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BREAST CANCER DETECTION FROM HISTOPATHOLOGY IMAGES USING MACHINE LEARNING

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Sanjida Akter Mou

Abstract

Breast cancer is an invasive tumor that develops in breast tissue. It is the most common cancer and the leading cause of cancer mortality among females worldwide. Survival from breast cancer can be increased through advances in screening methods and early diagnosis. Clinical examination, screening using imaging modalities and pathological assessment (biopsy test) are common methods of breast cancer diagnosis. Among these, pathological assessment can be taken as a gold standard due to its potential in identifying the cancer type, grade and stage. However, current diagnosis using biopsy test is commonly done through visual inspection. This manual diagnosis is time consuming, tedious and subjective which may lead to misdiagnosis.

A technique used to diagnose breast cancer is histopathology. In the medical field, supervised learning tasks have been successfully completed using machine learning (ML) techniques. In this article, I use histopathology images from traditional photo-microscopy to examine the effects of ML for the detection of breast cancer. The classification of pictures as cancerous (malignant) or benign (benign) is known as cancer diagnosis. It includes image pre-processing, features extraction, classification and performance analysis. I have discovered that deep learning has received most of the attention in ML research for breast cancer diagnosis. I have showed how ML techniques can aid in the conventional microscopy-based diagnosis of breast cancer based on conclusions drawn from recent research activity. Finally, I have gone through the research gaps of ML techniques for use in a real pathologic scenario and suggest future research suggestions.

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CHAPTER I

Introduction

1.1 Introduction

Breast tissue may experience aberrant cell division that results in a tumor, which can lead to breast cancer. Breast cancer accounts for around 30% of newly diagnosed cases and has the second-highest fatality rate after lung and bronchial cancer. The World Health Organization (WHO) estimates that cancer killed 9.6 million people in 2018 and would probably kill 10 million people in 2020 [1]. More than 8% of women are predicted to have breast cancer at some time in their lives. However, if we can make breast cancer screening widespread and simple to access, we may be able to save a great number of lives.

Cancer constitutes an enormous burden on society in more and less economically developed countries alike. Cancer cases are becoming more common due to the growth and aging of the population, as well as a widespread rise of established risk factors such as smoking, overweight, physical inactivity. Early detection of cancer significantly increases the probability of recovering through successful treatment. Delays in diagnosis results in late-stage presentation with consequences of lower likelihood of survival, higher costs of treatments and even death.

Proper diagnosis can help a patient to get rid of breast cancer risk if the state of cancer type is benign (non-cancerous) or malignant (cancerous). A histology image analysis system generally has a combination of hardware and software and it can be divided into two consecutive subsystems:

- Tissue preparation and image production.
- Image processing analysis.

1.2 Background

Mammography, Magnetic Resonance Imaging (MRI), Fine Needle Aspiration Cytology (FNAC), and Histopathology are the methods that are most frequently employed for cancer detection and diagnosis. However, these present innovations have a few downsides as they are very costly, extensive in size and are only affordable in large hospital facilities. The mentioned methods also may have some side effects and false positives.

Histopathology is regarded as the gold standard for cancer diagnosis among these. This technique involves removing infected breast tissue and microscopically examining it. The histology slide, however, exhibits complex visual patterns that are challenging to classify as benign or malignant [2].

Since the development of digital microscopy, machine learning (ML) models for cancer diagnosis have been increasingly popular. In the recent years, a number of scholars have reviewed cutting-edge techniques for creating CAD systems. Preprocessing, feature extraction and selection, classification, and performance analysis are the four processes in the diagnosis of cancer utilizing an ML-based, CAD system [3].

1.3 Objectives

The main objectives of this work are listed below:

- To build a deep learning model for cancer detection and diagnosis using histopathology images.
- To use ML techniques for histopathology images generated by conventional photo-microscopy.
- To use CNN (Convolutional Neural Network) for histopathology images.
- To know the correct diagnosis of breast cancer and classification of patients into malignant and benign groups is the center of this research.
- To segment the images using different types of image processing algorithm and train the CNN model using segmented images.
- To train another CNN model without using segmenting techniques.
- To classify between malignant (cancerous) and benign (non-cancerous) cells.
- To evaluate the performance of the model using EfficientNetB3, ResNet50, Resnet101, VGG16 and VGG19 architecture.

1.4 Scope

There are many researches on the diagnosis of breast cancer using various Machine Learning (ML) algorithms. But the concept has been put into practice in a lot of different ways. Accuracy can vary when the same method is used with significantly altered parameters in CNN architecture. A convolutional neural network (CNN) is a category of ML model, namely a type of Deep Learning algorithm well suited to analyzing visual data. CNN is sometimes referred to as 'convnets' which use principles from linear algebra, particularly convolution operations, to extract features and identify patterns within images. By varying the parameters, I attempted to use 2/3 of different CNN architectures in this study [4].

1.5 Unfamiliarity of the Problem

In the proposed method, I have collected the dataset from BreakHis [5] dataset which is histopathology images, pre-processed them using oversampling and scaling. Then I have applied image processing techniques to segment the images and see the uncontrolled increase of cells in malignant cells. After that, the dataset is split into train, test and validation. ML classifiers are applied on the dataset. Then I have evaluated the performance of the different ML classifiers.

To make the image simpler and more useful, preprocessing is necessary. It helps to locate the focal points and lowers image noise. To enhance local contrast, a Contrast-Limited Adaptive Histogram Equalization (CLAHE) technique is applied. To lessen the noise in the image, thresholding is utilized. Noise is defined as pixels in an image's intensity histogram that are below a threshold value [6]. After that, Gaussian blur technique has been applied to the images.

Otsu's threshold approach is used to determine the ideal threshold. Thresholding results can be enhanced by background removal and filtering. The segmented images are saved to another directories. After that, the dataset will be split into test and train CNN model will be applied on the dataset. I have also applied CNN model without segmenting the images. From the literature review, among existing solution, this system is best solution among other system comparing all stages.

1.6 Project planning

Among the countries in the Asia-Pacific region, women in Indonesia, the Philippines, Malaysia, Singapore, and Fiji have the highest breast cancer death rate. Breast cancer incidence in Bangladesh is almost 22.5 per 100000 females. Women in Bangladesh between the ages of 15 and 44 have been shown to have the highest prevalence rate (19.3 per 100,000) of breast cancer. At Bangabandhu Sheikh Mujib Medical University (BSMMU), Dhaka, Bangladesh, from July 2013 to June 2014, a cross-sectional study was created to evaluate the knowledge, attitude, and practices of community-dwelling women in Bangladesh regarding breast cancer.

All female participants who were attending the BSMMU outpatient department and were above 20 years old and had at least a JSC were purposefully chosen until the sample size reached 500. Only applying simple cost-free method like self-breast examination (SBE) and clinical breast examination (CBE) one can assess her breast. Thereby awareness develops regarding her breast so any mass newly appear can be assessed by the lady herself.

Early detection of breast cancer will lessen the financial, morbidity, and mortality burden of treatment. The project's research and development strategy aim to raise community members' awareness of breast cancer prevention. Mean age of the study population was 36.16 years. The Gantt chart below shows the whole work plan of my thesis work for 26 weeks. I have completed my work according to this chart.

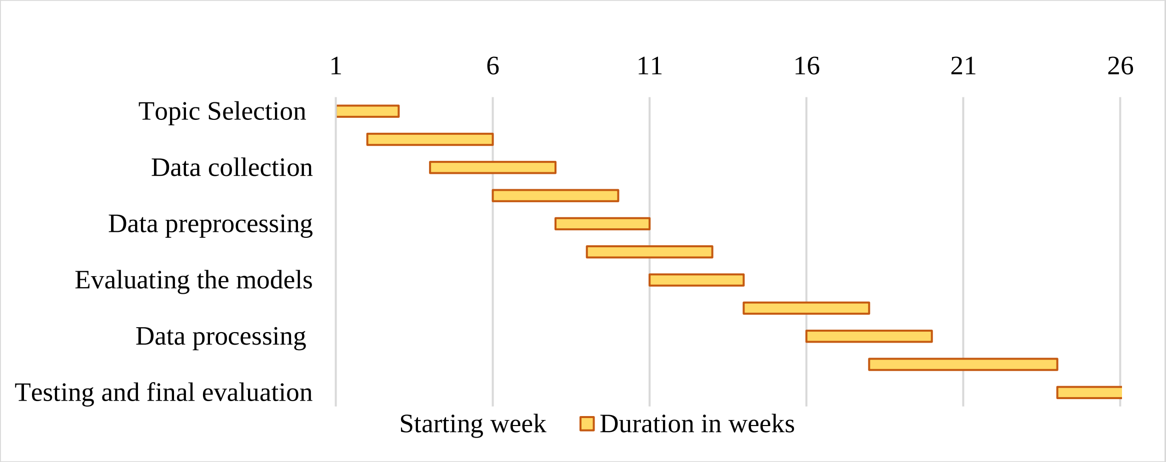


Fig 1.1: Gantt chart for work plan.

1.7 Application of the work

It is unnecessary for people to devote time and effort worrying about breast cancer detection. In the comfort of their house, they can detect themselves. They only require an internet connection and a mammogram or sonogram of their breast tissue. Given how closely the prediction matches the pathology test, it may eventually replace the entire set of laboratory tests for identifying cancer cells. Our health is greatly impacted by early detection and screening for breast cancer. Breast cancer can be found early, when there is a better chance of survival, and to screening tests. Some potential applications of this research are given below:

- The findings of the thesis can provide valuable insights into the causes of breast cancer. This information can be used to inform public health policies and programs aimed at detecting cancer.
- The research can guide healthcare professionals in designing effective interventions to detect breast cancer.
- Governments and non-governmental organizations can use the research findings to allocate resources more efficiently.
- The data collected and analyzed can serve as the basis for health education campaigns that raise awareness about the importance of proper checking of breast cancer.
- The thesis work can contribute to the body of knowledge surrounding women and child malnutrition.
- The research outcomes can be shared with the general public through various media channels. This can raise awareness about the uncontrolled growth of cancer tissue in breast, leading to increased public support and engagement in addressing the problem.
- The thesis work can foster collaboration between hospitals, healthcare professionals, researchers, and policymakers. By sharing the findings and insights, these stakeholders can work together to create a more comprehensive and coordinated approach to detect breast cancer.

