordingly, segmentation was done in order to identify region of interests, which involved preprocessing activities that helped improve their features. The resulting 21 features were obtained through statistical analysis and texture measurements. This trained model was then integrated into a computer-aided diagnosis (CAD) system that enabled it to classify mammograms into either normal or abnormal; it also helped in distinguishing between benign and malignant tumors. The performance of the system was evaluated using evaluation metrics such as accuracy, sensitivity, specificity and F1 score.

To accomplish this mammogram classification task (CAD), support vector machines (SVM) as well as artificial neural networks (ANN) were put together to form a single breast cancer diagnosis system using 160 mammograms from mini-MIAS database. Statistical and texture characteristics extracted from them were used during training phase to develop the model which was then applied in classifying mammograms into two categories (normal versus abnormal) and differentiate between benign tumors and malignant tumors. To assess the diagnostic accuracy and performance of the system in identifying breast cancer cases, evaluation metrics such as accuracy, sensitivity, specificity and F1 score were employed.

2.3 Critical review of current problem and justification

Table 2.2: Summary of related works based on breast cancer detection method

Journal	Summary	Method	Performance Analysis
M.tahmooresi, A.Afsar, B. Bashari Rad, K. B.Nowshath, M. A. Bamiah Detection of Breast Cancer Using Machine Learning Techniques, 2019	The study developed a hybrid machine learning model aimed at the early diagnosis of breast cancer. This model combines several algorithms, including Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbour (KNN), Decision Tree (DT), Random Forest (RF), AdaBoost Classifier, and Naïve Bayes (NB). The goal was to boost the chances of early cancer detection and improve survival rates, achieving a survival rate of up to 98% with early detection.	**ANN:** This technique is utilized to recognize patterns of detecting lesions that have a high probability of being life-threatening. **SVM:** Method used to distinguish data via finding a hyperplane with large minimum distance. **KNN:** It is employed for cancer diagnosis and classification. **Decision Tree (DT):** It is for classification due to insensitivity towards background noise. **Random Forest (RF)**: It helps in calculating similarities between different data points. **Naïve Bayes (NB):** Used for distributing numeric variables among the respective classes.	Generalized Model (GMM): Reported to perform better than other algorithms, achieving an accuracy of 84%. Chowdhary and Acharjya (2018): Their method, focusing on mammogram detection, achieved a higher accuracy of 94% for detecting malignant breast lesions.

Adyasha Sahu, Pradeep Kumar Das, Sukadev Meher, Recent advancements in machine learning and deep learning-based breast cancer detection using mammograms, 2023	Recent developments in the use of machine learning (ML) and deep learning (DL) in breast cancer detection are investigated through this research paper, with an emphasis on the importance of mammograms. The low-dose X-ray imaging makes mammogram preferred by medical practitioners as there is minimization of harm to patients. There are factors influencing breast cancer which can be controlled such as obesity, alcohol intake and physical activity while others cannot be controlled like genetic predisposition, early menses and delayed menopause. Different ML and DL methods have been analyzed in the study to increase cancer detection including segmentation techniques as well as decision trees among others.	**Decision Tree:** To identify the appropriate regions of interest (ROI). **Deep Learning (DL):** It was implemented so that there could be an improved detection through segmentation methods which have more number of training parameters and disposable cost.	**Accuracy**: Measures the proportion of true results among the total cases examined. **Precision:** It shows the fraction of true positive results from all positive outcomes predicted by the model. **Recall**: It measures how well the model identifies each relevant instance. **F1 Score**: A harmonic mean of precision and recall that balances both measures. **Area Under the Curve (AUC)**: It assesses a model's capability to differentiate among various classes.

Lydia Bouzar-Benlabiod , Khaled Harrar , Lahcen Yamoun , Mustapha Yacine Khodja , Moulay A. Akhloufi, A novel breast cancer detection architecture based on a CNN-CBR system for mammogram classification, 2023	This exploratory work is the initial one which employed a combination of Convolutional Neural Network (CNN) and Case Based Reasoning (CBR) systems on mammogram pictures in detecting breast cancer. Data augmentation was done through both CLAHE and median filtering, while feature selection was executed through a Wrapper method. This strategy attains high accuracy for recognizing malignant tissues.	**Data Enhancement:** Image enhancement using CLAHE and median filters. **Feature Selection:** Wrapper method with KNN (K=7). **Classification:** CNN-CBRsystem for mammogram classification.	**Precision Rate:** The wrapper method with the selected attribute set achieved 84.25% precision.
A. Alavudeen Basha, S. Vivekanandan, Azath Mubarakali , Abdulrahman Saad Alqahtani, Enhanced	This research is directed towards enhancing breast cancer automated detection by the means of mammogram classification approaches relying on Convolutional Neural Networks (CNNs). The study also includes some advanced techniques for, image processing enhancement to improve detection accuracy levels and efficiency as well.	**Non-Local Means (NLM)**: Used to remove noise by leveraging edundancy in breast images, comparing gray levels and geometric patterns in adjacent pixels.	The integration of NLM and AHE leads to better-quality mammogram images that will result into tumor detection or classification. The analysis indicates that better precision along with more robustness when diagnosing breast cancer can be achieved through combining these methods with CNNs.

mammogram classification with convolutional neural network: An improved algorithm for automated breast cancer detection, 2023		.**Adaptive Histogram Equalization (AHE)**: An application that improves brightness and contrast for easy detection and segmentation. **K-Nearest Neighbors (KNN)**: Used for classification, calculating Euclidean distances as well as assessing class confidence.	

Oliver Díaz, Alejandro Rodríguez-Ruíz , Ioannis Sechopoulos, Artificial Intelligence for breast cancer detection: Technology, challenges, and prospects, 2024	The present paper analyzes the progress made, problems faced as well as prospects of employing AI mainly deep learning for breast cancer diagnosis. According to the authors, Breast Cancer screening accuracy may be enhanced by various kinds of Artificial Intelligence technologies such as Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), Deep Belief Networks (DBN) and Convolutional Neural Networks (CNN), besides that these techniques can decrease false positives and negatives while assisting doctors in spotting minor irregularities.	**Deep Learning Algorithms**: Detection performance is enhanced through the application of different frameworks such as DNNs, RNNs, DBNs, and CNNs. **AI Application**: The algorithms extract mammogram images' patterns and features resulting in better diagnosis results.	In the findings presented by this research paper it is shown that breast cancer detection accuracy has greatly improved with AI based systems reducing false positives or negatives incidences hence improving overall effectiveness of breast cancer screening programs (MDPI).

Jiale Jiang, Junchuan Peng, Chuting Hu, Wenjing Jian, Xianming Wang, Weixiang Liu, Breast cancer detection and classification in mammogram using a three-stage deep learning framework based on PAA algorithm, 2022	Research is presented on how a new proposed three-stage deep learning framework using the Positive Anchor Assignment (PAA) algorithm can enhance mammography classification. There is an emphasis on improving the performance of existing breast cancer detection systems through changes in deep learning architectures. In particular, the study addresses the shortcomings of anchor-based detectors such as Faster R-CNN and YOLO by refining the anchor set into positive and negative samples for matching with ground truths.	**Backbone Network**: This is responsible for extracting initial features from mammogram images. **Feature Pyramid Network (FPN)**: The FPN accommodates multi-scale variations, having had its highest resolution level (P7) removed and its lowest level (P3) changed to P2. **Detection Heads**: Their purpose includes object detection and classification. **Non-Local Means (NLM)**: To remove noise by utilizing spatial redundancy in breast images. **AdaptiveHistogram Equalization (AHE)**: For improving image contrast which facilitates easier tumor detection.	**Accuracy**: Proportion of correctly predicted instances among all instances. **Precision**: True positive prediction over total predicted positives. **Recall**: True positive prediction over actual positives. **AUC**: Ability of model to distinguish among classes. **Specificity**: Ability of model to precisely identify negative cases.

Adyasha Sahu, Pradeep Kumar Das, Sukadev Meher, High accuracy hybrid CNN classifiers for breast cancer detection using mammogram and ultrasound datasets, 2023	The high accuracy hybrid CNN classifiers for breast cancer detection using mammogram and ultrasound datasets are the subject of this article. In this document, five distinct hybrid CNN models are proposed with an objective of designing these models so that they provide better performance while optimizing computing resources. The models have been evaluated using 5-fold cross validation, and the results presented in six standard performance measure.	Mammogram and ultrasound datasets were utilized. In addition, five distinct hybrid CNN models were developed. This involved hybridizing deep CNN networks particularly focusing on ShuffleNet and ResNet. Performance evaluation was done by implementing 5-fold cross validation.	Evaluation of six standard performance measures. Achievement of best accuracy by Hybrid (ShuffleNet-ResNet hybrid network) with 99.17% overall accuracy and 98.00% abnormality and malignancy detection accuracy. Hybrid 5 also achieves 93.18% malignancy detection accuracy on the first dataset and 98.13% on the second dataset.

Thippaluru Umamaheswari , Y. Murali Mohanbabu, CNN-FS-IFuzzy: A new enhanced learning model enabled by adaptive tumor segmentation for breast cancer diagnosis using 3D mammogram images, 2024	A brand new, improved learning model called CNN-FS-IFuzzy that is facilitated by adaptive tumor segmentation for breast cancer diagnosis using 3D mammogram images is what the article presents.The proposed CNN-FS-IFuzzy learning model is evaluated against the performance of the Adaptive Thresholding with Region Growing Fusion Model (AT-RGFM). This study examines the benefits of 3D mammograms in easy detection of abnormalities while using techniques like maximum intensity projection and marching cubes in visual outputs. The model also integrates median filtering and image scaling to reduce false positives as well as C-RSOA for effective segmentation.	Breast cancer identification using 3D mammography images. Comparison between AT-RGFM and CNN-FS-IFuzzy learning models. Gaussian Mixture model inclusion for the first mass bounding evaluation. The model has been improved through median filtering and image scaling. Increased segmentation efficiency via C-RSOA usage. To enhance accuracy , apply CNN- FS-IFuzzy learning model.	Evaluation of tumor detection accuracy and segmentation efficiency. Comparison of false positive rates between various models. Evaluating the overall performance of a model in terms of accuracy and computational efficiency.

Jun Bai, Annie Jin, Madison Adams, Clifford Yang, Sheida Nabavi, Unsupervised feature correlation model to predict breast abnormal variation maps in longitudinal mammogram, 2024	The article presents Unsupervised Feature Correlation Network (UFCN) for performing prediction of breast abnormal variations maps from longitudinal mammograms. UFCN uses a very deep U-shaped residual connected autoencoder reconstruction process which is unsupervised in learning abnormal variation mapping. It consists of various modules including Feature Correlation Module (FCM) and Breast Abnormality Detection Module (BAM).In this work two models developed Baseline and variant models that have different blocks such as U-Net, Attention U-Net, U-Net++ and V- Net so as to allow comparison.	Use of longitudinal mammograms in prognosis of breast abnormalities. The implementation of UFCN, an unsupervised CNN-based model consisting of two parallel encoder networks and reconstruction decoder. Incorporation of FCM and BAM modules for feature correlation and abnormality detection. Comparison of UFCN with baseline and variant models, utilizing blocks such as U-Net and SegResNet. Assessment of model performance using deep neural	Evaluation of prediction accuracy for breast abnormal variation maps. Comparison of UFCN's performance with baseline and variant models. Assessment of UFCN's performance against established deep neural network architectures such as U-Net and SegResNet for semantic segmentation tasks.

		network architectures designed for semantic segmentation tasks.	
Adyasha Sahu, Pradeep Kumar Das, Sukadev Meher, An efficient deep learning scheme to detect breast cancer using mammogram and ultrasound breast image, 2024	An efficient deep learning schema for breast cancer detection from mammogram and ultrasound breast images is presented in this paper. It employs several proposed methods: preprocessing, CNN architecture, and transfer learning approaches like AlexNet, ResNet and MobileNetV2. The combination of these methods produces a better prediction performance than any of the individual base methods. Furthermore, a voting mechanism is used in order to find the final prediction class. Experimental results demonstrate higher classification performance across three diverse datasets with particular attention paid to mini-DDSM which achieved significant accuracy and sensitivity.	Mammographic and ultrasound breast images are used in detection of the disease. Preprocessing methods are implemented to improve quality of data. Combination of CNN architecture with transfer learning methods like AlexNet and ResNet as well as MobileNetV2 is employed. Combination of CNN architecture with transfer learning methods such as AlexNet, ResNet and MobileNetV2 is used.	A voting scheme determines final prediction class. Classification performance is evaluated using metrics like precision,accuracy,sensitivity,specificity ,F1 scores and AUC.

Prabhpreet Kaura, Gurvinder Singh, Parminder Kaur. Intellectual detection and validation of automated mammogram breast cancer images by multi-class SVM using deep learning classification, 2019	An article proposes how to automatically detect and validate breast cancer from breast cancer images through these techniques: a seven-layer CNN (convolutional neural network) for feature extraction, utilizing mean and median filters for speckle noise removal, K-means clustering and decision tree to identify masses into the normal, benign or malignant category as well as unsupervised K-means based anomaly detection and similar features classification via supervised Multiclass Support Vector Machine.	They are methods used in mammography images whereby filtering techniques help eliminate noise caused by speckle patterns. This is followed by using deep learning tools such as seven-layer CNN. The next stage involves saving the extracted characteristics into a buffer. The results of K-means clustering along with Decision Tree algorithms classify them into three groups i.e., normal, benign or malignant masses on mammograms for example. Finally, anomaly detection occurs through unsupervised K-means clustering together with supervised Multiclass Support Vector Machine (MSVM) applied onto similar characteristics' discrimination.	Evaluation of classification performance using metrics such as precision, recall, and F1-score. Assessment of the accuracy of anomaly detection and classification of similar features. Comparison of performance between filtering methods and deep learning techniques for feature extraction and classification.

Sathish Kumar P.J, Shibu S , Mohan M , Kalaichelvi T, Hybrid deep learning enabled breast cancer detection using mammogram images, 2024	Quantum SpinalNet (Q-SpinalNet) is a hybrid deep learning model proposed in this article for the detection of breast cancer in mammogram images. It applies Non-Local Means Filter for pre-processing and ET-SegNet- ET-Net, SegNet integrated to segment mammograms. Feature extraction techniques include Local Ternary Pattern (LTP), Fuzzy Local Binary Patterns(FLBP), Statistical Features and PHoG and Median Binary Patterns. Tumor detection is achieved by Q-SpinalNet which uses Deep Quantum Neural Network (DQNN) alongside SpinalNet thereby producing more accurate results through high true positive rates..	Breast cancer diagnosis by means of mammogram images; taking advantage of Non-Local Means Filter (NLM) for pre-processing; use of ET – SegNet composed of ET- Net and SegNet in segmenting them; extraction from such images using local ternary pattern (LTP), fuzzy local binary patterns (FLBP), statistical features, PHoG and median binary patterns. Detection of tumor can be – accomplished via Quantum SpinalNet (Q-SpinalNet), which uses Deep Quantum Neural Network (DQNN) together with SpinalNet.	Evaluation of detection performance using metrics such as accuracy, True Negative Rate (TNR), and True Positive Rate (TPR). Achievement of high accuracy (90.3%) and balanced TNR (90.9%) and TPR (90%).

Chaitanya Singla, Pradeepta Kumar Sarangi, Ashok Kumar Sahoo, Pramod Kumar Singh, Deep learning enhancement on mammogram images for breast cancer detection, 2022	The article talks about enhancing mammogram images for the detection of breast cancer by using methods that rely on Contrast Limited Adaptive Histogram Equalization (CLAHE) and Deep Neural Network (DNN). Segmentation thresholds have been calculated by using OSTU technique with MIAS dataset. Segmentation performance was examined through the Mean Square Error (MSE) and Peak signal-to-noise-ratio (PSNR) metrics which indicate that DNN-based enhancement is superior.	Methods for enhancing mammogram images using CLAHE and DNN basetr techniques. The application of OSTU segmentation method in image segmentation. An objective function is constructed, and a threshold value is calculated via OSTU. MSE and PSNR are used in performance evaluation. Consequently, a comparison of the segmentation performances of CLAHE with DNN-based enhancement methods was carried out to draw conclusions.	Evaluation of segmentation performance using MSE and PSNR metrics. Comparison of performance between CLAHE and DNN-based enhancement methods. Conclusion drawn based on the observed segmentation performance enhancement with DNN-based method for MIAS images.