1.8 Organization of the report

This report's general structure is as follows:

- Literature review is presented in Chapter II.
- Methodology is presented in Chapter III.
- In Chapter IV, the topics of execution, outcomes, and discussions are covered. These topics include goal achievement and financial analysis and budget.
- Chapter V contains Societal, Health, Environment, Safety, Ethical, Legal and Cultural Issues with Intellectual Property Considerations, Ethical Consideration, Safety Consideration, Legal Consideration, Impact of the Project on Societal, Health and Cultural Issues, Environment and Sustainability.
- Complex engineering problems and activities associated with the current thesis are stated in Chapter 6.
- Chapter VII presents the conclusion.

CHAPTER II

Literature Review

This chapter includes literature review and discussion of research gap solution.

2.1 Literature review

Different approaches and manual networks have been put out by various academics to categorize breast cancer. For instance, RBF neural networks, Artificial Neural Networks, and the GRU-SVM model, which combines the ML technique with a form of recurrent neural network (RNN) and gated recurrent unit (GRU) with the support vector machine (SVM), all rely on MLE (Maximum Likelihood Estimation) [7].In addition to these methods, other researchers have created a process that yields superior outcomes with less computing complexity.

Karabatak et al. proposed the AR+NN approach, which reduces the number of features by using association rules, to lower the size of the input feature set [8]. Descriptors with a maximum accuracy of 85.1% for the classification of breast cancer, including CLBP, GLCM, LBP, LPQ, ORB, and PFTAS. Elif Derya Ubeyli aims at to the objective of implementing automated diagnosis systems to detect breast cancer. The objective of the paper was to be a guide to the readers, who want to develop an automated decision support system for detection of breast cancer [9].P.C. Pendharkar et al. used Data Mining (DM) technique to predict and diagnose the occurrence of breast cancer [10].

Seral Sahan et al. aimed at diagnosing breast cancer with a new hybrid machine learning method. By hybridizing a fuzzy-artificial immune system with K-Nearest Neighbor (KNN) algorithm, a method was obtained to solve this diagnosis problem via classifying Wisconsin Breast Cancer Dataset (WBCD). This data set is a very commonly used data set in the literature relating the use of classification systems for breast cancer diagnosis. They obtained a classification accuracy of 99.14%, which is the highest one reached so far [11]. Naghibi et al. presented a new approach for breast cancer detection based on Hierarchical Fuzzy Neural Network (HFNN) [12].

Pooja Shah et al. introduced a hybrid strategy for effectively diagnosing breast cancer by using a Novel Relief algorithm for feature selection with an Adaptive Neuro-Fuzzy Inference System (ANFIS) [13]. The efficiency of this proposed hybrid model and the ANFIS model without using any feature selection technique is estimated using the Wisconsin Breast Cancer Data set (WBCD). The study finds that the new hybrid model has attained the highest accuracy of 99.30% and is ideal for detecting breast cancer.

Manisha Arora et al. used Neuro-fuzzy expert system for breast cancer diagnosis [14]. The hybrid system trained on equally distributed dataset outperforms all other approaches. The sensitivity obtained in Neuro-Fuzzy system is 100% which outperforms sensitivity of 99.37%.

The studies stated earlier used a fresh training of the CNN model. The performance of this kind of training can be enhanced by using a big data collection, though. However, due to issues like affiliations with pathology laboratories, patient data access rights, and authorizations for diagnostic results, it is challenging to get such a sizable data set from neighborhood hospitals. Despite these challenges, the research study established a BreakHis(breast cancer histopathological data collection) and made it openly accessible for additional investigation [5]. Additionally, training from scratch necessitates a significant amount of work to adjust the CNN's parameters and a lengthy training period compared to the pre-trained model.

There have been researches in the recent past and there are on-going researches which aims to observe the features that are most helpful in predicting malignant or benign cancer and to see general trends that might help us in selecting particular models and hyper parameter selections. The aim of almost all researches have been to reach the highest accuracy possible in the shortest time. In the modern times, the vast amount of data available is not feasible for human being to keep up with and analyze them. Machine learning, which is a subset of computer science and an important branch of artificial intelligence, primarily focuses on the development and building of algorithms to over this problem. The very recent advancement in this field has opened up vast and almost limitless applications in fields ranging from financial industries, data security to medical fields. It is only going to improve and integrate in our daily lives making it easier and more convenient in the future.

2.1 Discussion of research gap solution

Late identification enhances the risk of developing uncontrolled growth in breast cells. Early identification of breast cancer is an important task for preventing cancer and death. Henceforth, there is a growing need for early identification of predicting a breast cell with malignant label using an automated standard system. Nowadays, ML-based algorithms have become very popular as an automated standard system for accurate prediction of disease at an early stage and its application is increasing rapidly day after day. However, several ML algorithms have been adopted for predicting breast cancer. The table below shows the summary of existing study on detecting breast cancer.

Table 2.1: Summary of the existing study on detecting breast cancer.

Reference	Method used	Remarks
Kumar Singh L et al [15].	SVMs, NB (Naive Bayes), KNN (K-Nearest Neighbors), and DTs	Their main aim was to assess the performance of the algorithms on multiple parameters to develop a novel fusion algorithm that would display optimal execution. They could achieve 97.31% accuracy.
Tafazal H et al [16].	FNAC	With the help of a Bayesian Network, they aimed to compare and contrast the task using a dataset containing the feature values that were collected from the images of cell slides using FNAC. The model showed 97.49% efficiency.
Munshi R et al [17].	LDA (Linear Discriminant Analysis), LR (Logistic Regression), RF (Random Forest), DT (Decision Tree).	They showed 96.49% accuracy.

Reference	Method used	Remarks
Saad G et al [18].	ANN (Artificial Neural Network)	The results indicated that there was a 99% chance of correct diagnosis if the ANN was functionally deployed. This also indicated that there was a 97.6% chance of them being negatively classified.
Karabatek et al [8].	Multilayer Perceptron KNN, Classification and Regression Trees, NB, and SVM	The accuracy shown by the MLP on the training data was 96.70%, which outperformed other algorithms. These models were later tested on unseen data to analyze their real-world performance.
Vijayarajeswari R et al [19].	Support Vector Machine, Naive Bayes, K-NN and C4.5 decision trees.	Based on the results of their experiment, they found that the SVM-based model could achieve the best performance with an accuracy of 97.13% and the lowest rate of error was 0.02%. The performance of the ML model based on other algorithms varied between 95.12% and 95.28%, and the error rate varied between 0.03 and 0.06.
Nguyen N et al [2].	ML methods	They showed 90.0% accuracy.
Shah P et al [13].	FIS (Fuzzy Inference System)	They showed 97% accuracy.

The hypothesis of this study is to propose a better system through a CNN model along with effective ML-based algorithm for the detection of breast cancer in Bangladesh.

CHAPTER III

Methodology

This section contains detailed methodology, description of datasets and theoretical background of the problem i.e. machine learning algorithms and CNN model.

3.1 Detailed Methodology

The diagrammatic representation of the system is presented in Fig 3.1.

3.1.1 Input Dataset

The input data which is histopathology images were collected from BreakHis dataset. There were about 5368 images. There are two types of data which are:

- **Malignant:** The one holds the images of Cancerous cells.
- **Benign:** The one holds the images of Non - cancerous cells.

3.1.2 Data preprocessing

- **Resizing images:** At first, the data was preprocessed using different image processing techniques. I have resized the images. Fig 3.1 shows the resized images of 2 classes (Malignant and Benign).

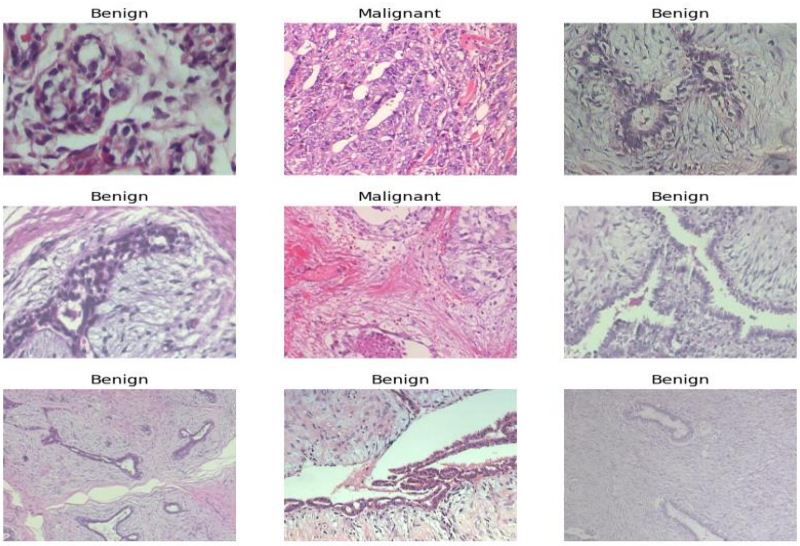


Fig 3.1: Resized images (224 × 224).

- **Contrast Stretching:** After resizing the images, I have applied contrast stretching.

Contrast stretching is a simple image enhancement technique that attempts to improve the contrast in an image by 'stretching' the range of intensity values it contains to span a desired range of values, the full range of pixel values that the image type concerned allows [20]. It changes the distribution and range of the digital numbers assigned to each pixel in an image. This is normally done to accent image details that may be difficult for the human viewer to observe. The mail goal is to apply a contrast enhancement technique to recover an image from blurred images, also improves image quality of it. Contrast Stretch dynamically adjusts the contrast of the image according to the range of brightness levels it contains. The adjustment takes place gradually over a period of time, so the player can be briefly dazzled by bright outdoor light when emerging from a dark tunnel, say. Equally, when moving from a bright scene to a dark one, the "eye" takes some time to adapt.

- **Contrast Limited Adaptive Histogram Equalization (CLAHE):** CLAHE was applied to each image of malignant cells and benign cells. CLAHE is used for improving the visibility level of foggy images [21].

  Adaptive Histogram Equalization (AHE) is an image pre-processing technique used to improve contrast in images. It computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the luminance values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. However, AHE has a tendency to over amplify homogeneous regions of an image. A variant of Adaptive Histogram Equalization (AHE) called Contrast Limited Adaptive Histogram Equalization (CLAHE) prevents this effect by limiting the amplification. The CLAHE algorithm has 3 major parts which are:

  - Tile generation
  - Histogram equalization
  - Bilinear interpolation

Fig 3.2 and 3.3 shows the plot and histogram of applying contrast stretching and CLAHE to the original images of malignant cell. Fig 3.4 and 3.5 shows the plot and histogram of applying contrast stretching and CLAHE to the original images of benign cell.

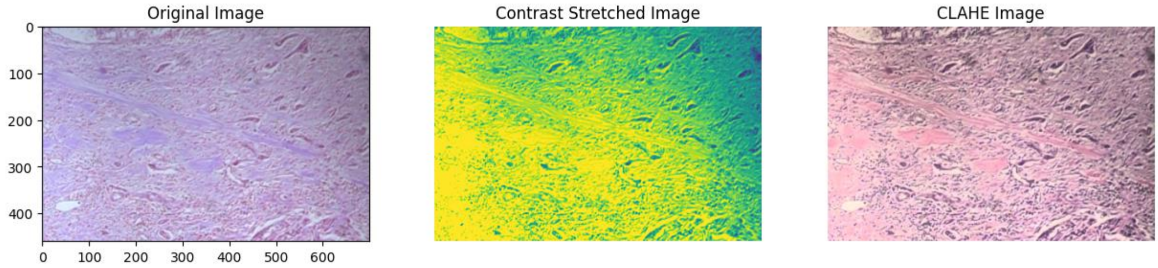


Fig 3.2: Plotting of original, contrast stretched and CLAHE image (Malignant cell).

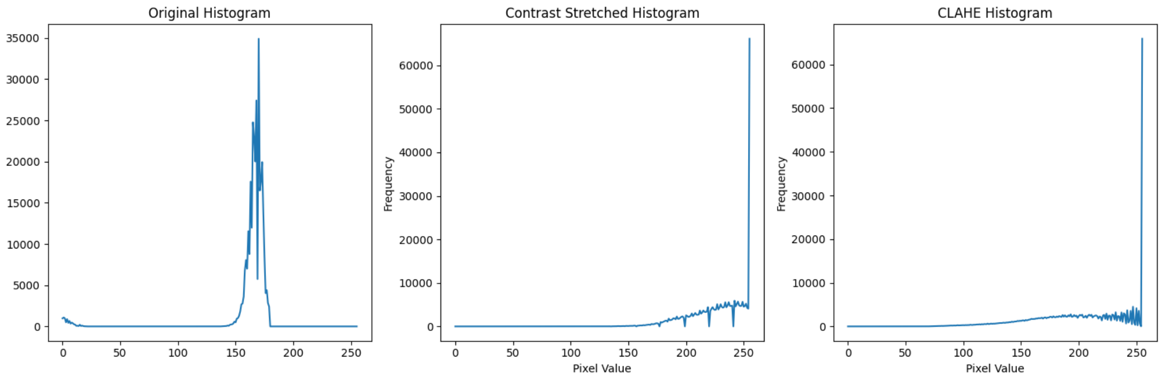


Fig 3.3: Histogram of original, contrast stretched and CLAHE image (Malignant cell).

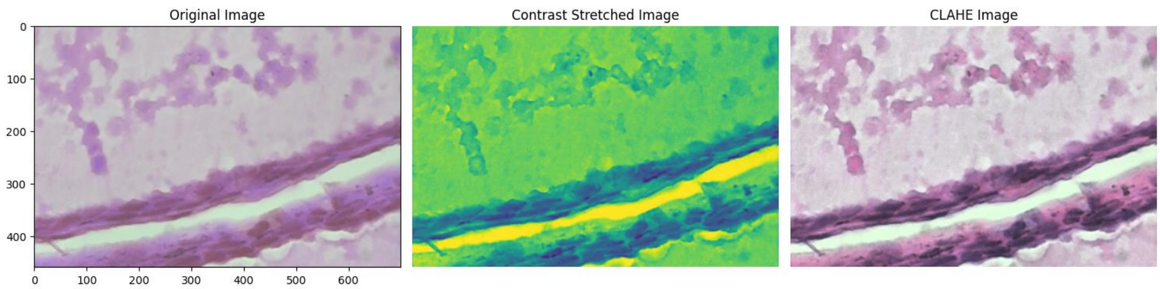


Fig 3.4: Plotting of original, contrast stretched and CLAHE image (Benign cell).

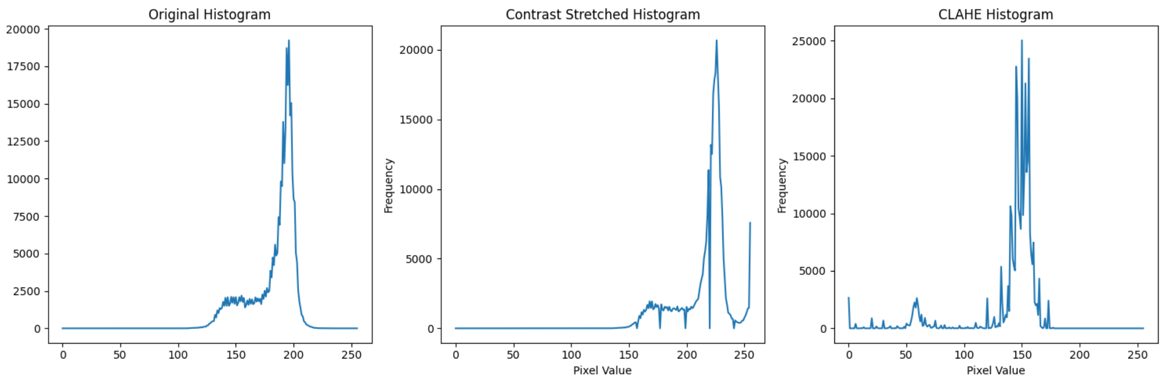


Fig 3.5: Histogram of original image, contrast stretched image and CLAHE image. (Benign cell)

- **Morphological opening:** On the CLAHE image, I have corrected the background using Morphological opening. Morphological opening refers to operations that reduce an object to a more revealing shape by hitting or fitting it with structuring features. These structural components are shape primitives that have been created to represent a particular characteristic of the data or noise. Morphological transformations are performed on data by applying these structuring elements to it using various algebraic combinations. In forensics, morphological image processing methods are used on binary images [22].
- **Gaussian Blur:** I have applied Gaussian blur after applying morphological opening. Gaussian blur describes blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen, distinctly different from the bokeh effect produced by an out-of-focus lens or the shadow of an object under usual illumination. Gaussian smoothing is also used as a pre-processing stage in computer vision algorithms in order to enhance image structures at different scales [23].
- **Otsu's Thresholding technique:** To segment the images, I have applied Otsu's thresholding technique. The process of separating the foreground pixels from the background is called thresholding. There are many ways of achieving optimal thresholding and one of the ways is called the Otsu's method. Otsu's method [24] is a variance-based technique to find the threshold value where the weighted variance between the foreground and background pixels is the least. The key idea here is to iterate through all the possible values of threshold and measure the spread of background and foreground pixels. Then find the threshold where the spread is least. The algorithm iteratively searches for the threshold that minimizes the within-class variance, defined as a weighted sum of variances of the two classes (background and foreground). The colors in grayscale are usually between 0-255 (0-1 in case of float). So, we choose a threshold of 100, then all the pixels with values less than 100 becomes the background and all pixels with values greater than or equal to 100 becomes the foreground of the image. Fig 3.6 and 3.7 shows the plotting of malignant cell and benign cell.

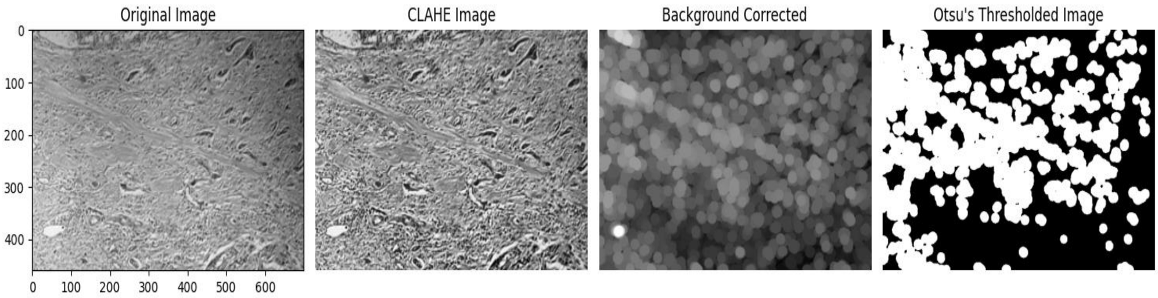


Fig 3.6: Plotting of original, CLAHE, background corrected and Otsu’s Thresholded image (Malignant cell).