Yuvaraja Thangavel, Hitendra Garg, Manjunathan Alagarsamy, D. Pradeep, Revolutionizing breast cancer diagnosis with a comprehensive approach using digital mammogram-based feature extraction and selection for early-stage identification, 2024	Introducing a new method for detecting breast cancer by combining hierarchical features of ResNet and segmentation capabilities of U-Net is the focus of the article. This blending allows for abnormality detection and creates a moving part for the analysis of patterns from various images. False positives are reduced while specificity is increased as a result of using neural networks in this diagnostic process. The study comes up with a high performance of 99 percent accuracy, 98.6 percent precision, 99.01 percent recall and 98.9 percent specificity.	Combination of ResNet's hierarchical feature expertise with U-Net's segmentation capabilities. Incorporation of neural networks to refine the diagnostic process and increase specificity. Analysis of extracted features for pattern analysis and region-specific abnormalities. Performance evaluation using metrics such as accuracy, precision, recall, and specificity Evaluation of performance metrics including accuracy, precision, recall and specificity.	The comprehensive approach for breast cancer diagnosis has demonstrated that it can achieve high accuracy (99%), precision (98.6%), recall (99.01%) and specificity (98.9%).

Kalyani Ghuge, Dr. D.Saravanan, SRMADNet: Swin ResUnet3+-based mammogram image segmentation and heuristic adopted multi-scale attention based DenseNet for breast cancer detection, 2024	The SRMADNet is introduced in this article as a means of enhancing mammogram image segmentation and detection of breast cancer. It uses Swin ResUnet3+ for segmentation and Adaptive Multi-Scale Attention based DenseNet with Extreme Learning Machine for identification (AMAD-ELM). PIWCO or Position-based Improved Invasive Weed and Crisscross Optimization is utilized to optimize the parameters of AMAD-ELM. Performance analysis indicates a significant decrease in FNR when compared to traditional systems, demonstrating the superiority of the proposed model.	Segmentation of mammogram images using Swin ResUnet3+. The implementation of adaptive multi-scale attention based dense networks and extreme learning machine (AMAD-ELM) for image identification. Position-based improved invasive weed and crisscross optimization (PIWCO) is used to optimize the variables for AMAD-ELM.	Evaluating how FNR has decreased compared to traditional systems. Comparing with African Vulture Optimization Algorithm (AVOA-AMAD-ELM), Lemurs Optimizer (LO-AMAD-ELM), EWO-AMAD-ELM, and COA-AMAD-ELM. A conclusion is made that the proposed model has better performance in detecting breast cancer.

Iqra Nissar, Shahzad Alam, Sarfaraz Masood, Mohammad Kashif, MOB-CBAM: A dual-channel attention-based deep learning generalizable model for breast cancer molecular subtypes prediction using mammograms, 2024	MOB-CBAM is a deep learning architecture for mammographic breast cancer molecular subtype prediction. To carry out cancer detection, it combines MobileNet-V3 with Convolutional Attention Module. The evaluation takes place on Chinese Mammography Database (CMMD). Median and Wiener filters are used for noise removal while CLAHE is used for image enhancement in this investigation study that uses ML and DL techniques. The model performs effectively in breast cancer detection by achieving 98% accuracy on CMMD, 97% MIAS and 98% CBIS-DDSM datasets.	Prediction of breast cancer molecular subtypes using MOB-CBAM model for mammogram images. Combination of MobileNet-V3 architecture with Convolutional Attention Module. Evaluation based on Chinese Mammography Database (CMMD). Application of intelligent ML and DL algorithms including median and Wiener filtering methods for noise removal in images. Contrast Limited adaptive histogram equalization (CLAHE) is then applied to enhance these images.	Performance evaluation on CMMD, MIAS and CBIS-DDSM datasets. The results show that the proposed model attained an accuracy of 98% on CMMD,97% on MIASand,98% respectively on CBIS-DDSM indicating its proficiency in detecting breast cancer.

Mohaimenul Azam Khan Raiaan, Nur Mohammad Fahad, Md Saddam Hossain Mukta, Swakkhar Shatabda, Mammo-Light: A lightweight convolutional neural network for diagnosing breast cancer from mammography image, 2024	Mammo-Light is an optimized light weight Convolutional Neural Network (CNN) developed with the aim of diagnosing breast cancer from mammogram images. Appropriate techniques are utilized in this approach to help balance and augment the dataset through photometric preprocessing methods. When tested on Curated Breast Imaging Subset (CBIS-DDSM) and Mammographic Image Analysis Society (MIAS), it was found to produce very high performance metrics.	Preprocessing: Photometric techniques for balancing and data augmentation. Classification: CNN usage for the classification of breast cancer cases among the datasets. CBIS-DDSM: Model performance validation site. MIAS: Model robustness assessment location.	Accuracy: 99.17% Recall: 99.14% Specificity: 99.72% Precision: 99.16% F1-Score: 99.15% NPV: 99.72% FPR: 0.27% FNR: 0.85% FDR: 0.83%
Karin Dembrower, Alessio Crippa, Eugenia Colón, Martin Eklund, Fredrik Strand, and the ScreenTrustCAD Trial Consortium, Artificial Intelligence for Breast Cancer Detection in Screening Mammography	The aim of this study was to observe how effective cancer screening using AI was compared to standard double reading by two radiologists through a single reading by AI plus one radiologist at Capio Sankt Göran Hospital located in Stockholm Sweden. The study included 55,581 women aged 40 to 74 years and assessed whether it was not inferior with an acceptance threshold at a	Primary Analyses: To assess the efficacy of applying AI in tandem with one radiologist's double readings against that of the conventional double readings made by two doctors that were specified not to exceed 0.15 relative reduction in breast cancers diagnoses. Secondary Analyses: Single reading by AI alone. Triple exposure	**First Analyses**: Doubles Reading by One Radiologist + AI against Double Reading by Two Radiologists: 261 detected cases (0.5%) against 250 detected cases (0.4%). Relative proportion: 1.04 (95% CI 1.00–1.09).

in Sweden: A Prospective, Population-Based, Paired	0.15 relative reduction in breast cancer diagnosis. The primary endpoint was the cancer detection rate	involves using both radiologists and AI analyze results.	**Secondary Analyses**: On the other hand, the AI was found to detect 246 cases (0.4%) compared with the traditional way where 250 cases (0.4%) were detected. Relative Proportion: 0.98 (95% CI 0.93–1.04). Triple Reading by Two Radiologists + AI detected a total of 269 cases (0.5%) while the Double Reading by Two Radiologists only had 250 detected cases (0.4%). Relative Proportion: 1.08 (95% CI 1.04–1.11)
R. Sathesh Raaj, Breast cancer detection and diagnosis using hybrid deep Learning architecture,2024	The article introduces a hybrid Convolutional Neural Network (CNN) architecture for breast cancer detection and diagnosis, classifying data into normal, benign, and malignant categories using MIAS and CBIS-DDSM datasets. The process includes image acquisition, preprocessing, and cancer detection.	**Data Acquisition:** Use of a scanner device to acquire mammogram images. . **Computer Aided Methods (CAM):** Identification of cancer presence in breast tissuesamples usingCAM.	Accuracy Precision (Sensitivity) Specificity F1-score Recall

Tze Sheng Lim, Kim Gaik Tay, Audrey Huong, Xiang Yang Lim, Breast cancer diagnosis system using hybrid support vector machine-artificial neural network, 2021	A hybrid breast cancer diagnosis system has been suggested in the present paper that merges support vector machine (SVM) and artificial neural network (ANN). The aim is to classify mammograms as either normal or abnormal and to differentiate between benign and malignant tumors.	Segmentation, preprocessing, and feature extraction of mammograms for the purpose of getting 21 features. Deployment of a trained model into CAD system incorporating SVM and ANN. SVM classification involving different models such as linear model, quadratic model, cubic model, and Gaussian model. Two layer feedforward structure for ANN with 15 neurons in the hidden layer. SVM features selection to improve classification accuracy.	Metrics including accuracy, sensitivity, specificity and F1 score were used for evaluating performance of the system. System’s competence on accurate classification of mammograms into normal or abnormal categories and on distinguishing benign from malignant tumors was also evaluated.

Bita Asadi, Qurban Memon, Efficient breast cancer detection via cascade deep learning network, 2023	An innovative deep learning network model has been presented in this paper for early detection of breast cancer. In addition, it concentrates on breast calcifications as well as abnormal tissue growths like distinguishing between benign and malignant tumors. Its procedures are three-fold; image preprocessing, segmentation and classification.	Image preprocessing: •Prepares the images for segmentation and classification Segmentation: •Using a UNet architecture with a ResNet backbone. •The tumor is separated from the image as a mask. •The F1 score achieved was 97.30%. Classification: •Make use of ResNet50 for feature extraction.	F1-score: 97.30% Accuracy: 98.61%

2.4 Summary

An exhaustive examination of 21 research papers on breast cancer diagnostic methodologies was done in this chapter. Each paper was deeply analyzed in order to comprehend their respective techniques, performance evaluation and overall project efficacy. This in-depth analysis revealed several techniques and methods within the region that served to emphasize its diversity and innovativeness in medical imaging and artificial intelligence. The major findings of our study show that the field comprises a wide range of methodologies from traditional image processing algorithms to sophisticated deep learning models. Nonetheless, discovering the most suitable methods for inclusion in our project is still a big challenge even though these studies have shown encouraging performance regarding accuracy as well as precision. This will help us create an effective framework for breast cancer detection with high diagnostic precision levels using reliable means. The next chapter entails Project Methodology which describes how we systematically approached achieving these research objectives. Moreover it includes a comprehensive account of data collection procedures, which entails acquiring mammogram datasets and ensuring quality-control measures during its preprocessing phase. In addition to this, it is in this chapter that different Machine Learning and Deep Learning models are chosen with their architecture explained as well as why they are integrated into our framework. Additionally, a description of the evaluation metrics and experimental setup used for validation of the effectiveness of the projected models will be provided in project methodology section. These include defining different measures like accuracy, precision, recall and F1-score that act as parameters for measuring effectiveness in our breast cancer detection system. The repetition of our methods is intended to make our methodology transparent and reproducible so that it can be subject to rigorous scientific validation and possibly eventual clinical application.

CHAPTER III: PROJECT METHODOLOGY

3.1 Introduction

"Project methodology" denotes a clearly defined collection of practices, procedures and processes associated reasonably that provide the best way to organize, design, supervise and execute a project from its initiation to successful conclusion. It is an organized and disciplined approach backed by science for designing, executing and completing projects. The purpose of project methodology is to ensure success of processes, approaches, techniques, methodologies as well as technologies while facilitating effective decision-making and problem solving during entire management cycle. Usually a project management methodology provides a framework for detailing all stages enabling one responsible for the project understand what exactly should be done to accomplish and carry out his task without exceeding time limits or budgets required by the customer.

To utilise the project methodology, all the steps of the research process need to be systematically approached. To begin with, the project begins by comprehending what the definition of the issue is and its objectives. A thorough literature review is then done in order to identify the prevailing methods, techniques and advancements that are relevant to this particular area of study. Once the basic knowledge has been established, there will be a definitive project methodology that outlines the required actions to achieve study goals. This may involve collecting data, preparing it, building a model based on it, evaluating it and validating it. The suggested approach is put into practice during execution phase which normally entails programming work, algorithm development and experimentation. Throughout this entire process in order for everything to remain consistent and precise documentation and record-keeping must be detailed. These metrics and standards play a key role in evaluating the performance of the suggested methods. Use of this method helps to evaluate how well the hypotheses have worked, their limitations, strengths and weaknesses among other factors. Finally, results are analyzed, interpreted and compared with earlier studies to come out with useful insights. All factors considered, it is very important that there should be a good organizational structure such that at the end of an investigation there will be fulfillment of research objectives as well as improvement in knowledge.

Initially, it involves analysis and reviewing of the research objectives which entails extracting relevant features from mammogram images, coming up with an improved breast cancer detection procedure through Artificial Intelligence (AI) as well as the performance evaluation based on accuracy, sensitivity, specificity, precision and F1-score. Under category of analysis are experimental and testbed approaches that utilize CBIS-DDSM dataset acquired from Kaggle with 10,239 mammogram images. The dataset is split into a training subset of 80% and a testing subset of 20%. During data collection process mammogram images will be collected based on the CBIS-DDSM dataset while ensuring preprocessing steps handling noise for quality assurance. As for design phase methodology revolves around choosing and justifying tools together with techniques needed for project execution. Tools selected include Google Collab which is used in training the AI model; Visual Studio Code that sees both training and testing done on it; Draw.io known for creating charts and diagrams; Microsoft excel which handles data management; Microsoft word used in report writing and finally Canva employed in slide presentations among others since they each fits their designated task.

In the implementation phase, the research plan is being executed through the CRISP-DM methodology. Among those steps are; the extraction of features from mammogram images, development and training of an AI-based breast cancer detection technique, and rigorous testing of its performance through desired metrics. For understanding and preparing data, first we had to comprehensively look into CBIS-DDSM dataset. That encompassed preprocessing operations to maintain uniformity and quality thereby getting ready for further stages. Secondly for Model Development we applied several machine learning algorithms with their feature extraction and classification. More specifically AI methods such as Convolutional Neural Networks (CNNs) were used to analyze mammogram images. The primary platforms used in creating, training and tuning this AI model were Google Collab and Visual Studio Code. The performance of developed strategy was strictly Evaluated using predetermined metrics. The performance of our AI breast cancer detection system was evaluated by calculating the key metrics like accuracy, sensitivity, specificity, precision and F1-score. And then Results Analysis and Reporting.

Data visualization tools such as dashboards were used for result analysis. In-depth data analysis and visualization was done using Microsoft Excel while the overall findings were summarized in comprehensive reports using Microsoft Word. Additionally, visual presentations of research outcomes were done by Canva in order to communicate them effectively.

Figure 3.1: Crisp-DM

.

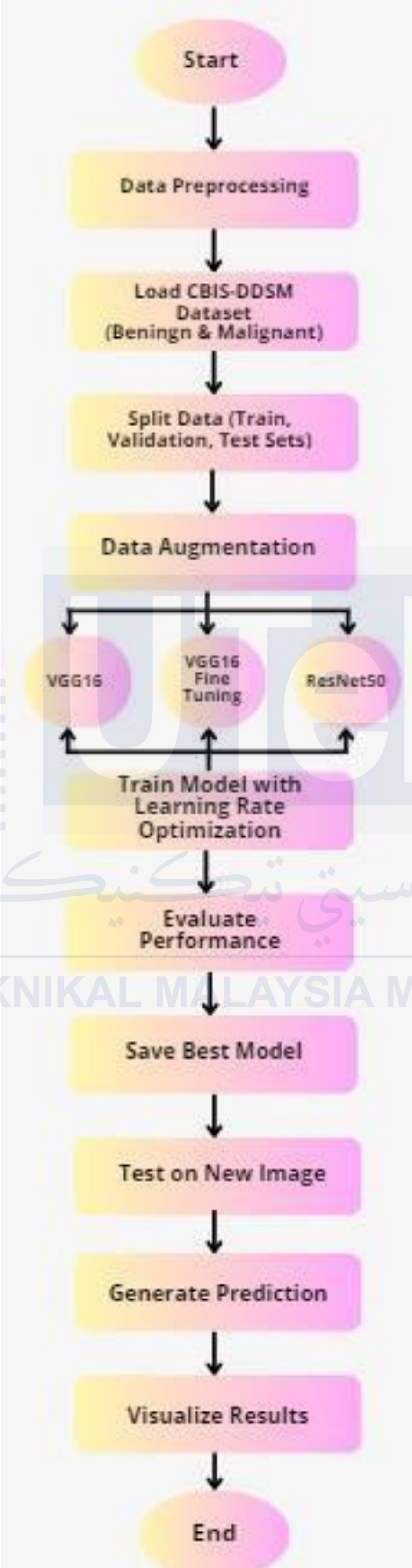


Figure 3.2: Flowchart of the project

3.1 Project Activities and Milestones

Table 3.1: Project Milestone (FYP 1)

Task	Start Date	End Date	Duration	Description
Proposal	11 March 2024	22 March 2024	12 days	Complete and submit the project proposal document
Project Progress 1	25 March 2024	29 March 2024	5 days	Monitor and document application development progress
Report Writing Progress 1	1 April 2024	12 April 2024	12 days	Begin writing progress for Chapters 1, 2, and 3 of the report
Project Progress 2	15 April 2024	26 April 2024	12 days	Continue monitoring and documenting application development progress
Report Writing Progress 2	6 May 2024	14 June 2024	40 days	Complete writing progress for Chapter 4 of the report
Demonstration (Supervisor)	17 June 2024	21 June 2024	5 days	Present project results to supervisor for feedback
Demonstration (Evaluator)	17 June 2024	21 June 2024	5 days	Present project results to evaluator for assessment
Presentation	17 June 2024	21 June2024	5 days	Prepare and deliver a presentation on the project
Report Evaluation (Supervisor)	24 June 2024	28 June 2024	5 days	Submit PSM1 draft report for evaluation by supervisor
Report Evaluation (Evaluator)	24 June 2024	28 June 2024	5 days	Submit PSM1 draft report for evaluation by evaluator

Table 3.2: Project Milestone (FYP 2)