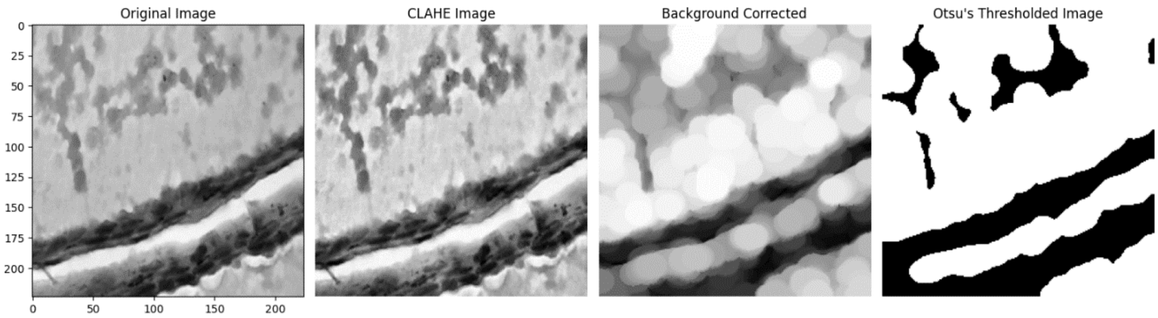


Fig 3.7: Plotting of original, CLAHE, background corrected and Otsu’s Thresholded image (Benign cell).

- **Local Binary Pattern (LBP):** After segmentation, I have applied Local Binary Pattern (LBP) on the segment images. LBP is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Fig 3.8 shows the LBP histogram of a malignant cell.

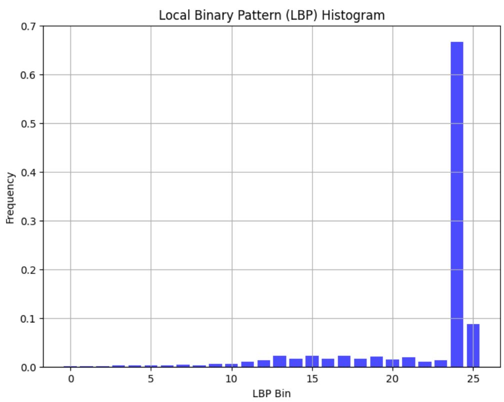


Fig 3.8: LBP Histogram (Malignant cell).

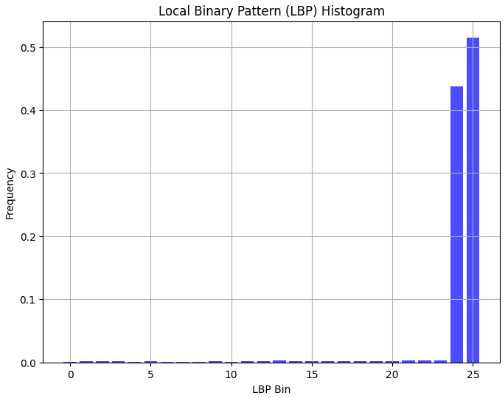


Fig 3.9: LBP Histogram (Benign cell)

3.1.3 Data Split

After pre-processing the images, the pre-processed data is splitted into two parts which are train and test set. 70% of the whole dataset is used for training and 10% of them are used for testing.

3.1.4 CNN Model

According to a study, computers are more sensitive to patterns and texture than the breast is to forms. Because of this, feature learning for manual versus machine is very different. In this scenario, splitted images are sent to a CNN-like architecture along with a classification label (Benign or Malignant).

CNN is able to extract the computational characteristics from the training process automated updating of filter values. In other words, features are things that are taken into consideration while testing a model for model evaluation for a specific architecture of CNN filters and their weights.

Using this method, CNN outputs learned filter weights from an image's raw pixels. These weights provide information for final prediction to the deep neural network's dense architecture. The convolutional neural network in this suggested architecture is composed of two different kinds of layers:

- Convolutional Layers
- Pooling Layers

The depth of input is increased by the number of filters employed during the convolution process, and when the pooling layer is applied, depth is maintained but size is decreased. Fig 3.10 shows the layers of CNN.

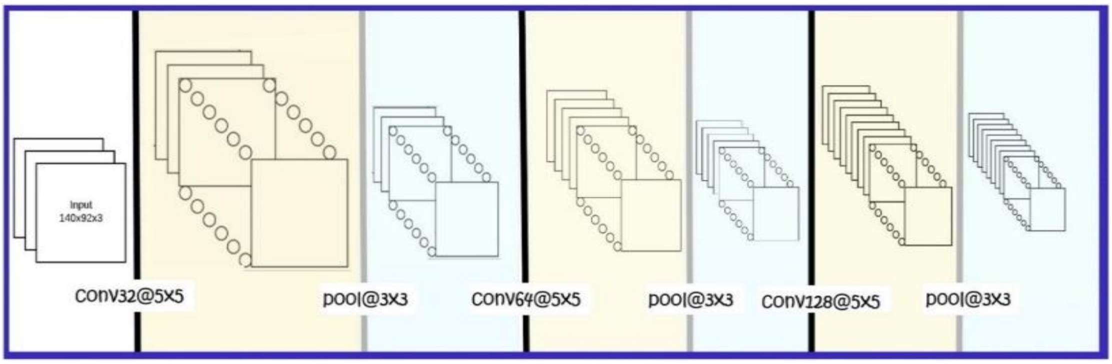


Fig 3.10: Layers of CNN

The following table shows the output shape and parameters of different types of layers used in pre-trained CNN model.

Table 3.1: Summary of layers in CNN

Layer (Type)	Output Shape	Parameter
Gaussian_noise	(None,7,7,1536)	0
Global_average_pooling	(None,1536)	0
dense	(None, 256)	393472
Batch_normalization	(None, 256)	1024
Gaussian_noise_1	(None, 256)	0
Dropout	(None, 256)	0
Dense_1	(None,1)	257

CNN architecture is inspired by the connectivity patterns of the human brain -- in particular, the visual cortex, which plays an essential role in perceiving and processing visual stimuli. The artificial neurons in a CNN are arranged to efficiently interpret visual information, enabling these models to process entire images. Because CNNs are so effective at identifying objects, they are frequently used for computer vision tasks such as image recognition and object detection, with common use cases including self-driving cars, facial recognition and medical image analysis.

EfficientNetB3, ResNet50, ResNet101, VGG16, VGG19 architecture has been used to the CNN model. It is a scaling technique that use a compound coefficient to scale all depth, breadth, and resolution dimensions consistently. The under-constrained neural network model has been given noise in order to mitigate the overfitting issue. Through a second layer known as the GaussianNoise layer, Keras permits the inclusion of Gaussian noise. An existing model can be given noise by using this layer.Additionally, The tf.layers.The global average pooling procedure for geographic data is applied using the globalAveragePooling2d() method. The ReLu and sigmoid activation functions have been employed in this model.

The BatchNormalization function has been used to normalize the input to the activation function. The distribution of the inputs (and these inputs are essentially the output) is normalized using batch processing.

The workflow shown above is the technique I have followed to complete this work. The workflow of the detailed methodology is given below:

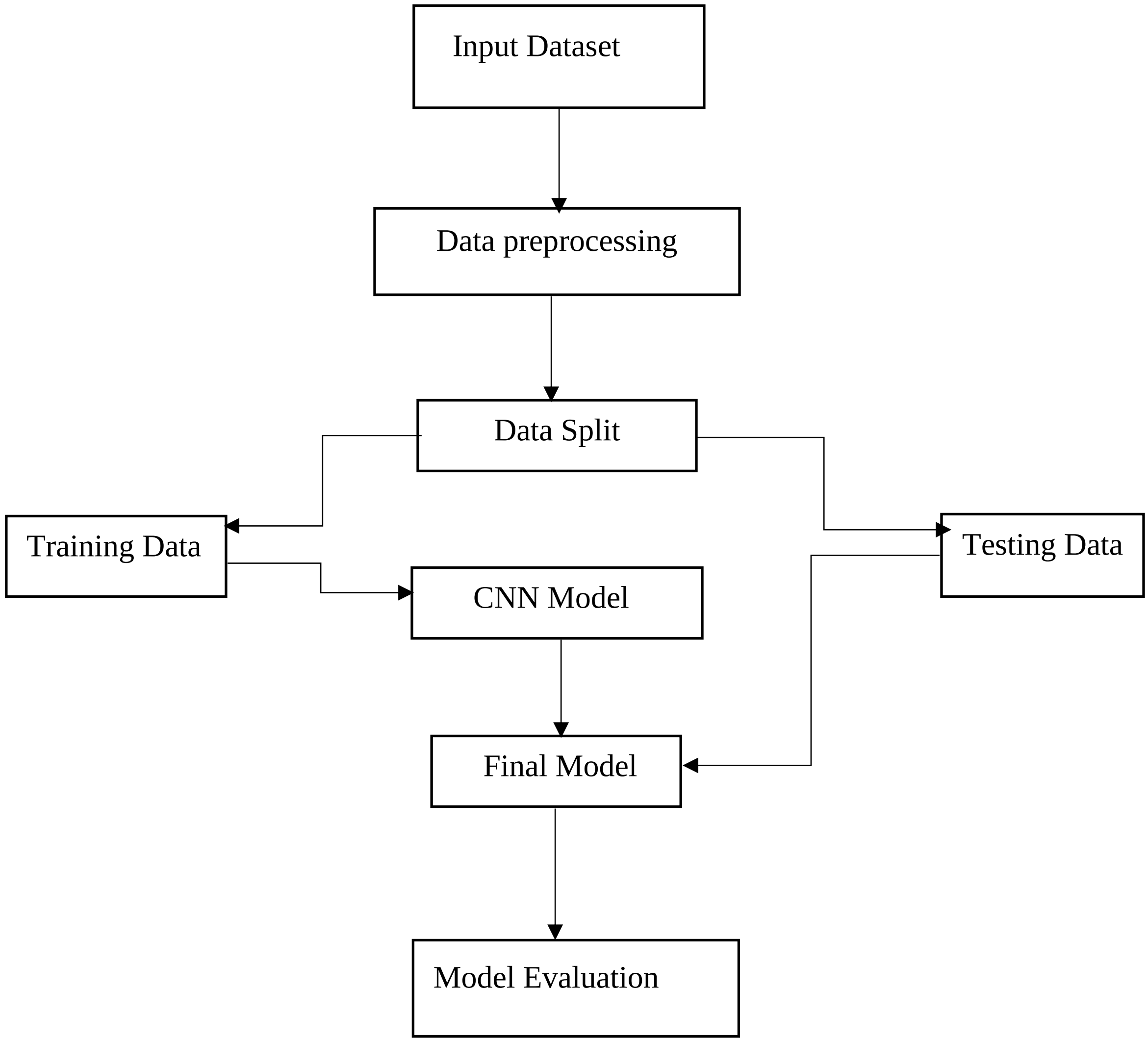


Figure 3.11: Flowchart for the detailed methodology.

3.2 Conclusion

The dataset has been pre-processed accordingly to the image processing technique discussed above. Then the dataset has been fitted to the pre-trained CNN model using EfficientNetB3, ResNet50, ResNet101, VGG16 and VGG19 architectures. The aim was to compare the performance applying 5 different architectures of CNN.

CHAPTER IV

Implementation, Results and Discussion

This chapter includes experimental setup, evaluation metrics, dataset, implementation and results, objective achieved and lastly financial analyses and budget.

4.1 Experimental Setup

Python programming language was used to implement the machine learning algorithms. Google Colab has been used to perform the ML operation.

4.2 Evaluation Metrices

Evaluation metrics are quantitative measures used to assess the performance or effectiveness of a system, model, algorithm, or process. In various fields such as machine learning, natural language processing, information retrieval, and more, evaluation metrics play a crucial role in determining the quality and utility of a solution.

The following evaluation metrics have been used in this work:

- **Accuracy:** In classification tasks, accuracy measures the proportion of correctly classified instances out of the total instances.
- **Precision:** Precision measures the ratio of true positive instances to the total predicted positive instances. It indicates the accuracy of positive predictions.
- **Recall (Sensitivity):** Recall measures the ratio of true positive instances to the total actual positive instances. It indicates the ability of the model to capture all positive instances.
- **F1 Score:** The F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall.
- **ROC-AUC:** Receiver Operating Characteristic - Area Under Curve (ROC-AUC) measures the area under the ROC curve, which plots the true positive rate against the false positive rate. It is commonly used for binary classification tasks.

4.3 Dataset

The input data which is histopathology images were collected from BreakHis dataset. There were about 5368 images. There were train, test and validation set. Each of the dataset contains 2 classes of images which are 'Malignant' and 'Benign'. The train set has 3758 images containing 1736 of them is 'Benign' cells and 2022 of them is 'Malignant' cells. The test set has total 576 images containing 248 of them is 'Benign' cells and rest of them is 'Malignant' cells. The validation set has 1074 images.

4.4 Implementation

The images were pre-processed according to the image-processing techniques like contrast stretching, CLAHE, morphological opening, Gaussian blur and Otsu's threshold algorithm for segmentation. The segmented images were then passed to the pre-trained CNN model to train the model accordingly. The images before segmentation were also fitted to the CNN model and the results were evaluated.

4.5 Results

1. EfficientNetB3 architecture:

After the implementation of EfficientNetB3 architecture, the model was tested using the testing dataset. Fig 4.1 and 4.2 shows the plotting of model accuracy and model loss. So, the model has 88.6% train accuracy and 71.5% test accuracy. The results for train and test are shown in table 4.1 and 4.2. The confusion matrix for train and test set has shown in fig 4.3 and 4.4. The ROC curve for the CNN model is shown in fig 4.5.

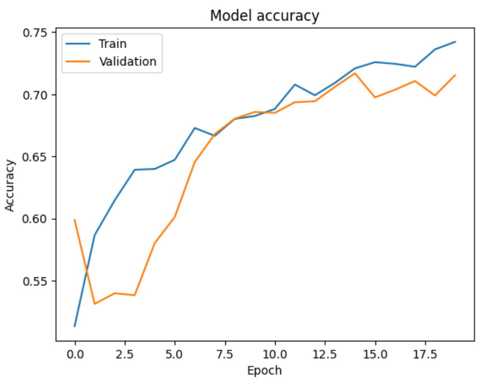


Fig 4.1: Plot of Model Accuracy.

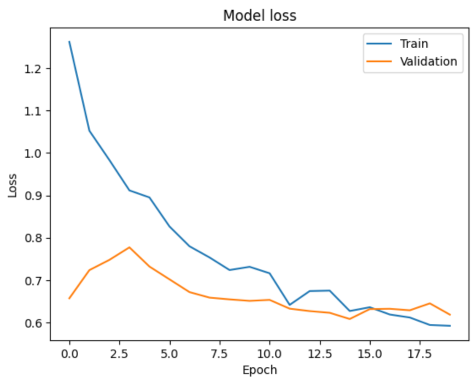


Fig 4.2: Plot of Model Loss.

Table 4.1: Results for Train set.

Evaluation Parameter (Train)	Result in Positive Outcome (%)	Result in Negative Outcome (%)
Accuracy	88	88
Precision	93	84
Recall	85	92
F1 Score	89	88

Table 4.2: Results for Test set.

Evaluation Parameter (Test)	Result in Positive Outcome (%)	Result in Negative Outcome (%)
Accuracy	72	72
Precision	75	68
Recall	67	77
F1 Score	71	72

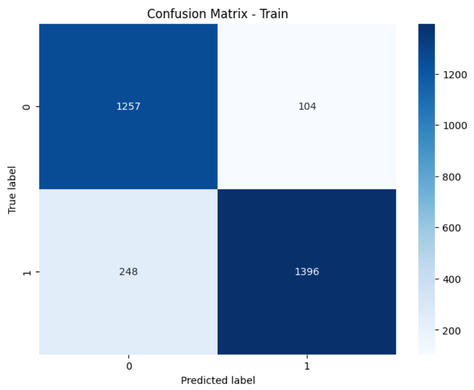


Fig 4.3: Confusion matrix for train set.

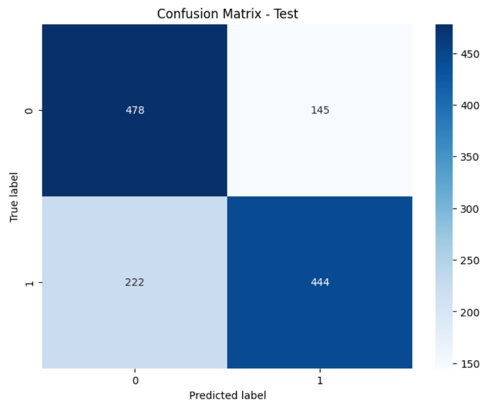


Fig 4.4: Confusion matrix for test set

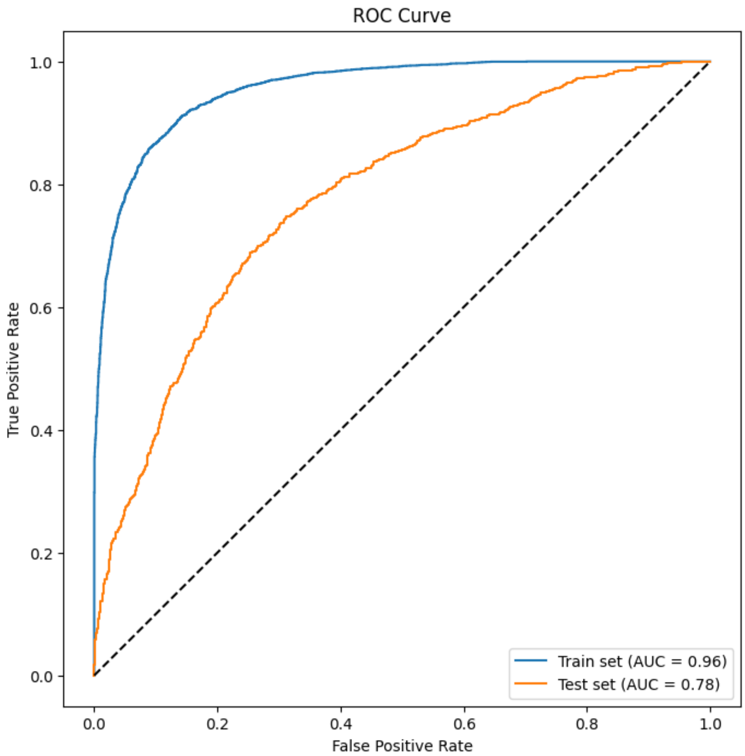


Fig 4.5: ROC curve for the EfficientNetb3 architecture.

2. For ResNet50 architecture:

After the implementation of ResNet50 architecture, the model was tested using the testing dataset. The model has 80% train accuracy and 72% test accuracy. Fig 4.6 and 4.7 shows the plotting of model accuracy and model loss. Table 4.3 and 4.4 shows the result of train and validation accuracy. The confusion matrix for train and test set has shown in fig 4.8 and 4.9. The ROC curve for the CNN model is shown in fig 4.10.

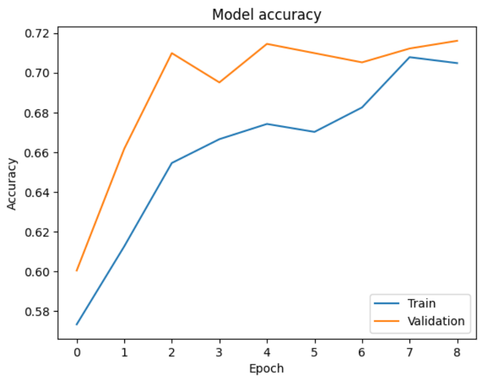


Fig 4.6: Plot of Model Accuracy.