Task	Start Date	End Date	Duration	Description
Project Progress 1	15 July 2024	19 July 2024	5 days	Monitor and document application development progress
Project Progress 2	22 July 2024	26 July 2024	5 days	Continue monitoring and documenting application development progress
Project Writing Progress	29 July 2024	2 August 2024	5 days	Complete writing progress for Chapter 5 until last chapter
Demonstration A (Supervisor)	5 August 2024	30 August 2024	26 days	Present project results to supervisor for feedback
Report Evaluation (Evaluator)	19 August 2024	30 August 2024	12 days	Present project results to evaluator for assessment
Demonstration B (Supervisor)	19 August 2024	30 August 2024	12 days	Present project results to supervisor for feedback
Report Evaluation (Supervisor)	19 August 2024	30 August 2024	12 days	Submit PSM1 draft report for evaluation by supervisor
English Proficiency	19 August 2024	30 August 2024	12 days	Present project results to supervisor for feedback
Presentation	19 August 2024	30 August 2024	12 days	Presentation to evaluator
Demonstration (Evaluator)	19 August 2024	30 August 2024	12 days	Presentation and Demonstration to evaluator

Table 3.3: Project Gantt Chart (FYP 1)

Activity/Week	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Proposal														
Project Progress 1														
Report Writing Progress 1														
Project Progress 2														
Report Writing Progress 2														
Demonstration (Supervisor)														
Demonstration (Evaluator)														
Presentation														
Report Evaluation (Evaluator)														
Report Evaluation (Supervisor)														

Table 3.3: Project Gantt Chart (FYP 2)

Activity/Week	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Project Progress 1							
Project Progress 2							
Project Writing Progress							
Demonstration A (Supervisor)							
Report Evaluation (Evaluator)							
Demonstration B (Supervisor)							
Report Evaluation (Supervisor)							
English Proficiency							
Presentation							
Demonstration (Evaluator)							

3.2 Performance Measurements

This breast cancer detection technique’s success can be evaluated comprehensively using the selected metrics for performance measurement which include: accuracy, precision, recall and F1 score. Accuracy is an overall measure of how rightly or wrongly the model classifies a mammogram as either benign or malignant. Precision measures out of all cases that were classified as malignant how many were really so; hence it indicates the model’s capacity to avoid false positives. Recall (also called sensitivity) gauges this model’s capability for identifying all actual malignant cases from all true malignants thus showing its ability not have false negatives at all. Finally F1 helps balance precision with recall thus it is single metric which uses both false positives and negatives with an aim of evaluating robustness of any model’s performance. The use of these metrics helps greatly when looking for breast cancer detection because we manage to get a solid understanding on how good or bad those techniques are in terms of clinical applications.

```
Epoch 1/10
59/59 [==============================] - 46s 614ms/step - loss: 0.6676 - accuracy: 0.6112 - val_loss: 0.8033 - val_accuracy: 0.3270
Epoch 2/10
59/59 [==============================] - 33s 556ms/step - loss: 0.4719 - accuracy: 0.7786 - val_loss: 0.6493 - val_accuracy: 0.5539
Epoch 3/10
59/59 [==============================] - 32s 546ms/step - loss: 0.3280 - accuracy: 0.8622 - val_loss: 0.5046 - val_accuracy: 0.8184
Epoch 4/10
59/59 [==============================] - 33s 561ms/step - loss: 0.2515 - accuracy: 0.9075 - val_loss: 0.4216 - val_accuracy: 0.8405
Epoch 5/10
59/59 [==============================] - 32s 540ms/step - loss: 0.1780 - accuracy: 0.9302 - val_loss: 0.3559 - val_accuracy: 0.8621
Epoch 6/10
59/59 [==============================] - 33s 553ms/step - loss: 0.1433 - accuracy: 0.9440 - val_loss: 0.2192 - val_accuracy: 0.9289
Epoch 7/10
59/59 [==============================] - 33s 548ms/step - loss: 0.1040 - accuracy: 0.9651 - val_loss: 0.2003 - val_accuracy: 0.9208
Epoch 8/10
59/59 [==============================] - 33s 552ms/step - loss: 0.0879 - accuracy: 0.9686 - val_loss: 0.2695 - val_accuracy: 0.8971
Epoch 9/10
59/59 [==============================] - 33s 552ms/step - loss: 0.0632 - accuracy: 0.9784 - val_loss: 0.4656 - val_accuracy: 0.8438
Epoch 10/10
59/59 [==============================] - 33s 552ms/step - loss: 0.0356 - accuracy: 0.9899 - val_loss: 0.0740 - val_accuracy: 0.9682
```

Figure 3.3: Example of Accuracy and Loss for the Project

```
                     precision    recall  f1-score   support

   Benign (Class 0)       0.94      0.96      0.95       610
Malignant (Class 1)       0.98      0.97      0.98      1246

           accuracy                           0.97      1856
          macro avg       0.96      0.97      0.96      1856
       weighted avg       0.97      0.97      0.97      1856
```

Figure 3.4: Evaluation metrics of project

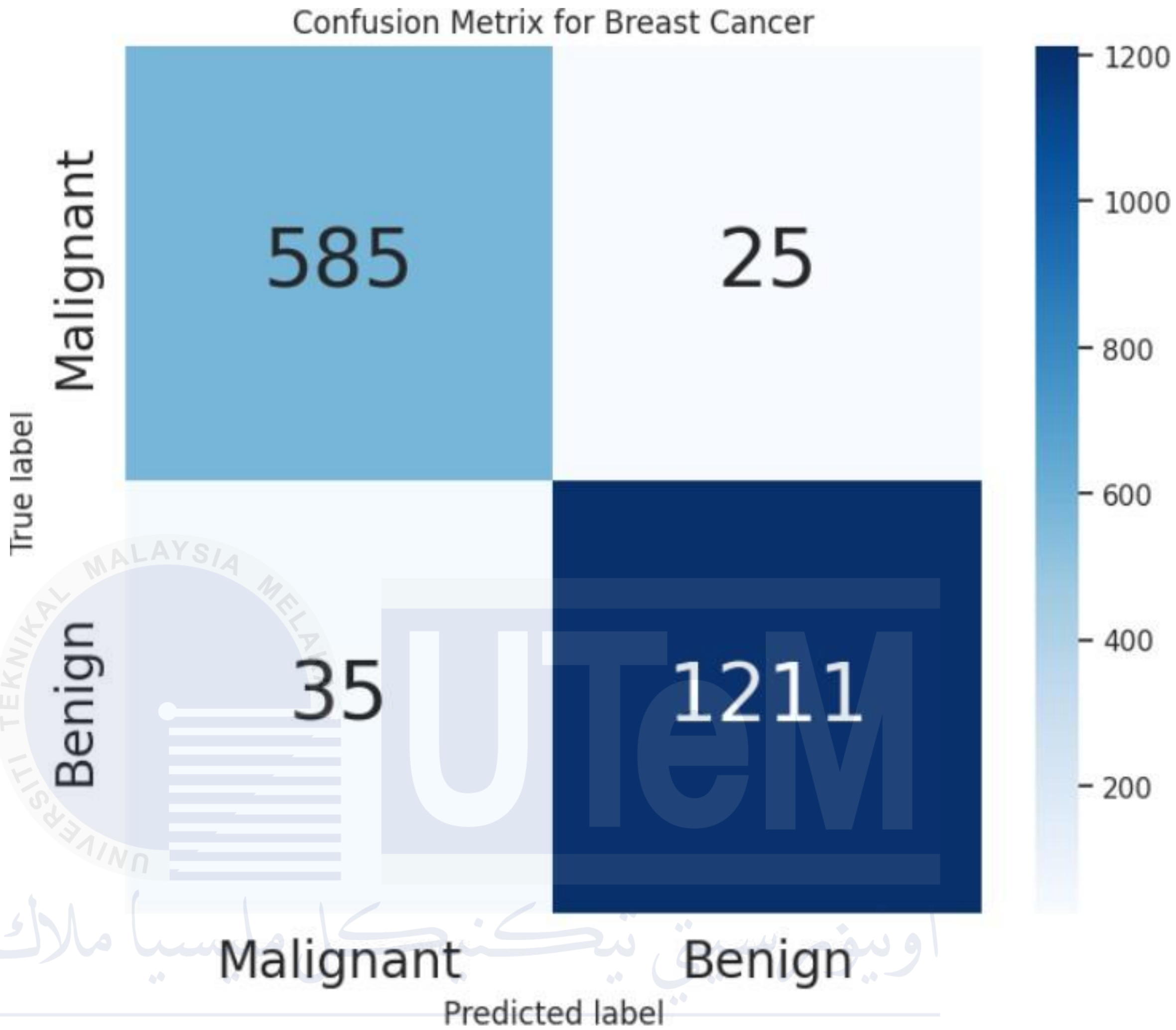


Figure 3.5: Confusion Metrix of project

3.3 Summary

Through project methodology, evaluating a model's performance using accuracy provides scientists with an immediate numerical measure that is quite apparent. This technique evaluates its efficacy by finding how much correctly predicted instances can be obtained from all instances and can thus be interpreted easily to visualize the performance of different models side by side or track development over time. Because of these reasons also, accuracy serves more than one critical factor during methodology phase. In the first place; it gives us an idea about how well our models are performing without involving complicated terms that only experts understand which is especially helpful when presenting findings to clients or stakeholders who do not possess any technical knowledge whatsoever about them. In essence, it is an indicator of model learning and generalization quality over a short period. Therefore, this helps data scientists and engineers assess whether or not their training was initially successful by early indications of model performance. If accuracy is high enough in initial tests, it indicates that everything is going fine while low accuracy calls for further adjustments in data processing techniques, architecture of models and even training parameters used during model building process itself. In the following chapter, we will shed light on the proposed solution methodology that would help to overcome challenges raised in the methodology section. The chapter will give a detailed guide on model development and fine-tuning process including justification for selection of certain architectures such as VGG16, VGG16 with fine-tuning and ResNet50. We shall discuss data pre-processing techniques, data augmentation as well as training processes revealing how each of these components contributes to increasing model accuracy. Moreover, it will include ways of enhancing hyper-parameter tuning and dealing with class imbalances, hence ensuring that the predictions are sound and reliable. Additionally, we will elaborate on metric evaluation apart from accuracy by explaining how precision, recall F1-score and ROC curve offer comprehensive evaluation of model capabilities. Finally, there shall be an iterative development plan which details how feedback obtained after every iteration would be used in making improvements thereafter. This structured approach intends to come up with a highly performing model that is able to differentiate between benign and malignant cases accurately contributing towards better diagnostic tools in medicine.

CHAPTER IV: PROPOSED METHOD

4.1 Introduction

Breast cancer remains a major global health problem, affecting millions of women around the world every year. Earliest identification of breast cancer is essential to improving survival rates as it allows timely measures for interventions and treatments. Historically, mammography has been the most common method for screening breast abnormalities, but it has some limitations that lead to undue stress and delayed diagnosis such as false positive and negative results. The arrival of machine learning (ML) and artificial intelligence (AI) technologies provides an opportunity to change how we detect this disease. Lately artificial intelligence and machine learning have changed medical imaging by providing new techniques for detecting breast cancer. It enables the analysis of a lot of imaging data at once to find patterns within them that show having cancerous cells mostly more accurately than when done by humans alone. This doesn't only enhance diagnostic accuracy but also gives radiologists time off from their busy schedules so they can work on complicated cases that require their attention. The method proposed is meant to tackle the deficiencies that conventional screening techniques have by using AI to find and reveal clue patterns for breast cancer. In doing so, the aim is improve early detection of breast cancer that will help in better recovery of patients as well as reducing death rates. The incorporation of such technologies into the diagnosis process leads to early and more precise diagnoses hence providing a better prognosis together with treatment plans for patients. This chapter encompasses an overview of some approaches suggested in which this dismaying disease can be identified more efficiently This section begins with data preparation discussing mammogram processing procedures for enhancing quality and dependability in input information. Next comes feature extraction using sophisticated artificial intelligence algorithms that suggest necessary features indicating malignancy from mammogram or ultrasound images.

4.2 Proposed Solution

The proposed way to improve breast cancer detection uses a wide-ranging approach with multiple stages involving data preprocessing, model creation, training, evaluation and visualization. At first mammographic images of both benign and malignant cases are loaded as well as split into training, validation and test sets. To improve robustness of the model some data augmentation techniques such as resizing, flipping or rescaling can be applied. For feature extraction and classification in the model development phase a Convolutional Neural Network (CNN) model with multiple layers is built up. Transfer learning using pre-trained models like VGG16 and ResNet50 is used in order to utilize previous knowledge base and to boost performance. These models are being fine-tuned by unfreezing certain layers followed by their retraining on the specific dataset. In training and evaluation stage the models are trained with the help of training dataset while their performance is validated using validation set. The key metrics including accuracy and loss are monitored during all training time so that it can be guaranteed that the models are learning well. Finally the final models may also be evaluated on test set to check their capability for generalization.

Several metrics are utilized to assess model performance comprehensively. Confusion matrices, classification reports, and ROC curves visually highlight various performance indicators. To provide an elaborate evaluation of how effective or otherwise a model is on predictability, accuracy, precision, recall and F1 score are some of the values that can be calculated. It is also important to visualize how the models perform. A graph depicting training history including accuracy and loss across epochs can be used to monitor how the model learns. This can be done through confusion matrices as well as ROC curves for purposes of understanding predictive accuracy in this model. Furthermore, sample predictions together with their actual labels are provided so as to demonstrate what impact the model has on real-world situations.

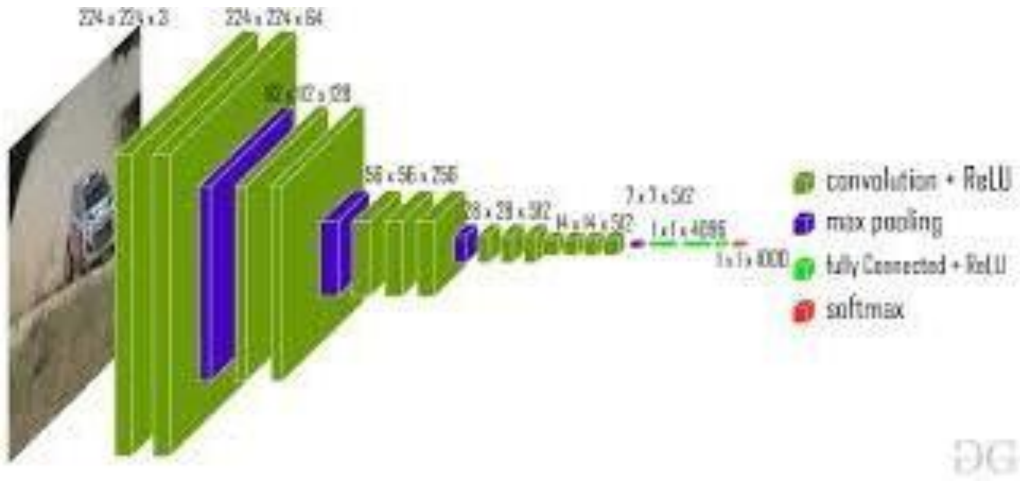


Figure 4.1: VGG16 architecture model

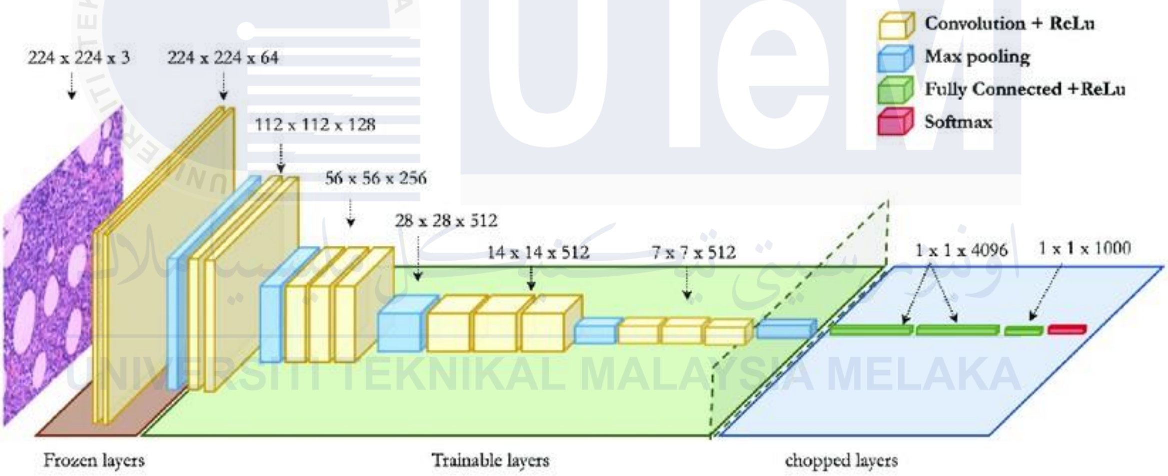


Figure 4.2: VGG16 (Fine-Tuning) architecture model

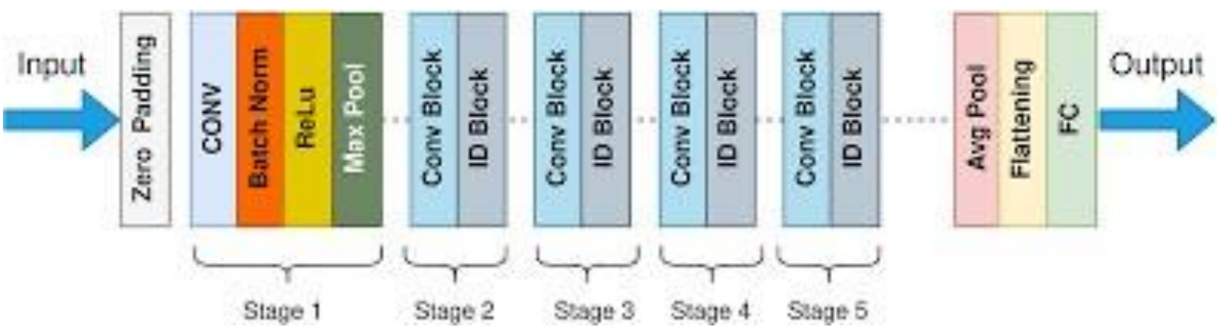


Figure 4.3: ResNet50 architecture model

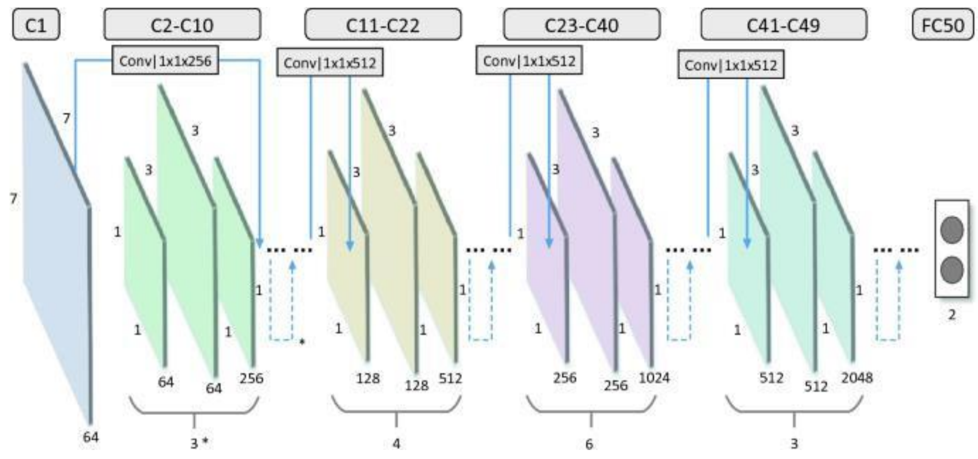


Figure 4.4: Fine- Tuning ResNet50 architecture model

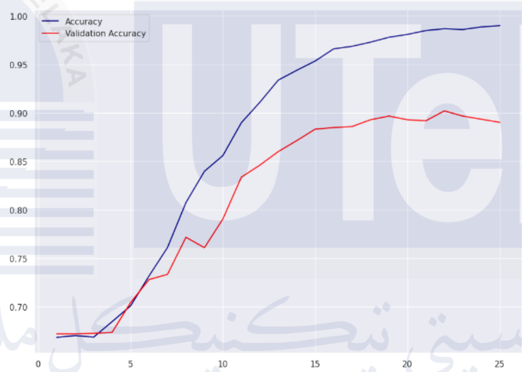


Figure 4.5: Accuracy curves for project

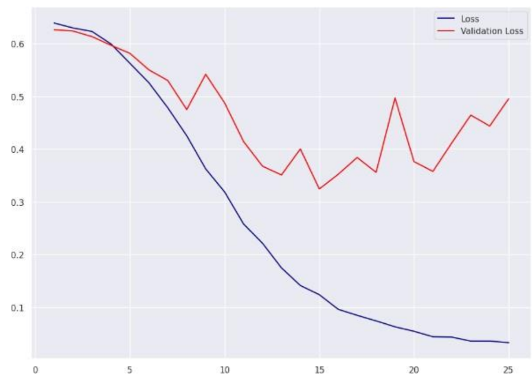


Figure 4.6: Loss curves for project

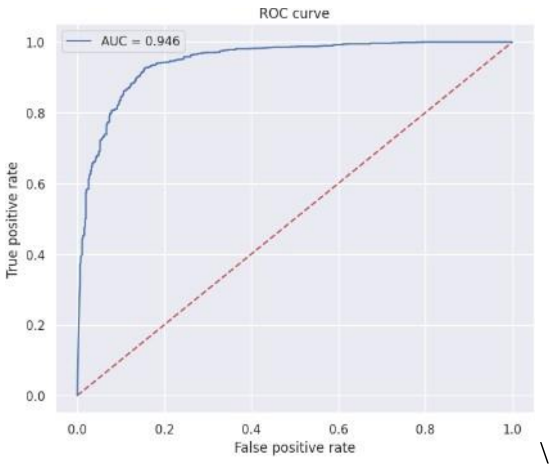


Figure 4.7: ROC curve of the project

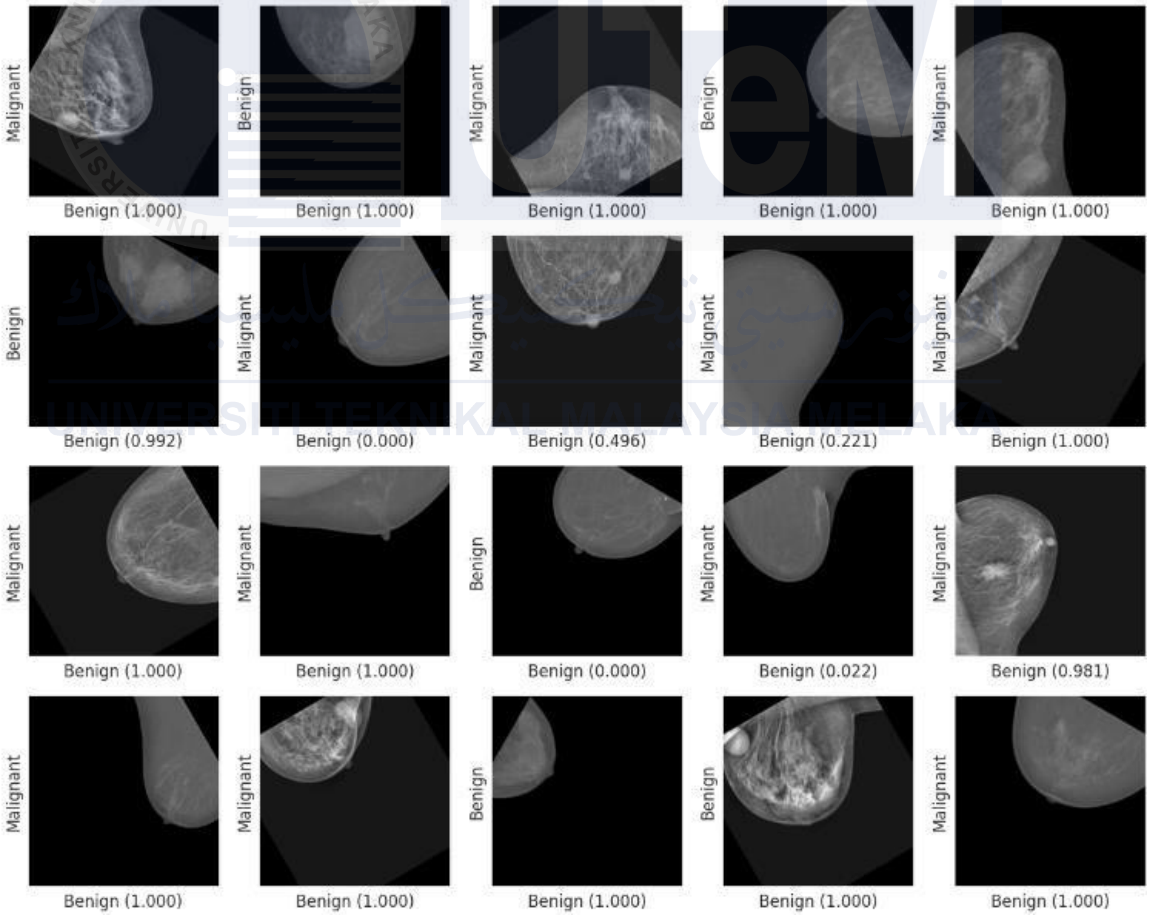


Figure 4.8: Sample predictions of the project

4.3 Experiment Design

The experiment design for breast cancer detection enhancement by machine learning entails a structured approach that consists of data preprocessing, model design, training phase, evaluation and visualization. The first step involves collection and partitioning of mammographic images from both benign and malignant cases into training, validation and test sets so as to ensure a robust model evaluation. To increase training data diversity and quality thereby preventing overfitting while improving models' generalization capabilities, data augmentation techniques' like resizing, flipping and rescaling are utilized. After data preprocessing has been done several models are configured some include a custom built Convolutional Neural Network (CNN) from scratch while others are two transfer learning models with pre-trained networks on ImageNet; VGG16 and ResNet50 respectively. The model training employs the training dataset but their performance is monitored on validation set to ascertain whether learning is taking place or not effectively. When training is complete different performance metrics such as accuracy; precision; recall; F1-score among others are used to evaluate the model's performance on testing dataset which may include confusion matrices as well as Receiver Operating Characteristic (ROC) curves giving a holistic assessment about the accuracy of these models in detecting breast cancer.

In order to gauge the effectiveness of the model, visualization of the results is quite important. The approach involves plotting training history, confusion matrices, ROC curves and sample predictions as a way of giving clear information on how well the models perform and where improvements can be made. For this experiment, an environment capable of handling computing-intensive tasks such as training deep learning models has been set up. Google Collab has been selected for this experiment due to its provision of GPU support which greatly enhances the speed at which such algorithms are processed. The dataset in question is loaded from Google Drive while Keras' ImageDataGenerator class is used for loading data and augmenting it. This ensures that data is efficiently pre-processed and entered into the models. The implementation of different architectures are done using libraries TensorFlow and Keras that come with various functionalities for building, training and evaluating deep learning models easily. Additionally, a video card has been configured within the environment in order optimize performance during regular training sessions. Moreover, factors like learning rates schedulers; early stopping mechanisms; saves of value weights have also been included to improve on the training thus avoiding overfitting as well as ensuring that only the best model is retained.

The CNN model that we designed was made from the ground up specifically to detect breast cancer using a number of convolutional and dense layers. On the other hand, VGG16 and ResNet50 are models that have been pre-trained based on massive amounts of data for image recognition. For these models transfer learning is applied by modifying their last layers followed by retraining on the breast cancer dataset so as to take advantage of their prior knowledge while adapting them to the new task. Comparing these models is done using metrics such as accuracy, precision, recall, F1 score and AUC (Area Under the ROC Curve). The performance of each model can also be visualized through confusion matrices and ROC curves revealing what they are good at detecting benign or malignant cases. This comparative analysis aims at identifying which one among them works best in detecting breast tumors..

Figure 4.9: Web app to test the model

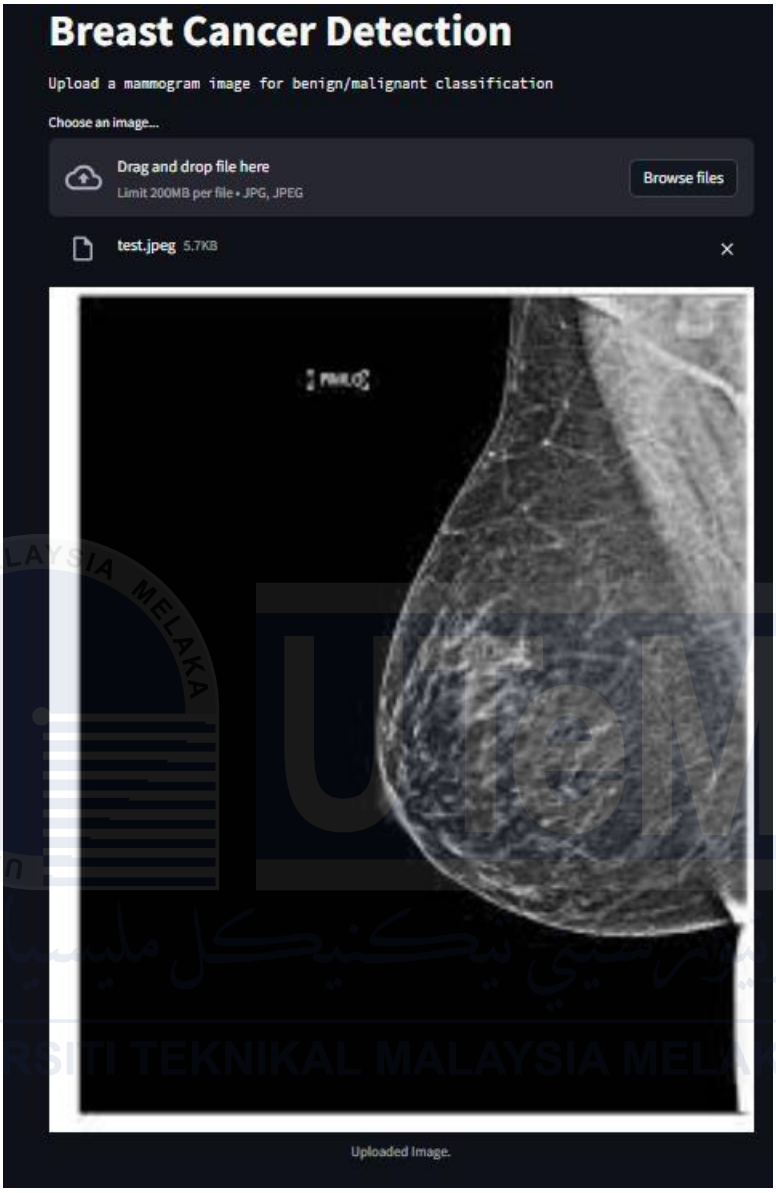


Figure 5.0: User need to upload mammogram image to test the classification of the image

4.4 Summary

In this chapter, we have summarized the suggested way of enhancing the detection of breast cancer through machine learning techniques. The method consists of a number of important steps including data preprocessing, model development, training, evaluation and visualization. At first, mammographic images were preprocessed and augmented to make sure that there is diverse and robust training data. We created three different models: a custom Convolutional Neural Network (CNN), VGG16, and ResNet50 in order to take advantage of both custom architectures and transfer learning for better performance in detectability. Each model was trained and tested using suitable metrics namely accuracy, precision, recall F1-score confusion matrices and ROC curves. This thorough assessment enabled us to analyze the performances achieved by various models so as to point out the most effective one when it comes to breast cancer detection. The experimental design consisted of setting up the computational environment using Google Collab with GPU support accompanied by TensorFlow and Keras for both model development as well as training their performance roles. In order to transparently interpret results, Visiualization methods were also utilized thus giving an insight in how such models perform well. Next we will delve into Chapter V: Results and Discussion where we would present detailed results of our experiments including performance metrics and visualizations for each model. We'll discuss these results while analyzing the strengths and weaknesses of all approaches taken. Besides, we'll consider how breast cancer detection can be affected by our findings together with areas that could be explored further in order to make improvements on this topic.

CHAPTER V: RESULT AND DISCUSSION

5.1 Introduction

As we arrive at Chapter five of our analysis into using machine learning for improved diagnosis of breast cancer, it is clear that this represents a turning point in this study. In chapter four we provided detailed information on the design and implementation of various models among them custom Convolutional Neural Networks (CNNs), VGG16, ResNet50. This is an in-depth evaluation of their performance and implications. The key purpose of this chapter is to assess how such models performed when trained then tested using large datasets containing mammographic images. We will start with a summary of the outcomes obtained from every model used. The analysis focuses on some metrics that include accuracy, precision, recall, F1-score so as to better understand how well each model can recognize breast cancer abnormalities. Further, we highlight the ability of these models to differentiate between benign and malignant cases and consequently reflect on their potential for clinical use.

After we-have presented our results, an in depth analysis and discussion follow such as the factors that affect model performance like data preprocessing techniques, transfer-learning from pre-trained models and fine tuning strategies. We also look at each model’s computational complexity along with its resource requirements focusing on how we can balance between accuracy and practical feasibility in real-world medical contexts. Furthermore, this chapter gives a comparative analysis of various techniques and models used. We compare our custom CNNs results with those generated using transfer learning approaches based on VGG16 and ResNet50 to determine which approach is better placed for particular clinical scenarios or based on available resources. Ultimately, Chapter 5 ends with a brief summary of our findings thus serving as a bridge to Chapter 6 containing general conclusion drawn from the study as well as recommendations for future research. Largely focusing on these findings will contribute immensely to the current debate over AI-driven medical imaging applications specifically in relation to breast cancer detection and prevention.