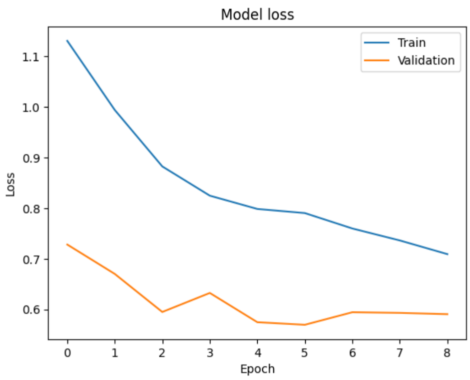


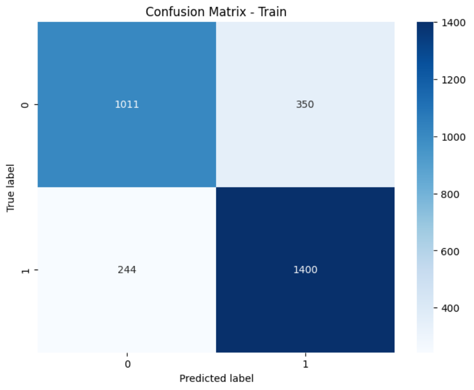
Fig 4.7: Plot of Model Loss.

Table 4.3: Results for Train set.

Evaluation Parameter (Train)	Result in Positive Outcome (%)	Result in Negative Outcome (%)
Accuracy	80	80
Precision	80	81
Recall	85	74
F1 Score	82	77

Table 4.4: Results for Test set.

Evaluation Parameter (Train)	Result in Positive Outcome (%)	Result in Negative Outcome (%)
Accuracy	72	72
Precision	70	73
Recall	78	65
F1 Score	74	69



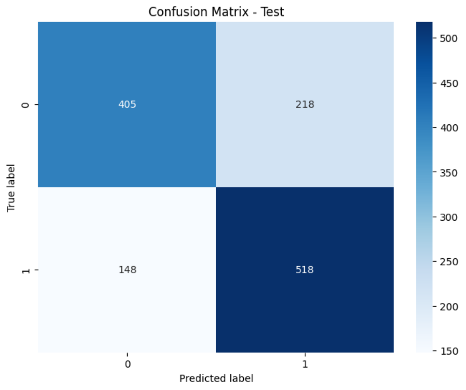


Fig 4.8: Confusion matrix for train set.

Fig 4.9: Confusion matrix for test set.

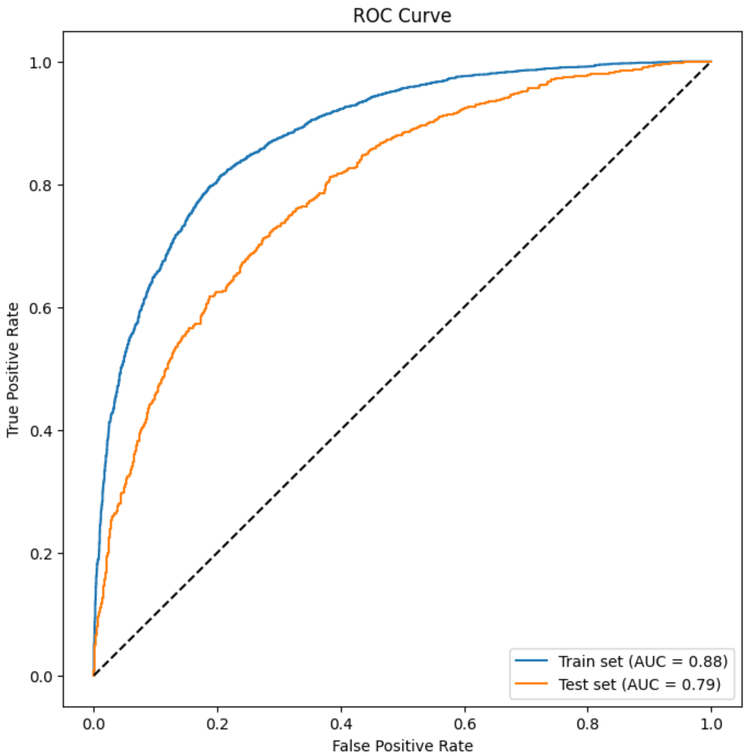


Fig 4.10: ROC curve for the ResNet50 architecture.

3. For ResNet101 architecture:

After the implementation of ResNet101 architecture, the model was tested using the testing dataset. The model has 77% train accuracy and 69% test accuracy. Fig 4.11 and 4.12 shows the plotting of model accuracy and model loss. Table 4.5 and 4.6 shows the result of train and validation accuracy. The confusion matrix for train and test set has shown in fig 4.13 and 4.14. The ROC curve for the CNN model is shown in fig 4.15.

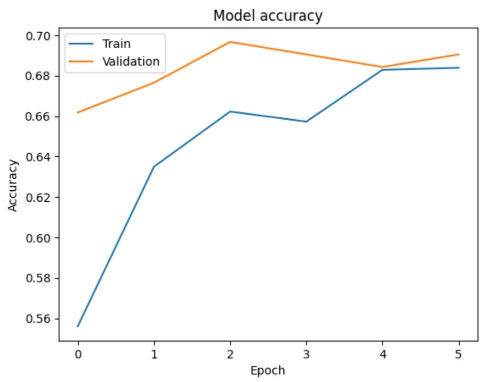


Fig 4.11: Plot of Model Accuracy.

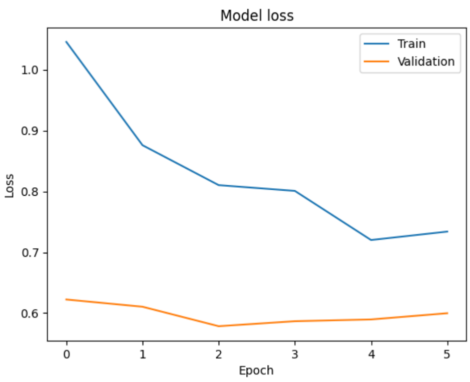


Fig 4.12: Plot of Model Loss.

Table 4.5: Results for Train set.

Evaluation Parameter (Train)	**Result in Positive Outcome (%)**	**Result in Negative Outcome (%)**
Accuracy	77	77
Precision	75	81
Recall	87	65
F1 Score	81	72

Table 4.6: Results for Test set.

Evaluation Parameter (Train)	**Result in Positive Outcome (%)**	**Result in Negative Outcome (%)**
Accuracy	69	69
Precision	66	74
Recall	82	55
F1 Score	73	63

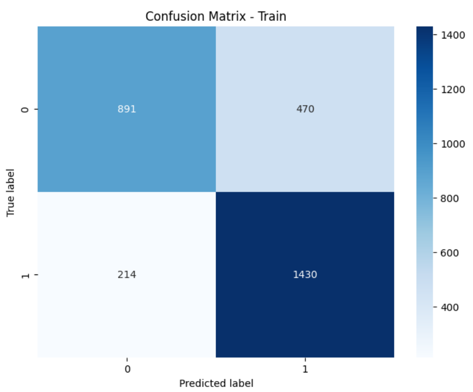


Fig 4.13: Confusion matrix for train set.

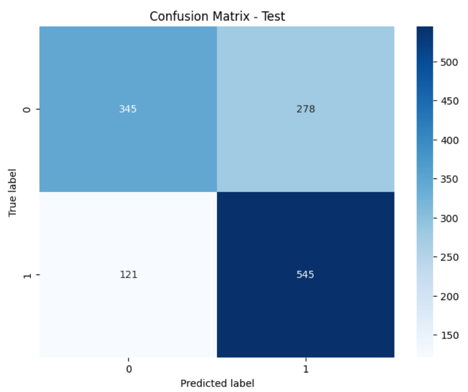


Fig 4.14: Confusion matrix for test set.

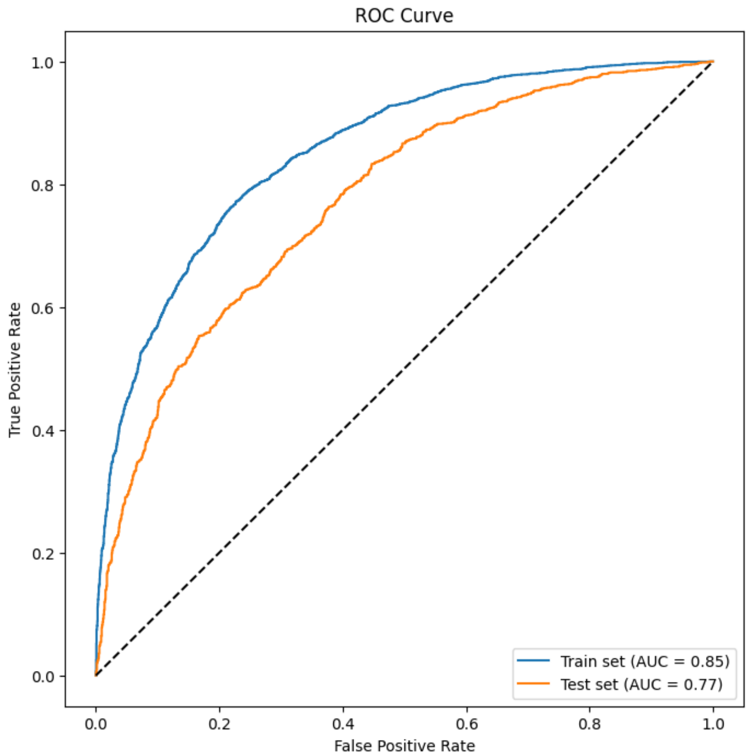


Fig 4.15: ROC curve for the ResNet101 architecture.