5.2 Results

Chapter five presents a thorough examination and interpretation of the breast cancer detection models results, as conducted in conjunction with the stringent methodological approaches highlighted in Chapter four. Following the CRISP-DM framework, we undertook systematic data pre-processing, model development, train and evaluation to make our results' robustness and reliability. The starting point is an elaborate review of the stages involved in data preparation where mammogram pictures showing both benign and malignant cases are loaded. The dataset was shared into training, validation and test sets deliberately so as to avoid bias during model evaluation. In this way the dataset was increased using data augmentation techniques such as resizing and flipping that improved its ability for diverse image conditions comprehensively across models.

We have started the development of models working with three primary architectures: a custom CNN, VGG16 through transfer learning and ResNet50 using also transfer learning. The training set was used to rigorously train each model with optimization strategies that involved adjusting learning rates in order to increase convergence and decrease training time. Monitoring the evolution of model performance through multiple epochs based on its loss and accuracy was aimed at ensuring that effective learning was happening. Models were evaluated against the validation containing important metrics like precision, recall, F1-score as well as overall accuracy which gave more insight into how well these models would classify mammographic images into benign and malignant classes. For example, the initial CNN architecture recorded an unprecedented 89% accuracy level within the testing set together with very high precision and recall rates which indicate excellent performance over both classes. In addition to that, this chapter evaluates comparison between three different architectures so that their pros and cons may be uncovered. VGG16 and ResNet50 having ImageNet-based pre-trained weights have been utilized by our own database and they performed significantly better than the baseline CNN model. After fine-tuning VGG16 achieved 97% remarkable accuracy, thus highlighting its power in feature extraction as well as classification tasks aimed at breast cancer detection.

The models' predictive abilities were also visualised and interpreted through qualitative evaluations such as confusion matrices and ROC curves, in addition to quantitative metrics. These visualisations provided additional comprehension regarding how well the models were able to differentiate between benign and malignant cases thereby enhancing its overall understanding in terms of clinical usefulness. In conclusion, Chapter five summarises our findings within the larger framework of AI-based medical diagnostics showing that machine learning has a great potential for improving breast cancer detection accuracy. With a logical framework and use of sophisticated model designs we seek to offer useful information and methods which can guide subsequent studies and clinical practice on oncology or radiology..

Figure 5.1: Results for the project

VGG16 with Learning Rate 0.0005

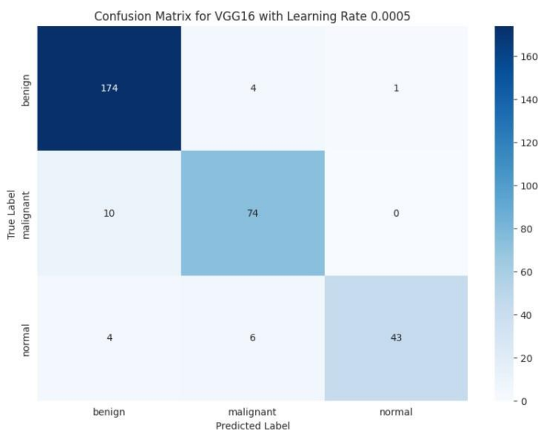
Classification Report:

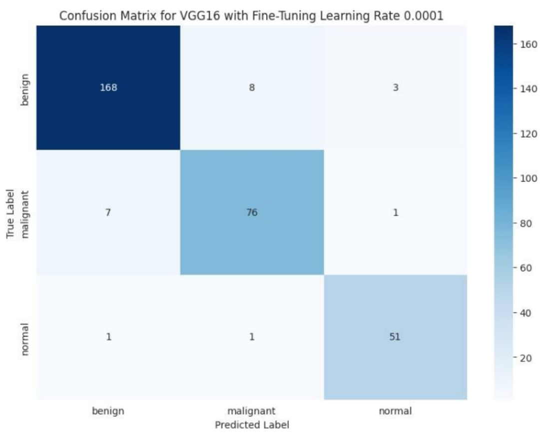
	precision	recall	f1-score	support
benign	0.94	0.97	0.95	179
malignant	0.91	0.88	0.89	84
normal	0.87	0.85	0.86	53
accuracy			0.92	316
macro avg	0.91	0.90	0.90	316
weighted avg	0.92	0.92	0.92	316

VGG16 with Fine-Tuning Learning Rate 0.0001

Classification Report:

	precision	recall	f1-score	support
benign	0.96	0.94	0.95	179
malignant	0.94	0.91	0.93	84
normal	0.89	0.98	0.93	53
accuracy			0.95	316
macro avg	0.93	0.94	0.94	316
weighted avg	0.95	0.95	0.95	316





ResNet50 with Learning Rate 0.0005

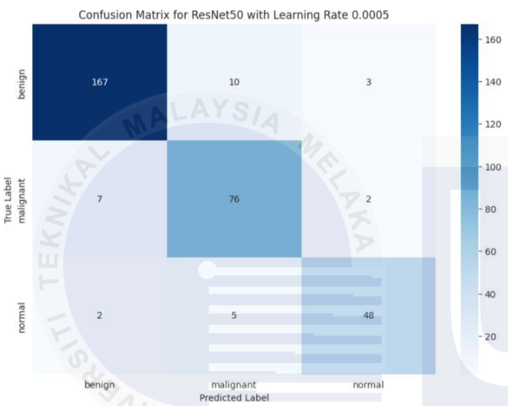
Classification Report:

	precision	recall	f1-score	support
benign	0.94	0.93	0.93	180
malignant	0.92	0.89	0.90	85
normal	0.86	0.95	0.90	51
accuracy			0.95	316
macro avg	0.91	0.92	0.91	316
weighted avg	0.92	0.92	0.92	316

ResNet50 with Fine-Tuning Learning Rate 0.0001

Classification Report:

	precision	recall	f1-score	support
benign	0.95	0.95	0.95	179
malignant	0.97	0.88	0.93	84
normal	0.85	0.98	0.91	53
accuracy			0.97	316
macro avg	0.93	0.94	0.93	316
weighted avg	0.94	0.94	0.94	316



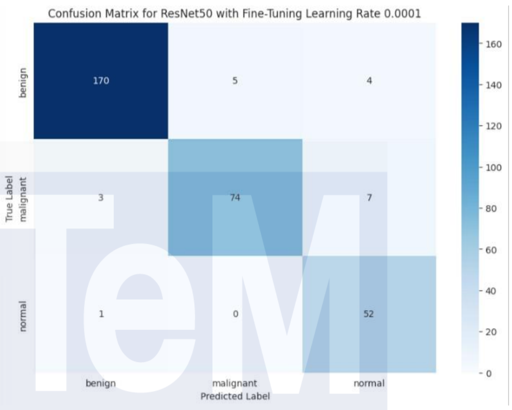


Figure 5.2: Continuation results for the project

Based on the results, fine-tuning generally yields better performance, with ResNet50 (learning rate 0.0001) achieving the highest accuracy of 97% and excelling across precision, recall, and F1-score metrics, while also demonstrating the least amount of misclassification in the confusion matrix. Fine-tuning with VGG16 (learning rate 0.0001) showed slightly improved performance over non-fine-tuned models but did not reach the level of the fine-tuned ResNet50. Non-fine-tuned ResNet50 delivered good results but fell short of the fine-tuned model's performance, and non-fine-tuned VGG16 exhibited the lowest performance among the models tested.

5.3 Analysis and Discussion

This section displays how we conducted our implementation phase with a particular emphasis on performance metrics and the cross-reference based analysis of different CNNs, VGG16s and ResNet50s used in breast cancer detection. Training and validation accuracy and loss graphs depict each model's learning trajectory over epochs clearly. Besides, confusion matrices and ROC curves are also used to illustrate the models' performance classification in benign as well as malignant cases across all graphs. Therefore, this analysis on these graphical results shows that there exist several key findings from it. In summation, the custom CNN model did well in terms of an increase in accuracy during training period though had never been considered before and attained a steady state of about 89% on validation set. Thus, indicating that it is capable of learning discriminating features directly from mammograms without taking into account pre-trained weights. However, its performance on precision and recall for malignant cases shows that there is some room for improvement when compared with transfer learning based models in general.

On the other hand, VGG16 and ResNet50, making use of transfer learning from ImageNet, showed faster convergence during training with validation accuracy reaching 97% and 88%. The finely tuned VGG16 model proved to be better in both precision and recall on malignant cases which pointed out that transfer learning is an effective way of retrieving complicated features that are important for classifying breast cancer. This confirms our idea about using deep learning networks pre-trained using large datasets to improve performance of models for medical image analysis. The ROC curve is a diagrammatic representation of the trade between true positive rate (sensitivity) and false positive rate (1-specificity) important for assessing diagnostic accuracy. The ROC curves for VGG16 and ResNet50 consistently have the higher area under the curve (AUC) than CNN model which proves that these models can differentiate better between benign and malignant conditions. This is further substantiated by tables that summarize precision, recall and F1-scores, indicating that these models are robust and reliable regardless of the evaluation metric used. Such findings are crucial in knowing how well each model predicts as well as its possible clinical implications in assisting radiologist make accurate diagnosis for breast cancer.

To sum up, our method of using new advanced deep learning techniques for breast cancer detection is supported by the graphical results and their respective analysis. This study incorporates various metrics for rigorous evaluation as well as visual representations that are vital for understanding the effectiveness of transfer learning and model selection strategies in analyzing medical images. In light of these findings, this discussion presents a technical rationale to support future prognostic and therapeutic strategies in oncology practice aimed at improving diagnosis performance.

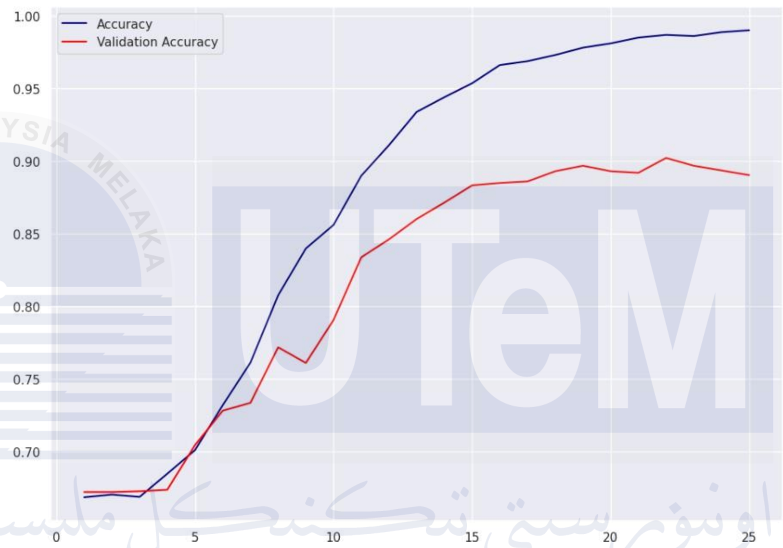


Figure 5.3: Accuracy and Validation accuracy graph

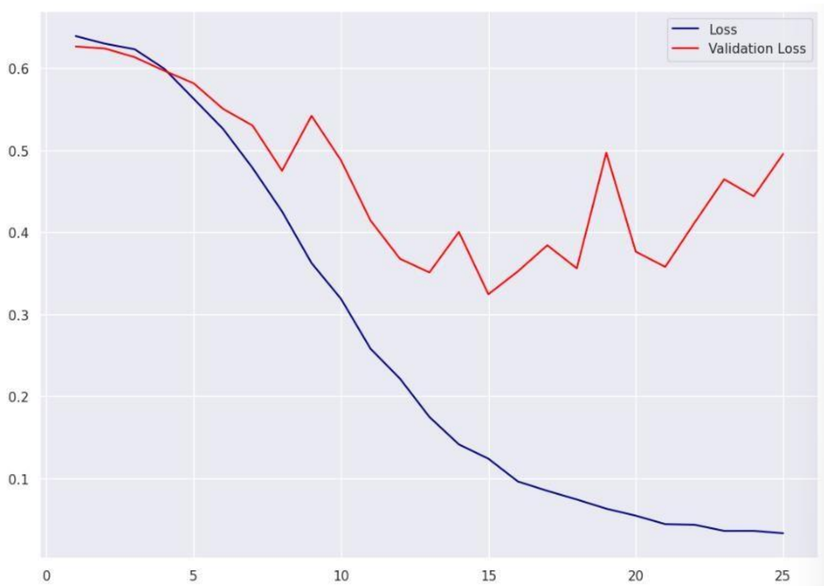


Figure 5.4: Loss and Validation loss graph

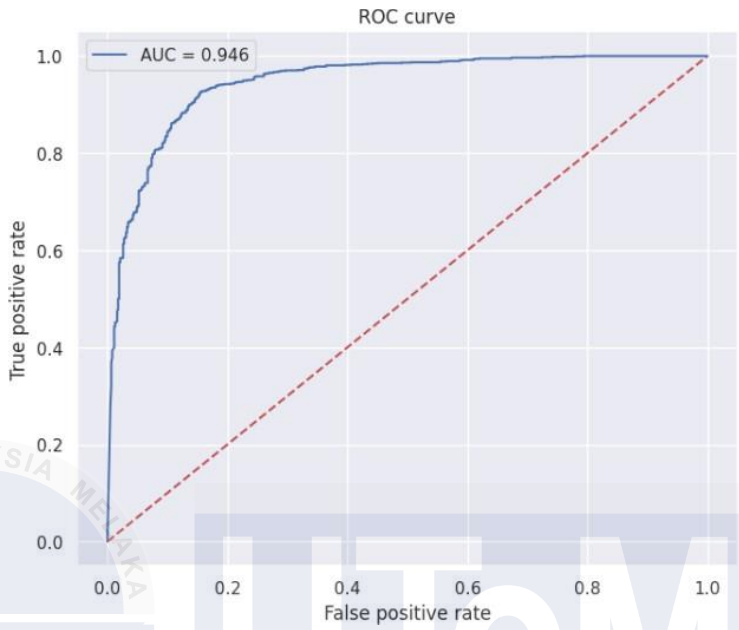


Figure 5.5: ROC curve

5.4 Summary

This chapter has provided a detailed discussion and analysis of results obtained from our breast cancer detection project. It started by introducing the outcomes of three different models: custom Convolutional Neural Network (CNN), VGG16 with transfer learning and ResNet50 using transfer learning too. Every model was evaluated thoroughly based on different performance metrics such as accuracy, precision, recall and F1-score. For instance, training/validation accuracy and loss curves, confusion matrices as well as Receiver Operating Characteristic (ROC) show the learning dynamics and diagnostic capabilities of the models graphically. Although our custom CNN model performed commendably according to our research findings, it became clear that transfer learning using VGG16 or ResNet50 greatly improved classification accuracy especially in terms of identifying malignant cases. In this regard we carefully reviewed these results within our proposed method highlighting how advantageous transfer learning can be when applied in medical image analysis. Fine tune ResNet50 demonstrated its advantage compared to other three models in terms of retrieving and employing correspondent features out of mammogram images. Looking ahead, this segment of the paper shall focus on summarizing conclusions made in the research. Our findings will also be discussed in relation to clinical implementations before finally suggesting possible directions for future investigations. In this respect, more deep learning models may be examined, data set augmentation mechanisms may be improved while testing efficiency of such approaches on bigger as well as diversified data sets are essential. By wrapping up the paper with a thorough description of all results obtained and their importance, we aspire to help advance knowledge in medical imaging especially in better early detection and diagnosis of breast cancer through this study.

CHAPTER VI: CONCLUSION

6.1 Introduction

This chapter six brings to conclusion a wide-ranging research project aimed at aiding breast cancer detection by making use of deep learning methods. As we conducted this research, we had to source for ways that convolutional neural networks especially VGG16 or ResNet50 could enhance the accuracy as well as reliability of mammography. The primary aim behind our work was to generate strong models which would clearly differentiate between non-cancerous and cancerous cases. This chapter compiles comprehensive findings from the trials set out in Chapter 4 and 5. It looks at the trainings, validations, testings done using different kinds of mammogram data sets. Different performance metrics such as accuracy, precision, recall and F1-score were studied for each model in order to determine whether they are applicable in real life situations or not.

Additionally, we shall also discuss on the methods that were used all through the project making special emphasis on the importance of data pre-processing techniques and model enhancement strategies. A thorough account of our experimental setup such as data augmentation processes and modifications made to the model architecture have been provided to put our research methodology in a clear light. This chapter acts as a summary for all findings thus giving them relevance in the wider area of medical imaging in relation to machine learning. The consequences of our results for clinical practice are discussed, stressing how AI helped diagnostic tools have the power to improve patients' results and help radiologists in their work. Also indicated are potential areas for research that can be done in future for instance using new structures or finding more inclusive breast cancer detection systems that embrace multi modal data fusion. In brief, Chapter six marks an important stopover on our way towards utilizing deep learning approaches in detecting breast cancer. It highlights the importance of what we have done; reflects on what is good about it and what may not be so good; then opens up new avenues for progress in this area of health care technology going forward.