4. **For VGG16 architecture:**

After the implementation of VGG16 architecture, the model was tested using the testing dataset. The model has 79% train accuracy and 70% test accuracy. Fig 4.16 and 4.17 shows the plotting of model accuracy and model loss. Table 4.7 and 4.8 shows the result of train and validation accuracy. The confusion matrix for train and test set has shown in fig 4.18 and 4.19. The ROC curve for the CNN model is shown in fig 4.20.

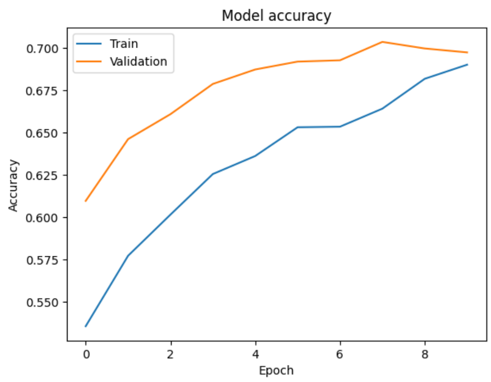


Fig 4.16: Plot of Model Accuracy.

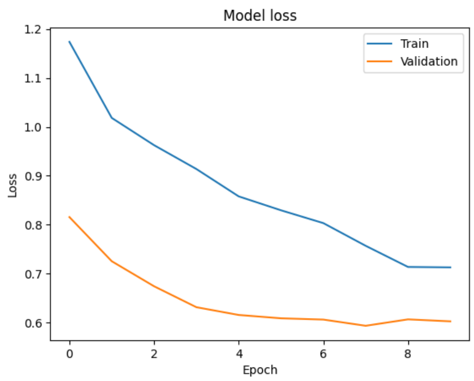


Fig 4.17: Plot of Model Loss.

Table 4.7: Results for Train set.

Evaluation Parameter (Train)	**Result in Positive Outcome (%)**	**Result in Negative Outcome (%)**
Accuracy	79	79
Precision	77	83
Recall	89	68
F1 Score	82	75

Table 4.8: Results for Test set.

Evaluation Parameter (Train)	**Result in Positive Outcome (%)**	**Result in Negative Outcome (%)**
Accuracy	70	70
Precision	67	75
Recall	83	56
F1 Score	74	64

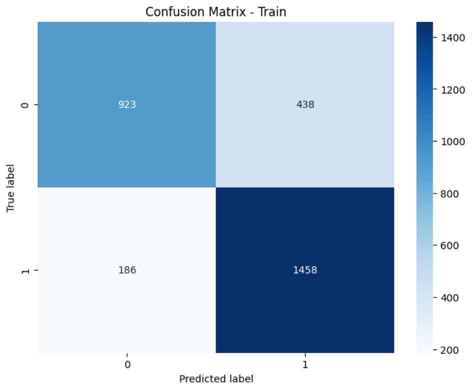


Fig 4.18: Confusion matrix for train set.

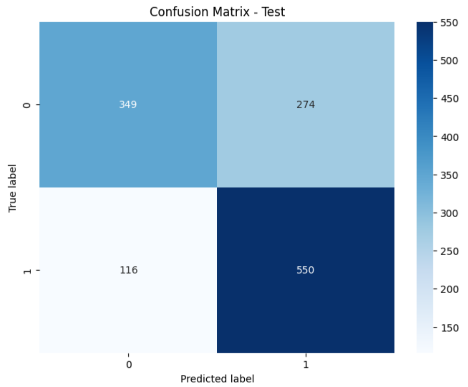


Fig 4.19: Confusion matrix for test set.

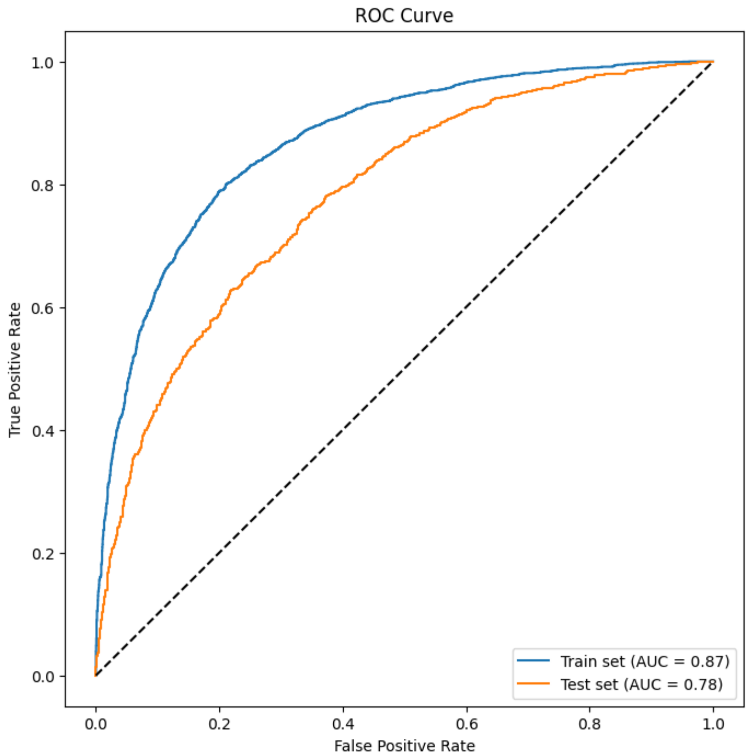


Fig 4.20: ROC curve for the VGG16 architecture.

5. **For VGG19 architecture:**

After the implementation of VGG19 architecture, the model was tested using the testing dataset. The model has 79% train accuracy and 70% test accuracy. Fig 4.21 and 4.22 shows the plotting of model accuracy and model loss. Table 4.9 and 4.10 shows the result of train and validation accuracy. The confusion matrix for train and test set has shown in fig 4.23 and 4.24. The ROC curve for the CNN model is shown in fig 4.25.

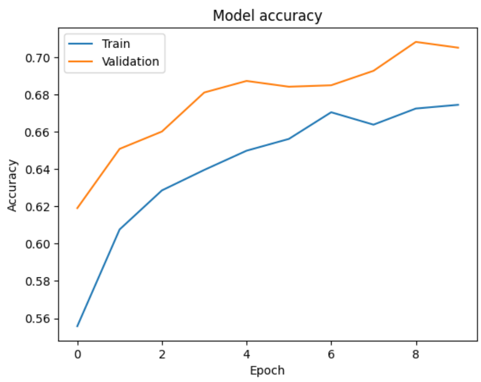


Fig 4.21: Plot of Model Accuracy.

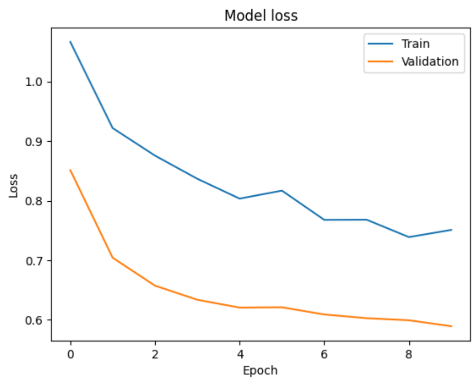


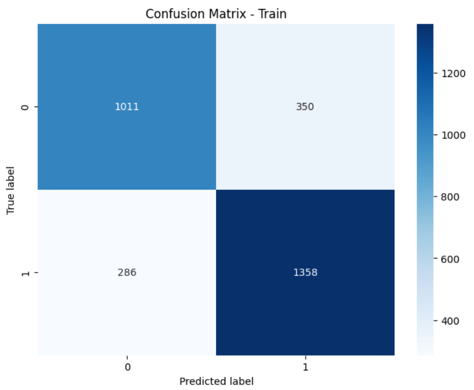
Fig 4.22: Plot of Model Loss.

Table 4.9: Results for Train set.

Evaluation Parameter (Train)	**Result in Positive Outcome (%)**	**Result in Negative Outcome (%)**
Accuracy	79	79
Precision	80	78
Recall	83	74
F1 Score	81	76

Table 4.10: Results for Test set.

Evaluation Parameter (Train)	**Result in Positive Outcome (%)**	**Result in Negative Outcome (%)**
Accuracy	71	71
Precision	69	72
Recall	77	64
F1 Score	73	68



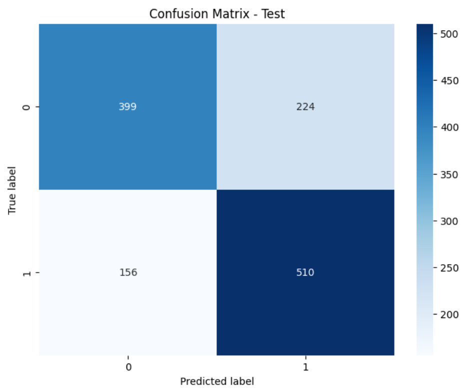


Fig 4.18: Confusion matrix for train set.

Fig 4.19: Confusion matrix for test set.

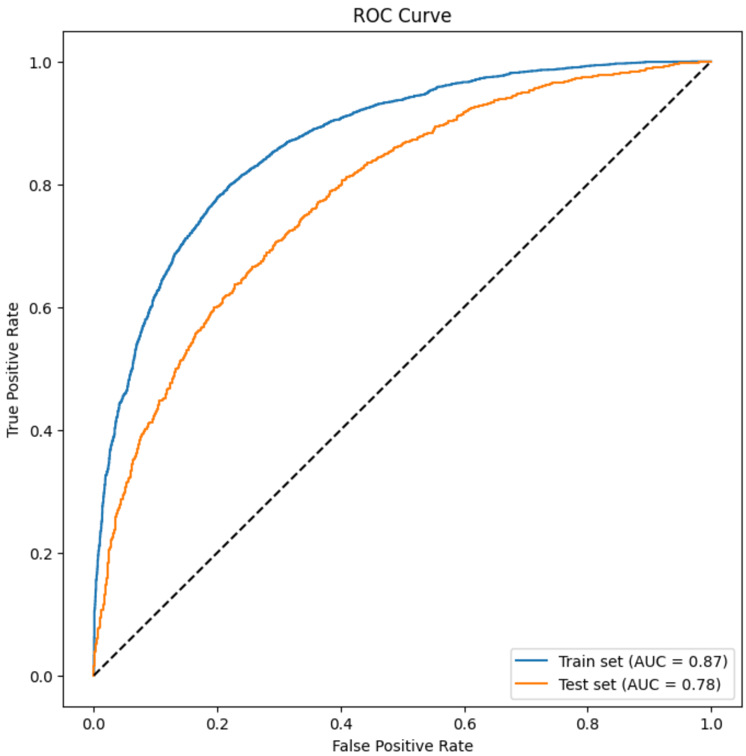


Fig 4.25: ROC curve for the VGG19 architecture.