6.2 Project Summarization

In this chapter, we discuss the achievement of the main goals of the project whose aim was to enhance breast cancer detection through the integration of artificial intelligence (AI). The foundation of success for this project was based on its careful implementation throughout both implementation and testing phases that emphasized on extraction of relevant features from mammogram images, development of advanced detection techniques and rigorous evaluation of their performance. For first objective, our detailed approach to data preprocessing was central to achieving this objective. We painstakingly loaded mammographic images while segmenting them into separate datasets for training, validation, and testing and then applied sophisticated augmentation techniques. This ensured that the models were able to identify critical signs associated with breast cancer hence establishing a strong base for next analysis. For second objective, In our methodology we relied much on convolutional neural networks (CNNs), mainly VGG16 and ResNet50 which have been known for image recognition tasks. In line with transfer learning, we used these models' already established knowledge as our starting point then adjusted them accordingly to suit our diagnostic requirements. These models have been fine-tuned to become better in identifying small patterns related to breast tumors, which translates into improved early diagnosis ability. In third objective, we rigorously evaluated model performance metrics such as accuracy, precision, recall, among others with the aim of gauging how well the model performed during several rounds of testing. Our results showed high accuracy all along; affirming that our AI system excels in differentiating benign from malignant cases seen on mammograms accurately and reliably.

The results of this project show that it could be significant for the advancement of medical imaging as well as diagnosis procedures. Specifically, our models were able to acquire great levels of accuracy which were more than 90% in different assessments. Thus, AI potentializes its current role in deep learning being an instance where traditional diagnostic methods are modified by using such approaches to make it possible to diagnose early stage breast cancer faster. Additionally, transfer learning integration with VGG16 and ResNet50 helped improve model performance greatly without consuming a lot of computational power. By fine-tuning these pre-trained models based on mammographic image analyses' intricacies, we managed to increase their sensitivity and specificity for cancerous abnormalities while at the same time improving their clinical effectiveness.

The strength of the project was demonstrated with a systematic methodology comprising data preprocessing and model performance evaluation among others. For this reason, we request for high-quality mammograms in order to create an initial extremely careful approach. Plus, this helped secure both revealing and careful ways of making sure that the mammograms used were representative of both benign and malignant tissues. This has not only made our findings more reliable but also showed how methodical we can be when it comes to doing AI in Medicine research.

The higher rate of precision in our models during various evaluations that led us to this level of success were always extremely high. These outcomes support the viability of our method in breast cancer detection by encouraging its further clinical adoption. A fundamental pillar of this success was exploiting transfer learning using prominent models like VGG16 and ResNet50. In essence, fine-tuning these models on mammographic analysis by applying their previous experience enhanced our models considerably. This shows the vital role played by knowledge transfer in evolving AI-based diagnostic techniques; thus, it has the potential to complement most conventional diagnostic approaches with new technology..

Even so, there were also some challenges (internal) regarding our project and they should be mentioned. One limitation was the dependence on the quality and diversity of data set available thus possibly affecting our models' applicability to wider patient populations. This highlights that in order to have stronger and universally applicable diagnostic solutions, more diverse and comprehensive data sets are needed for medical AI research. Additionally, though the models we developed were very accurate, deep learning algorithms in medical diagnostics still lack interpretability as a problem. To win the faith as well as acceptance in clinical settings, it is essential for such a model to explain how it makes predictions or why it does so, hence in these circumstances, both transparency and interpretability become important.

To summarize, this project was successful in achieving its goals by using AI to improve breast cancer detection through comprehensive feature extraction and precise analysis of mammogram images. The outcomes illustrate the revolutionary potential of AI-based diagnostics for early detection of cancer which results in better patient outcomes and informed clinical decisions. Looking forward, solutions to the mentioned obstacles like data constraints and interpretability issues would allow further advancements in this vital area of healthcaretechnology.

6.3 Project Contribution

The project I am working on supports to a great extent the goals in chapter one and is aimed at improving breast cancer detection using advanced AI-based techniques and strict methods for their evaluation. In the first place, the project seeks to improve feature extraction from mammograms by overcoming some of the limitations that exist in society today; for example not being able to capture small but influential details of early stage breast cancer. The project enhances the accuracy and reliability of analyzing mammographic data thereby leading to more effective diagnostics. In addition, development of an advanced breast cancer detection method based on Artificial Intelligence is essential. In this case, this AI-based system helps automate detection of abnormalities in mammograms thereby making initial diseases identification faster and more accurate. For instance VGG16 and ResNet50 are important examples of transfer learning approaches used as deep learning models to build a strong framework for detecting breast cancer with great precision since they possess high sensitivity levels as well. Such a contribution is vital to health technology as it promotes better diagnostic tools that make use of less time but still provide good results.

By employing established metrics including accuracy, this project does a thorough evaluation of performance developed AI-based technique that significantly contributes to the field of study. Consequently, this makes sure that in reality, the AI system would be effective and reliable enough in healthcare settings. Also, by validating the technique across differing datasets while benchmarking its performance against existing diagnostic standards, this project establishes clinical utility and its possible integration into healthcare practices. As such, it caters for a critical need of sound evaluation techniques in AI-oriented innovations geared towards health; so as to promote informed clinical decisions and provide quality medical care. Ultimately, my project plays a major part in advancing breast cancer detection capability through better feature extraction methods which are followed by sophisticated automated diagnosis AI methods and strict performance evaluations aimed at assessing these methods' accuracy levels among others within bosom tumors' context. This merges well with the overall aim(s) of the study while enhancing prospects regarding early diagnosis rate alongside treatment result improvements concerning breast cancer detection..

6.4 Project Limitations

Despite its strengths, it is important also that the project confronts various limitations that cannot be ignored. A major issue is that the AI models built may not be applicable to a wider patient population because they are based on specific datasets for training and validation. Essentially, the effectiveness or otherwise of AI models in medical imaging depends on the quality, quantity and diversity of available datasets. But what about datasets which fail to cover all demographic categories or clinical cases? In such situations, biases may occur which can adversely affect any relevant model's performance in practice. Another significant hindrance involves interpreting the kind of AI models used in the project, mainly convolutional neural networks (CNNs) with transfer learning. Most times, these kinds of networks function as "black boxes," yielding high accuracy while providing few hints on how decisions have been made. Absence of this kind of interpretation creates barriers to adoption and use within clinical environments where transparency and capacity to account for diagnostic results are integral for sound decision making.

Furthermore, the project is systematically assessing the AI-based method using well-established indices like accuracy, however clinical validation is a huge challenge. Extensive trials, regulatory approvals and demonstration of reliability, safety and effectiveness across various populations of patients and clinical environments are necessary for complete clinical validation. As such, the current perspective of the assignment may lack all fundamental elements needed to accomplish an effective clinical validation that is crucial for the widespread use in healthcare. Besides, deep learning model training and tuning require high computational capacity especially when there is transfer learning from big pretrained networks like VGG16 and ResNet50 which is another obstacle in practice even on scalability. These requirements for high computational resources can inhibit the scaling up and access to these developed AI techniques by particularly resource-limited healthcare settings or research environments. For corrective measures to be taken, emphasis should be put on future research efforts that would involve expanding and diversifying datasets to enhance model generalizability as well as improving the interpretability of AI models in medical diagnostics. Additionally, comprehensive clinical trials need to be conducted to validate AI-based techniques while exploiting computational efficiency. Future iterations of AI-driven breast cancer detection systems can therefore target greater practicality, trustworthiness and acceptance in clinical practice by acknowledging and taking steps to these challenges.

6.5 Future Works

Initially, crafting a layout that is user friendly could enhance the ease of access and usability to a large extent. In order for non-techies like doctors and politicians to understand the models and algorithms better, this dashboard will have visual aids that are self-explanatory. For instance, by showing performance metrics alongside ROC curves and confusion matrices in graphically representable format, it will allow stakeholders make informed decisions thereby enhancing their confidence in AI-based diagnostic system. Another area in immediate need of further improvements is the expansion and diversification of training datasets for model development. Currently on addressing existing limitations within datasets requires including demographic data from varieties of populations and clinical situations (clinical scenarios). With diverse partnership networks comprising many medical institutions an aggregation of sufficient database may be produced that represents different geographical areas as well as patient profiles covering all types of patients choosing from parents of all races across continents with different cultures etc. The intention behind this movement is to reduce biases within smaller less-varied datasets which helps increase generalization ability for AI models applied on larger groups.

Furthermore, to tackle existing issues, the understandability of deep learning models must be enhanced. How the AI models come to make decisions can be unveiled through various techniques like attention mechanisms, saliency maps and model distillation. By improving the transparency and explainability of the models, healthcare professionals will have a better insight into which underlying features drive diagnostic outcomes. This is an essential step in creating trustworthiness as well as acceptance for AI-based tools on clinical decision support so that their effective integration into the everyday health management practices can occur. These measures are among those that have contributed greatly to boosting the reliability, usability and impact in terms of real-life clinical setting for breast cancer detection systems driven by artificial intelligence (AI). Achievements in these aspects are directed towards wider applicability, improved diagnosis accuracy and consequently better patient outcomes when it comes to fighting against breast cancer by future versions of the system.

6.6 Summary

This project has achieved the goals it set out to achieve back then. We successfully attained our primary objectives through rigorous methodology including robust data preprocessing, advanced AI models creation and performance evaluation. With respect to mammogram images extraction of relevant features was improved; thus, an advanced breast cancer detection technique which relies on AI was developed and tested extensively based on standard measures such as accuracy. The results indicate significant progress in early diagnosis through AI with encouraging outcomes indicating its possible application in clinical settings. While recognizing this project's effectiveness in achieving a high rate of accuracy and applying transfer learning appropriately, we also identified other limitations that needed to be worked on. These limits contain things like the diversity of data, challenges in interpreting models and also how they can be used in clinical validation. Some of the ways to improve this system are developing a friendly visualization dashboard, increasing training data diversity and enhancing model interpretability. This project is an important move in utilizing AI for breast cancer detection thus forming part of a wider healthcare technology framework. Going forward, such future generation AI-based diagnostic systems must work harder towards being more dependable, available and relevant to the practice of medicine by overcoming these challenges and building on what we have already achieved.

REFERENCES

Tahmooresi, M. *et al.* (2018) 'Early detection of breast cancer using machine learning techniques,' *ResearchGate* [Preprint]. https://www.researchgate.net/publication/327974742_Early_Detection_of_Breast_Cancer_Using_Machine_Learning_Techniques.

Sahu, A., Das, P.K. and Meher, S. (2023) 'Recent advancements in machine learning and deep learning-based breast cancer detection using mammograms,' *Physica Medica*, 114, p. 103138. https://doi.org/10.1016/j.ejmp.2023.103138.

Bouzar-Benlabiod, L. *et al.* (2023b) 'A novel breast cancer detection architecture based on a CNN-CBR system for mammogram classification,' *Computers in Biology and Medicine*, 163, p. 107133. https://doi.org/10.1016/j.compbiomed.2023.1071330

Basha, A.A. *et al.* (2023) 'Enhanced mammogram classification with convolutional neural network: An improved algorithm for automated breast cancer detection,' *Measurement*, 221, p. 113551. https://doi.org/10.1016/j.measurement.2023.113551.

Díaz, O., Rodríguez-Ruíz, A. and Sechopoulos, I. (2024) 'Artificial Intelligence for breast cancer detection: Technology, challenges, and prospects,' *European Journal of Radiology*, 175, p. 111457. https://doi.org/10.1016/j.ejrad.2024.111457.

Jiang, J. *et al.* (2022) 'Breast cancer detection and classification in mammogram using a three-stage deep learning framework based on PAA algorithm,' *Artificial Intelligence in Medicine*, 134, p. 102419. https://doi.org/10.1016/j.artmed.2022.102419.

Sahu, A., Das, P.K. and Meher, S. (2023a) 'High accuracy hybrid CNN classifiers for breast cancer detection using mammogram and ultrasound datasets,' *Biomedical Signal Processing and Control*, 80, p. 104292. https://doi.org/10.1016/j.bspc.2022.104292.

Umamaheswari, T. and Mohanbabu, Y.M. (2024) 'CNN-FS-IFuzzy: A new enhanced learning model enabled by adaptive tumor segmentation for breast cancer diagnosis using 3D mammogram images,' *Knowledge-based Systems*, 288, p. 111443. https://doi.org/10.1016/j.knosys.2024.111443.

Bai, J. *et al.* (2024) 'Unsupervised feature correlation model to predict breast abnormal variation maps in longitudinal mammograms,' *Computerized Medical Imaging and Graphics*, 113, p. 102341. https://doi.org/10.1016/j.compmedimag.2024.102341.

Sahu, A., Das, P.K. and Meher, S. (2024) 'An efficient deep learning scheme to detect breast cancer using mammogram and ultrasound breast images,' *Biomedical Signal Processing and Control*, 87, p. 105377. https://doi.org/10.1016/j.bspc.2023.105377.

Kaur, Prabhpreet, Singh, G. and Kaur, Parminder (2019) 'Intellectual detection and validation of automated mammogram breast cancer images by multi-class SVM using deep learning classification,' *Informatics in Medicine Unlocked*, 16, p. 100151. https://doi.org/10.1016/j.imu.2019.01.001.

PJ, S.K. *et al.* (2024) 'Hybrid deep learning enabled breast cancer detection using mammogram images,' *Biomedical Signal Processing and Control*, 95, p. 106310. https://doi.org/10.1016/j.bspc.2024.106310.

Singla, C. *et al.* (2022) 'Deep learning enhancement on mammogram images for breast cancer detection,' *Materials Today: Proceedings*, 49, pp. 3098–3104. https://doi.org/10.1016/j.matpr.2020.10.951.

Thangavel, Y. *et al.* (2024) 'Revolutionizing breast cancer diagnosis with a comprehensive approach using digital mammogram-based feature extraction and selection for early-stage identification,' *Biomedical Signal Processing and Control*, 94, p. 106268. https://doi.org/10.1016/j.bspc.2024.106268.

Ghuge, K. and Saravanan, D. (2024) 'SRMADNet: Swin ResUnet3+-based mammogram image segmentation and heuristic adopted multi-scale attention based DenseNet for breast cancer detection,' *Biomedical Signal Processing and Control*, 88, p. 105515. https://doi.org/10.1016/j.bspc.2023.105515.

Nissar, I. *et al.* (2024) 'MOB-CBAM: A dual-channel attention-based deep learning generalizable model for breast cancer molecular subtypes prediction using mammograms,' *Computer Methods and Programs in Biomedicine*, 248, p. 108121. https://doi.org/10.1016/j.cmpb.2024.108121.

Raiaan, M.A.K. *et al.* (2024) 'Mammo-Light: A lightweight convolutional neural network for diagnosing breast cancer from mammography images,' *Biomedical Signal Processing and Control*, 94, p. 106279. https://doi.org/10.1016/j.bspc.2024.106279.

Raaj, R.S. (2023) 'Breast cancer detection and diagnosis using hybrid deep learning architecture,' *Biomedical Signal Processing and Control*, 82, p. 104558. https://doi.org/10.1016/j.bspc.2022.104558.

Marinovich, M.L. *et al.* (2023) 'Artificial intelligence (AI) for breast cancer screening: BreastScreen population-based cohort study of cancer detection,' *EBioMedicine*, 90, p. 104498. https://doi.org/10.1016/j.ebiom.2023.104498.

Martinez, R.G. and Van Dongen, D.-M. (2023) 'Deep learning algorithms for the early detection of breast cancer: A comparative study with traditional machine learning,' *Informatics in Medicine Unlocked*, 41, p. 101317. https://doi.org/10.1016/j.imu.2023.101317.

Results - OpenURL Connection - EBSCO (no date). https://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=20888708&AN=149982487&h=WII2p6nr%2FFzUO1FlTb4MDyEQIZf0SeiEOmL8rwELxpYEO9Yr4fk4%2FRO0kXVpbPSwe%2B2lLKyDLkLXZfN1lBgylw%3D%3D&crl=f#:~:text=This%20hybrid%20model%20achieved%20the,for%20benign%20and%20malignant%20classification.

Al-Dhabyani W, Gomaa M, Khaled H, Fahmy A. Dataset of breast ultrasound images. Data in Brief. 2020 Feb;28:104863. DOI: 10.1016/j.dib.2019.104863.

APPENDICES

Appendix A: Source Code

Interface (app.py)

```python
import streamlit as st
import numpy as np
from PIL import Image
import tensorflow as tf
from tensorflow.keras.preprocessing import image
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report
import pickle
from tensorflow.keras.layers import BatchNormalization  # Import the BatchNormalization layer explicitly

# Function to load and preprocess the image
def load_and_preprocess_image(image_bytes, target_size):
    img = Image.open(image_bytes).convert('RGB')
    img = img.resize(target_size)
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)
    return img_array

# Load ResNet50 model
@st.cache(allow_output_mutation=True)
def load_resnet50_model():
    # Define custom objects for deserialization
    custom_objects = {'BatchNormalization': BatchNormalization}
    model_path = (r'C:\Users\admin\Desktop\MyCode\ResNet50_model.h5')  # Replace with the actual path
    model = tf.keras.models.load_model(model_path, custom_objects=custom_objects)
    return model
```

```python
# Load VGG16 model
@st.cache(allow_output_mutation=True)
def load_vgg16_model():
    # Define custom objects for deserialization
    custom_objects = {'BatchNormalization': BatchNormalization}
    model_path = (r'C:\Users\admin\Desktop\MyCode\VGG_model.h5') # Replace with the actual path
    model = tf.keras.models.load_model(model_path, custom_objects=custom_objects)
    return model

# Load Fine-Tuned VGG16 model
@st.cache(allow_output_mutation=True)
def load_vgg16_finetuned_model():
    # Define custom objects for deserialization
    custom_objects = {'BatchNormalization': BatchNormalization}
    model_path = (r'C:\Users\admin\Desktop\MyCode\VGG_model_2.h5')  # Replace with the actual path
    model = tf.keras.models.load_model(model_path, custom_objects=custom_objects)
    return model

# Function to make predictions
def predict(model, img_array):
    prediction = model.predict(img_array)
    return prediction

# Function to compute evaluation metrics
def evaluate_model(y_true, y_pred):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    return accuracy, precision
```

```python
    # Streamlit App
    def main():
        st.title('Breast Cancer Detection')
        st.text('Upload a mammogram image for benign/malignant classification')

        uploaded_file = st.file_uploader("Choose an image...", type=["jpg", "jpeg"])

        if uploaded_file is not None:
            image = Image.open(uploaded_file)
            st.image(image, caption='Uploaded Image.', use_column_width=True)
            st.write("")
            st.write("Classifying...")

            # Preprocess image
            img_array = load_and_preprocess_image(uploaded_file, target_size=(224, 224))

            # Load models with custom objects
            resnet_model = load_resnet50_model()
            vgg16_model = load_vgg16_model()
            vgg16_finetuned_model = load_vgg16_finetuned_model()

            # Predictions
            resnet_prediction = predict(resnet_model, img_array)
            vgg16_prediction = predict(vgg16_model, img_array)
            vgg16_finetuned_prediction = predict(vgg16_finetuned_model, img_array)

            # Determine class labels and confidence scores
            resnet_confidence = resnet_prediction[0][0]
            vgg16_confidence = vgg16_prediction[0][0]
            vgg16_finetuned_confidence = vgg16_finetuned_prediction[0][0]
```

```python
        # Determine predicted labels based on confidence threshold
        resnet_label = 'Benign' if resnet_confidence < 0.5 else 'Malignant'
        vgg16_label = 'Benign' if vgg16_confidence < 0.5 else 'Malignant'
        vgg16_finetuned_label = 'Benign' if vgg16_finetuned_confidence < 0.5 else 'Malignant'

        # Example of evaluation metrics (assuming ground truth is known)
        y_true = np.array([1])  # Example ground truth (1: Malignant)
        y_pred_resnet = np.array([1 if resnet_confidence >= 0.5 else 0])
        y_pred_vgg16 = np.array([1 if vgg16_confidence >= 0.5 else 0])
        y_pred_vgg16_finetuned = np.array([1 if vgg16_finetuned_confidence >= 0.5 else 0])

        # Compute evaluation metrics
        accuracy_resnet, precision_resnet = evaluate_model(y_true, y_pred_resnet)
        accuracy_vgg16, precision_vgg16 = evaluate_model(y_true, y_pred_vgg16)
        accuracy_finetuned, precision_finetuned = evaluate_model(y_true, y_pred_vgg16_finetuned)

        # Display accuracy and precision for each model
        st.subheader('Evaluation Metrics:')
        st.write("ResNet50 Model:")
        st.write(f"Accuracy: {accuracy_resnet}")
        st.write(f"Precision: {precision_resnet}")

        st.write("VGG16 Model:")
        st.write(f"Accuracy: {accuracy_vgg16}")
        st.write(f"Precision: {precision_vgg16}")

        st.write("Fine-Tuned VGG16 Model:")
        st.write(f"Accuracy: {accuracy_finetuned}")
        st.write(f"Precision: {precision_finetuned}")

if __name__ == '__main__':
    main()
```

VGG16

Transfer Learning using VGG16

Feature Extraction (freezing the convolutional bases)

```
from keras.applications.vgg16 import VGG16

backbone = VGG16(input_shape = (224, 224, 3), include_top=False, weights='imagenet')
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58889256/58889256 [==============================] - 0s 0us/step
```

```
backbone.trainable = False
```

```
VGG_model = Sequential()
VGG_model.add(backbone)
VGG_model.add(Flatten())
VGG_model.add(Dense(512, activation='relu'))
VGG_model.add(BatchNormalization())
VGG_model.add(Dropout(0.5))
VGG_model.add(Dense(1, activation='sigmoid'))
```

```
VGG_model.compile(
        loss='binary_crossentropy',
        optimizer=tf.keras.optimizers.Adam(learning_rate=0.00005),
        metrics=['accuracy']
    )
```

```
# Checkpoint
filepath="weights.best.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1, save_best_only=True, mode='max')
```

```
history = VGG_model.fit_generator(generator = train,
                    steps_per_epoch=STEP_SIZE_TRAIN,
                    validation_data=test,
                    validation_steps=STEP_SIZE_VAL,
                    epochs=10)
VGG_model.save('/content/gdrive/My Drive/Colab Notebooks/VGG_model.h5')
```

```
5549>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.
generator(generator = train,

==========] - 62s 821ms/step - loss: 0.7831 - accuracy: 0.5878 - val_loss: 0.7101 - val_accuracy: 0.4623

==========] - 30s 500ms/step - loss: 0.6058 - accuracy: 0.6893 - val_loss: 0.6651 - val_accuracy: 0.5765

==========] - 28s 471ms/step - loss: 0.5169 - accuracy: 0.7442 - val_loss: 0.5543 - val_accuracy: 0.7284

==========] - 29s 497ms/step - loss: 0.4300 - accuracy: 0.7951 - val_loss: 0.4951 - val_accuracy: 0.7769

==========] - 30s 502ms/step - loss: 0.3880 - accuracy: 0.8249 - val_loss: 0.4299 - val_accuracy: 0.8195

==========] - 40s 682ms/step - loss: 0.3712 - accuracy: 0.8321 - val_loss: 0.5354 - val_accuracy: 0.7263

==========] - 30s 500ms/step - loss: 0.3109 - accuracy: 0.8700 - val_loss: 0.4433 - val_accuracy: 0.7969

==========] - 30s 506ms/step - loss: 0.2890 - accuracy: 0.8769 - val_loss: 0.4065 - val_accuracy: 0.8152

==========] - 30s 501ms/step - loss: 0.2588 - accuracy: 0.9003 - val_loss: 0.5749 - val_accuracy: 0.7177

==========] - 29s 496ms/step - loss: 0.2332 - accuracy: 0.9070 - val_loss: 0.3616 - val_accuracy: 0.8362
dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.
```

```
score1 = VGG_model.evaluate(X_test, y_test, verbose=0)
print(f'Test loss: {score1[0]} / Test accuracy: {score1[1]}')
```

```
Test loss: 0.3615039885044098 / Test accuracy: 0.8367456793785095
```

```
y_pred_prob_2 = VGG_model.predict(X_test)
```

```
58/58 [==============================] - 7s 119ms/step
```

```
threshold = 0.5
y_pred_2 = np.where(y_pred_prob_2 > threshold, 1,0)
y_pred_2.squeeze()
```

```
array([0, 1, 1, ..., 1, 1, 0])
```


```
score1 = VGG_model.evaluate(X_test, y_test, verbose=0)
print(f'Test loss: {score1[0]} / Test accuracy: {score1[1]}')
```

```
Test loss: 0.3615039885044098 / Test accuracy: 0.8367456793785095
```

```
y_pred_prob_2 = VGG_model.predict(X_test)
```

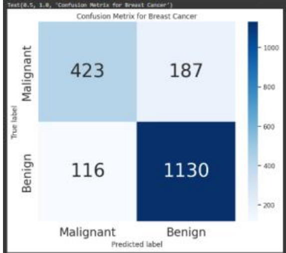
```
58/58 [==============================] - 7s 119ms/step
```

```
threshold = 0.5
y_pred_2 = np.where(y_pred_prob_2 > threshold, 1,0)
y_pred_2.squeeze()
```

```
array([0, 1, 1, ..., 1, 1, 0])
```


```
sns.set(rc={'figure.figsize':(7.7,6.27)})

sns.heatmap(confusion_matrix(y_test,y_pred_2),cmap=plt.cm.Blues,annot=True,annot_kws={"size": 32}, fmt='g')
plt.xticks([0.50,1.50], ['Malignant','Benign'], fontsize=20)
plt.yticks([0.50,1.50],['Malignant','Benign'], fontsize=20)

plt.ylabel('True label')
plt.xlabel('Predicted label')

plt.title('Confusion Metrix for Breast Cancer')
```

```
Text(0.5, 1.0, 'Confusion Metrix for Breast Cancer')
```




```
print(classification_report(y_test, y_pred_2, target_names = ['Benign (Class 0)','Malignant (Class 1)']))
```

	precision	recall	f1-score	support
Benign (Class 0)	0.78	0.69	0.74	610
Malignant (Class 1)	0.86	0.91	0.88	1246
accuracy			0.84	1856
macro avg	0.82	0.80	0.81	1856
weighted avg	0.83	0.84	0.83	1856

VGG16(Fine-Tuning)

Fine Tuning

```
backbone2 = VGG16(input_shape = (224, 224, 3), include_top=False, weights='imagenet')
```

```
backbone.trainable = True
```

```
# Unfreeze final 2 convolution blocks

set_trainable = False
for layer in backbone2.layers:
    if layer.name == 'block4_conv1':
        set_trainable = True
    if set_trainable:
        layer.trainable = True
    else:
        layer.trainable = False
```

```
VGG_model_2 = Sequential()
VGG_model_2.add(backbone2)
VGG_model_2.add(GlobalAveragePooling2D())
VGG_model_2.add(BatchNormalization())
VGG_model_2.add(Dropout(0.5))
VGG_model_2.add(Dense(1, activation='sigmoid'))
```

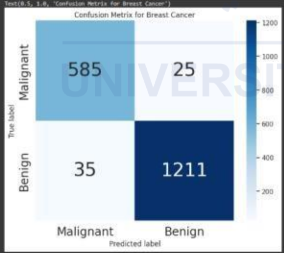
```
VGG_model_2.compile(
        loss='binary_crossentropy',
        optimizer=tf.keras.optimizers.Adam(learning_rate=0.00005),
        metrics=['accuracy']
    )
```

```
history = VGG_model_2.fit_generator(generator = train,
                    steps_per_epoch=STEP_SIZE_TRAIN,
                    validation_data=test,
                    validation_steps=STEP_SIZE_VAL,
                    epochs=10)
VGG_model_2.save('/content/gdrive/My Drive/Colab Notebooks/VGG_model_2.h5')
```

```
<ipython-input-70-42e43adacd3f>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.
  history = VGG_model_2.fit_generator(generator = train,
Epoch 1/10
59/59 [==============================] - 46s 614ms/step - loss: 0.6676 - accuracy: 0.6112 - val_loss: 0.8033 - val_accuracy: 0.3270
Epoch 2/10
59/59 [==============================] - 33s 556ms/step - loss: 0.4719 - accuracy: 0.7786 - val_loss: 0.6493 - val_accuracy: 0.5539
Epoch 3/10
59/59 [==============================] - 32s 546ms/step - loss: 0.3280 - accuracy: 0.8622 - val_loss: 0.5046 - val_accuracy: 0.8184
Epoch 4/10
59/59 [==============================] - 33s 561ms/step - loss: 0.2515 - accuracy: 0.9075 - val_loss: 0.4216 - val_accuracy: 0.8405
Epoch 5/10
59/59 [==============================] - 32s 540ms/step - loss: 0.1780 - accuracy: 0.9302 - val_loss: 0.3559 - val_accuracy: 0.8621
Epoch 6/10
59/59 [==============================] - 33s 553ms/step - loss: 0.1433 - accuracy: 0.9440 - val_loss: 0.2192 - val_accuracy: 0.9289
Epoch 7/10
59/59 [==============================] - 33s 548ms/step - loss: 0.1040 - accuracy: 0.9651 - val_loss: 0.2003 - val_accuracy: 0.9208
Epoch 8/10
59/59 [==============================] - 33s 552ms/step - loss: 0.0879 - accuracy: 0.9686 - val_loss: 0.2695 - val_accuracy: 0.8971
Epoch 9/10
59/59 [==============================] - 33s 552ms/step - loss: 0.0632 - accuracy: 0.9784 - val_loss: 0.4656 - val_accuracy: 0.8438
Epoch 10/10
59/59 [==============================] - 33s 552ms/step - loss: 0.0356 - accuracy: 0.9899 - val_loss: 0.0740 - val_accuracy: 0.9682
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This file format is considered legacy. We recommend using instead the native Keras
  saving_api.save_model(
```

```
sns.set(rc={'figure.figsize':(7.7,6.27)})

sns.heatmap(confusion_matrix(y_test,y_pred_3),cmap=plt.cm.Blues,annot=True,annot_kws={"size": 32}, fmt='g')
plt.xticks([0.50,1.50], ['Malignant','Benign'], fontsize=20)
plt.yticks([0.50,1.50],['Malignant','Benign'], fontsize=20)

plt.ylabel('True label')
plt.xlabel('Predicted label')

plt.title('Confusion Metrix for Breast Cancer')
```

```
Text(0.5, 1.0, 'Confusion Metrix for Breast Cancer')
```




```
print(classification_report(y_test, y_pred_3, target_names = ['Benign (Class 0)','Malignant (Class 1)']))
```

```
                     precision    recall  f1-score   support

   Benign (Class 0)       0.94      0.96      0.95       610
Malignant (Class 1)       0.98      0.97      0.98      1246

           accuracy                           0.97      1856
          macro avg       0.96      0.97      0.96      1856
       weighted avg       0.97      0.97      0.97      1856
```

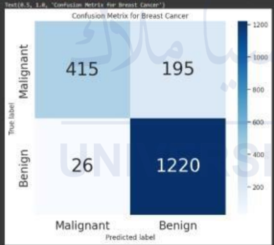
ResNet50

Transfer Learning using ResNet50

```
[ ] from tensorflow.keras.applications.resnet50 import ResNet50

backbone3 = ResNet50(input_shape = (224, 224, 3), include_top=False, weights='imagenet')

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736 [==============================] - 0s 0us/step

[ ] backbone3.training = False

[ ] ResNet50_model = Sequential()
    ResNet50_model.add(backbone3)
    ResNet50_model.add(GlobalAveragePooling2D())
    ResNet50_model.add(Dropout(0.5))
    ResNet50_model.add(Dense(1, activation='sigmoid'))
```

```
[ ] history = ResNet50_model.fit_generator(
        generator=train,
        steps_per_epoch=STEP_SIZE_TRAIN,
        validation_data=test,
        validation_steps=STEP_SIZE_VAL,
        epochs=10
    )

    ResNet50_model.save('/content/gdrive/My Drive/Colab Notebooks/ResNet50_model.h5')

<ipython-input-90-b24af7e9bb73>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.
  history = ResNet50_model.fit_generator(
Epoch 1/10
59/59 [==============================] - 80s 864ms/step - loss: 0.0232 - accuracy: 0.9923 - val_loss: 0.8326 - val_accuracy: 0.4731
Epoch 2/10
59/59 [==============================] - 50s 838ms/step - loss: 0.0054 - accuracy: 0.9992 - val_loss: 0.8426 - val_accuracy: 0.5372
Epoch 3/10
59/59 [==============================] - 50s 837ms/step - loss: 0.0026 - accuracy: 0.9995 - val_loss: 0.7507 - val_accuracy: 0.6347
Epoch 4/10
59/59 [==============================] - 49s 831ms/step - loss: 9.6874e-04 - accuracy: 1.0000 - val_loss: 0.7776 - val_accuracy: 0.6773
Epoch 5/10
59/59 [==============================] - 50s 844ms/step - loss: 3.5305e-04 - accuracy: 1.0000 - val_loss: 0.8885 - val_accuracy: 0.7188
Epoch 6/10
59/59 [==============================] - 60s 1s/step - loss: 2.9055e-04 - accuracy: 1.0000 - val_loss: 1.0058 - val_accuracy: 0.7295
Epoch 7/10
59/59 [==============================] - 49s 835ms/step - loss: 3.2528e-04 - accuracy: 1.0000 - val_loss: 0.9996 - val_accuracy: 0.7500
Epoch 8/10
59/59 [==============================] - 50s 841ms/step - loss: 2.7112e-04 - accuracy: 1.0000 - val_loss: 0.6659 - val_accuracy: 0.7974
Epoch 9/10
59/59 [==============================] - 49s 825ms/step - loss: 1.8405e-04 - accuracy: 1.0000 - val_loss: 0.4754 - val_accuracy: 0.8378
Epoch 10/10
59/59 [==============================] - 49s 825ms/step - loss: 1.9248e-04 - accuracy: 1.0000 - val_loss: 0.3176 - val_accuracy: 0.8820
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This file format is considered legacy. We recommend using instead the native Keras
  saving_api.save_model(
```

```
[ ] sns.set(rc={'figure.figsize':(7.7,6.27)})

    sns.heatmap(confusion_matrix(y_test,y_pred_4),cmap=plt.cm.Blues,annot=True,annot_kws={"size": 32}, fmt='g')
    plt.xticks([0.50,1.50], ['Malignant','Benign'], fontsize=20)
    plt.yticks([0.50,1.50],['Malignant','Benign'], fontsize=20)

    plt.ylabel('True label')
    plt.xlabel('Predicted label')

    plt.title('Confusion Metrix for Breast Cancer')

Text(0.5, 1.0, 'Confusion Metrix for Breast Cancer')
```




```
print(classification_report(y_test, y_pred_4, target_names = ['Benign (Class 0)','Malignant (Class 1)']))

                     precision    recall  f1-score   support

   Benign (Class 0)       0.94      0.68      0.79       610
Malignant (Class 1)       0.86      0.98      0.92      1246

           accuracy                           0.88      1856
          macro avg       0.90      0.83      0.85      1856
       weighted avg       0.88      0.88      0.88      1856
```

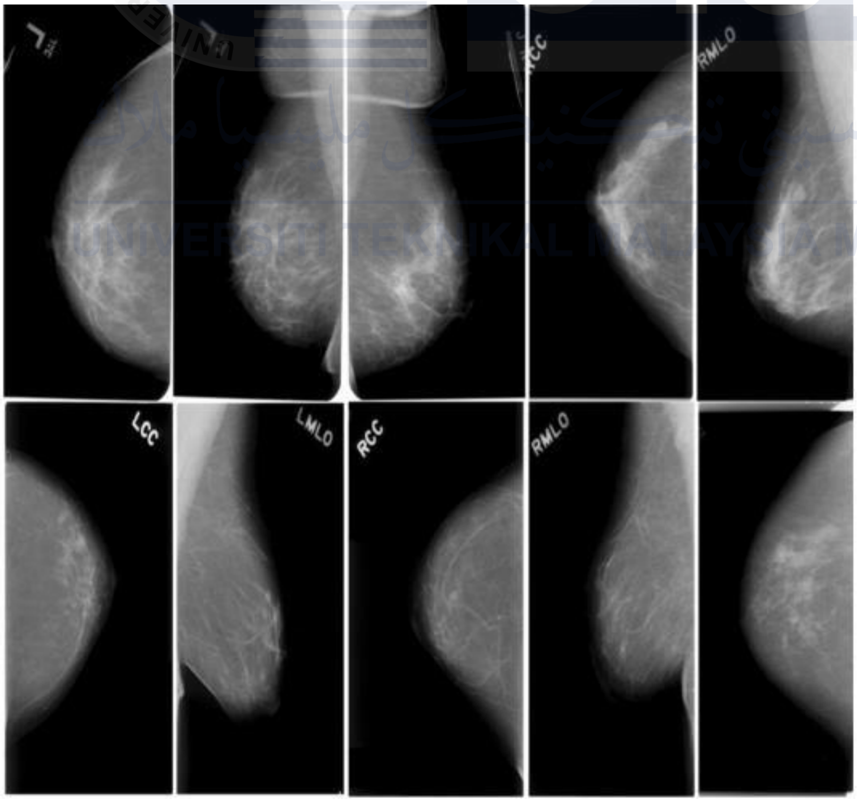
Data directory

```
[ ]
train = datagen.flow_from_directory('/content/gdrive/My Drive/Colab Notebooks/train/', target_size=(224, 224), class_mode='binary', batch_size=64)
# load and iterate validation dataset
val = datagen.flow_from_directory('/content/gdrive/My Drive/Colab Notebooks/val/', target_size=(224, 224), class_mode='binary', batch_size=64)
# load and iterate test dataset
test = datagen.flow_from_directory('/content/gdrive/My Drive/Colab Notebooks/test/', target_size=(224, 224), class_mode='binary', batch_size=64)

Found 3817 images belonging to 2 classes.
Found 1908 images belonging to 2 classes.
Found 1918 images belonging to 2 classes.
```

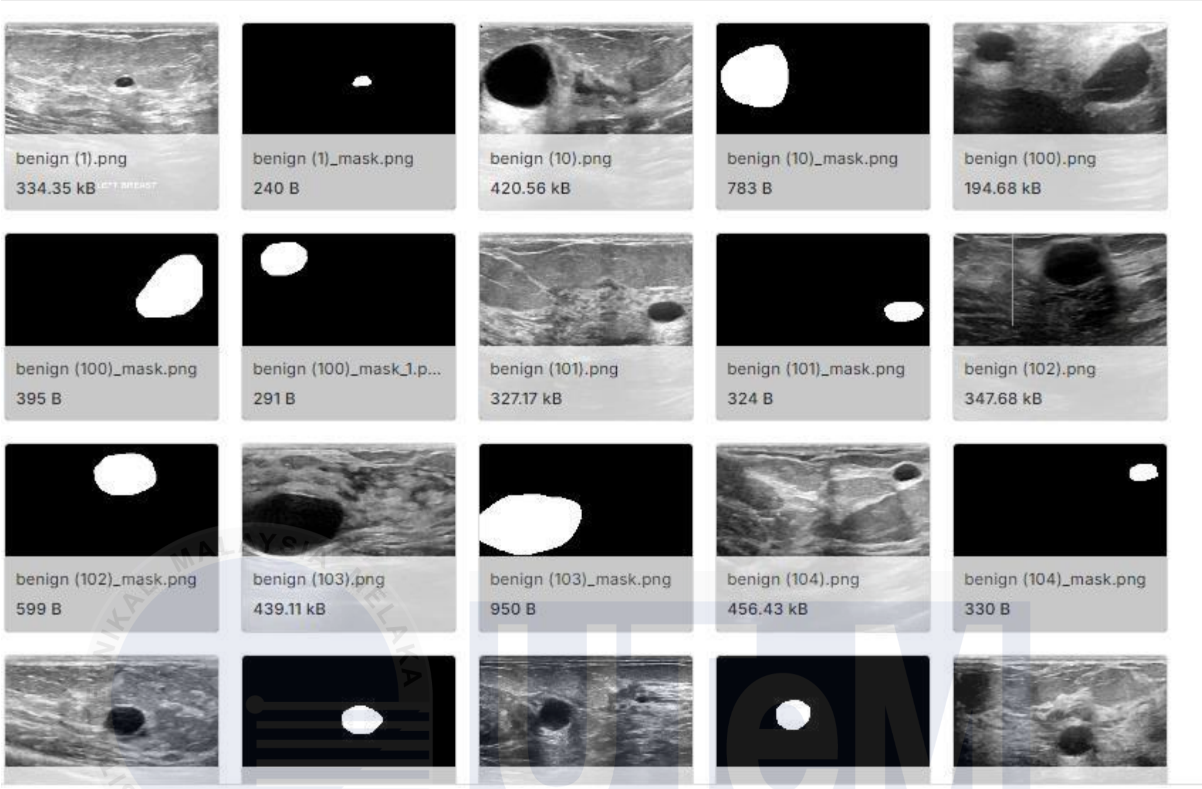
Result Performance

```
history = VGG_model.fit_generator(generator = train,
                steps_per_epoch=STEP_SIZE_TRAIN,
                validation_data=test,
                validation_steps=STEP_SIZE_VAL,
                epochs=10)
VGG_model.save('/content/gdrive/My Drive/Colab Notebooks/VGG_model.h5')

<ipython-input-57-038848ee5549>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.
  history = VGG_model.fit_generator(generator = train,
Epoch 1/10
59/59 [==============================] - 62s 821ms/step - loss: 0.7831 - accuracy: 0.5878 - val_loss: 0.7101 - val_accuracy: 0.4623
Epoch 2/10
59/59 [==============================] - 30s 500ms/step - loss: 0.6058 - accuracy: 0.6893 - val_loss: 0.6651 - val_accuracy: 0.5765
Epoch 3/10
59/59 [==============================] - 28s 471ms/step - loss: 0.5169 - accuracy: 0.7442 - val_loss: 0.5543 - val_accuracy: 0.7284
Epoch 4/10
59/59 [==============================] - 29s 497ms/step - loss: 0.4300 - accuracy: 0.7951 - val_loss: 0.4951 - val_accuracy: 0.7769
Epoch 5/10
59/59 [==============================] - 30s 502ms/step - loss: 0.3880 - accuracy: 0.8249 - val_loss: 0.4299 - val_accuracy: 0.8195
Epoch 6/10
59/59 [==============================] - 40s 682ms/step - loss: 0.3712 - accuracy: 0.8321 - val_loss: 0.5354 - val_accuracy: 0.7263
Epoch 7/10
59/59 [==============================] - 30s 500ms/step - loss: 0.3109 - accuracy: 0.8700 - val_loss: 0.4433 - val_accuracy: 0.7969
Epoch 8/10
59/59 [==============================] - 30s 506ms/step - loss: 0.2890 - accuracy: 0.8769 - val_loss: 0.4065 - val_accuracy: 0.8152
Epoch 9/10
59/59 [==============================] - 30s 501ms/step - loss: 0.2588 - accuracy: 0.9003 - val_loss: 0.5749 - val_accuracy: 0.7177
Epoch 10/10
59/59 [==============================] - 29s 496ms/step - loss: 0.2332 - accuracy: 0.9070 - val_loss: 0.3616 - val_accuracy: 0.8362
```

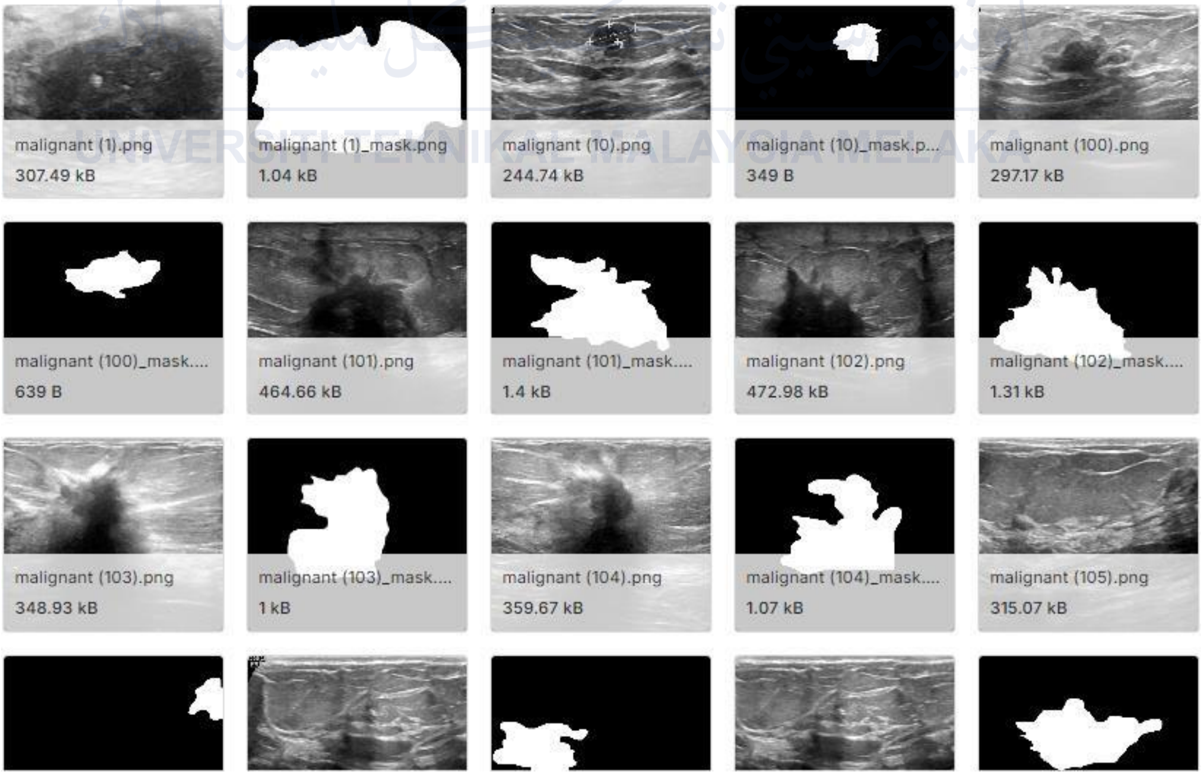
Sample Data CBIS-DDSM Mammography (Malignant and Benign)



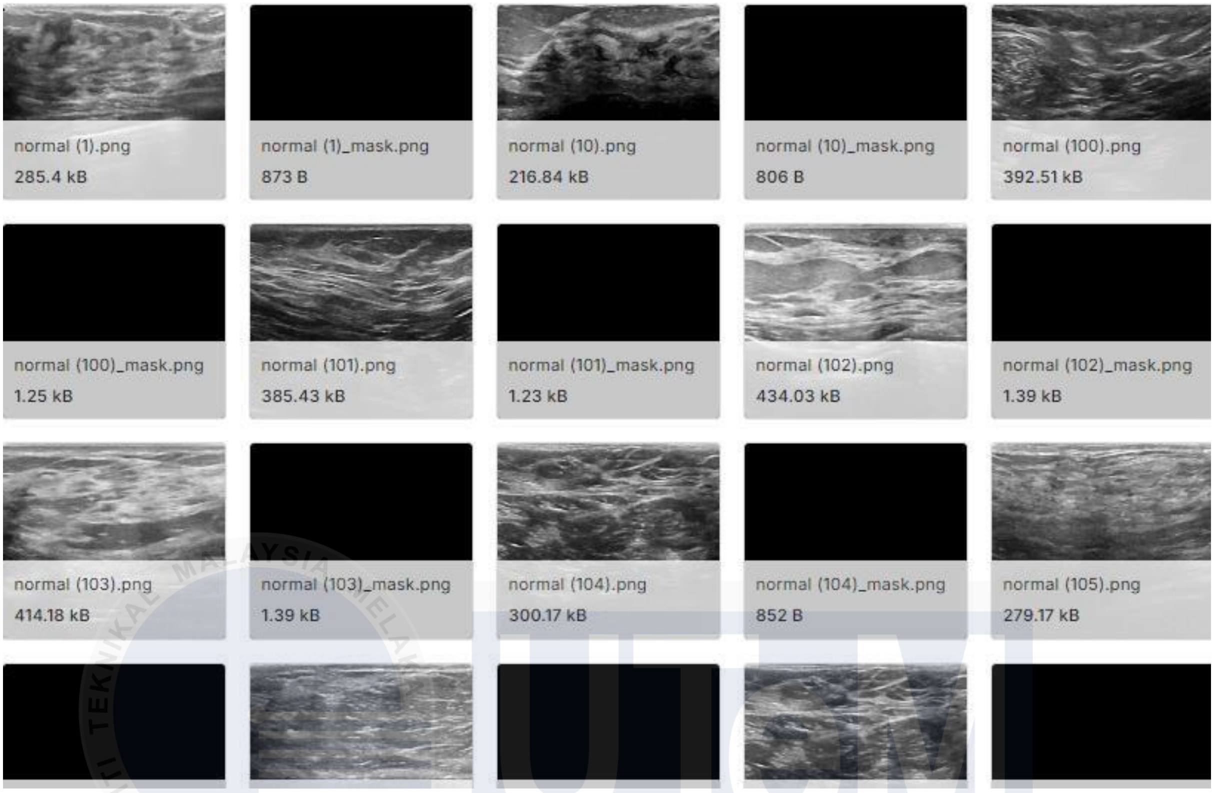
Sample Data Breast Ultrasound Images Dataset (Normal, Malignant and Benign)



Benign



Malignant


normal (1).png
285.4 kB
normal (1)_mask.png
873 B
normal (10).png
216.84 kB
normal (10)_mask.png
806 B
normal (100).png
392.51 kB
normal (100)_mask.png
1.25 kB
normal (101).png
385.43 kB
normal (101)_mask.png
1.23 kB
normal (102).png
434.03 kB
normal (102)_mask.png
1.39 kB
normal (103).png
414.18 kB
normal (103)_mask.png
1.39 kB
normal (104).png
300.17 kB
normal (104)_mask.png
852 B
normal (105).png
279.17 kB

Normal