4.6 Objectives achieved

The goals that have previously been met are listed below:

- Gathering data from authentic sources.
- Gathering the data into a dataset.
- Pre-processing the dataset to use in model.
- Fitting the dataset into 5 different architectures of CNN model.
- Evaluating the performance of the model.
- Decide which model works better for detection.

4.1 Financial Analyses and Budget

The financial components of the research described in this thesis are described in this section. It is significant to highlight that no financial costing or allocation was necessary for this investigation due to its nature. Without spending money on supplies, tools, or services, the research's main tasks included reviewing the available literature, analyzing the data, and exploring various theoretical possibilities. As a result, this thesis work's execution was free of any direct financial expenses. The investigation was carried out within the allotted timeframe and without any financial restrictions because there were no cost outlays.

4.8 Conclusion

From the result shown above, it can be said that the accuracy of the model is better using the EfficientNetB3 and ResNet50 architecture. The accuracy 72% for both of the architecture. So, the model which I trained with EfficientNetB3 and ResNet50 architecture performs much better.

CHAPTER V

Societal, Health, Environment, Safety, Ethical, Legal and Cultural Issues

This chapter contains Societal, Health, Environment, Safety, Ethical, Legal and Cultural Issues with Intellectual Property Considerations, Ethical Consideration, Safety Consideration, Legal Consideration, Impact of the Project on Societal, Health and Cultural Issues, Environment and Sustainability.

5.1 Intellectual Property Considerations

It is essential to consider intellectual property (IP) considerations to ensure that my work is properly protected and that I adhere to ethical standards. Here are some key considerations:

- **Originality:** It was ensured that my thesis work was original and did not infringe upon the intellectual property rights of others. This means conducting a thorough literature review to understand existing research and properly citing any sources was used.
- **Data Usage**: As using BreakHis dataset for this research, proper permissions from the authority were taken to use them. This might include considering copyright, licensing agreements, and any data privacy regulations.
- **Software and Algorithms:** The software and algorithms that were used in this work was not proprietary.
- **Ethical Consideration:** This research adhered to ethical standards, including protecting sensitive information, and avoiding any practices that could cause harm or exploitation.

5.2 Ethical Considerations

The ethical issues and difficulties that surfaced throughout the research process are covered in this section. Ensuring the welfare of all participants and adhering to ethical norms have been essential components of this research. All participants gave their informed consent prior to data collection, after being fully informed about the goals, methods, possible risks, and advantages of the study. A special focus was placed on keeping the data safe and comfortable. Potential biases based on ethnicity, or any other characteristic were to be minimized in the research.

Efforts were made to ensure fairness and inclusivity in participant selection and data analysis. One of the fundamental ethical principles underlying this study is the commitment to maintaining originality and avoiding plagiarism. Plagiarism, the uncredited use of others' ideas, words, or work, undermines the integrity of academic research. To uphold this principle, every effort was made to meticulously attribute and reference all external sources used in this thesis. Proper citation practices were observed to acknowledge the contributions of other scholars and to ensure that credit was given where it was due.

5.3 Safety Considerations

- Improve workplace safety.
- Aid emergency responses.

5.4 Legal Considerations

- Establishing cancer detection standards.
- Protecting women rights.

5.5 Impact of the Project on Societal, Health and Cultural Issues

This concept has implications for many facets of society, including health, safety, law, and culture.

Societal Impact:

- Increases production.
- Lowers healthcare expenses.
- Improves education.
- Eases social welfare.

Health Impact:

- Reduces mortality.
- Protects against cancer.
- Promotes growth.

Cultural Impact:

These cultural elements appear to fall into these categories:

- Use of health services, folk beliefs, fundamentalist religious beliefs.
- Relationships with men.
- Perception of danger or fatalism.
- Belief in different breast cancer therapies.
- Breast cancer awareness.

5.6 Impact of the Project on the Environment and Sustainability

The impact of the thesis work on the environment and sustainability lies in its potential to contribute to the improvement of public health outcomes, particularly for vulnerable populations such as women. By detecting breast cancer using advanced techniques like Machine Learning, the research can inform targeted interventions and policies aimed at identifying cancer. Ultimately, addressing breast cancer can lead to long-term benefits for environmental sustainability by promoting healthier, more resilient communities and reducing strain on natural resources and ecosystems.

CHAPTER VI

Addressing Complex Engineering Problems and Activities

Breast cancer detection is one of the trending Machine Learning problems currently. In recent years, significant advancements have been made in breast cancer detection, the credit goes to the fast adaptation of deep learning techniques. Despite the advancements, there are still a lot of scopes of improvement left in the problem. This chapter discusses about the complex engineering problems associated with this thesis work as well as the complex activities associated with the research.

6.1 Complex engineering problems associated with the current thesis

Breast cancer detection from histopathology images using Machine Learning approach is a complex engineering problem that has many characteristic which needs to be discussed. The target is to be able to detect cancerous cells, so the possibilities are endless here. Here, some of the aspects of this thesis has been discussed:

Table 6.1: Complex engineering problems associated with the current thesis.

Attribute	Addressing the Attributes of Complex Engineering Problems	
Depth of knowledge required	P1	This thesis work requires deep understanding about some of the most important aspects of machine learning and image processing, including CNN model, how the images are segmented using CLAHE, Otsu's threshold method, and how they can be implemented to different architectures of CNN model to improve the accuracy.
Range of conflicting requirements	P2	One of the goals of this thesis work is balancing the need for high performance (e.g. fast inference speed) with the requirement for high accuracy in machine learning model can be challenging. Often, increasing model complexity can improve accuracy but may also lead to longer inference times. I have chosen the CNN model, as it offers high performance.

Attribute	Addressing the Attributes of Complex Engineering Problems	
Depth of analysis required	P3	The problem that had been targeted for the thesis work, to accomplish a good result while segmenting the histopathology images and training CNN model with 5 different architectures such as EfficientNetB3, ResNet50, ResNet101, VGG16, VGG19 requires deep analysis on image processing and CNN model.
Familiarity of issues	P4	Familiarity with histopathology images and the ability to interpret microscopic tissue features are fundamental. This includes recognizing cellular structures, tissue patterns, and pathological abnormalities indicative of breast cancer. Knowledge of machine learning algorithms and image processing techniques is necessary to analyze histopathology images. Familiarity with methods such as convolutional neural networks (CNNs), feature extraction, and classification algorithms is essential.
Extent of applicable codes	P5	The research and development process, including the design, implementation, and evaluation of the CNN model, implicitly adhere to best practices in medical field, software engineering and machine learning model development.
Extent of stakeholder involvement and conflicting requirements	P6	The thesis uses ethically relevant publicly available dataset “BreakHis” to engage stakeholders and advance academic understanding of machine learning challenges. The technical goals of improving performance conflict with computational resource constraints and the ethical implications of generative models.
Interdependence	P7	The algorithmic development of the CNN model, dataset pre-processing and management, performance evaluation metrics, and ethical considerations are highly interdependent in breast cancer detection research.

6.2 Complex engineering activities associated with the current thesis

The activities that involves conducting a research includes considering the resources, the innovation in the idea, the impact of this thesis socially and economically. The following table discusses the complex engineering activities relevant with this thesis. Some of these activities include:

Table 6.2: Complex engineering activities associated with the current thesis.

Attribute	Addressing the Attributes of Complex Engineering Activities	
Range of resources	A1	The thesis work requires a broad range of resources. This includes computational resources for training deep learning models, an extensive dataset of histopathology images of breast tissue samples, high-performance computing infrastructure, including CPUs, GPUs, and cloud computing services, is essential for training and evaluating CNN models on large datasets of histopathology images, deep knowledge about image processing and machine learning model. Most importantly, the constant guidance of my supervisor has helped me to find the relevant resources for this work.
Level of interaction	A2	The thesis work involves addressing complex technical challenges related to image analysis, feature extraction and predictive modeling. Researchers must develop innovative algorithms and methodologies to overcome these challenges and achieve high accuracy in cancer detection. It involves close collaboration between experts in medical imaging, deep learning, and computational methods. The iterative nature of model development requires constant communication and feedback loops to refine and optimize the segmentation approach. The high level of interaction reflects the complexity of coordinating multidisciplinary efforts in this engineering endeavor.

Attribute	Addressing the Attributes of Complex Engineering Activities	
Innovation	A3	The work integrates machine learning techniques with medical imaging, particularly histopathology images, to develop predictive models for breast cancer detection. One of the primary innovations of the work is the creation of automated screening and diagnosis systems for breast cancer. By automating the process of analyzing histopathology images, the system can assist pathologists in identifying and characterizing suspicious lesions more efficiently and accurately, leading to earlier detection and treatment initiation. The innovation of the thesis work lies in its transformative potential to revolutionize breast cancer diagnosis and management through the application of cutting-edge engineering principles, advanced computational techniques, and multidisciplinary collaboration.
Consequences for society and the environment	A4	The thesis has significant societal benefits, enhancing diagnostic reliability and healthcare efficiency. It can reduce errors, streamlines workflows, and adapts to diverse clinical scenarios, potentially leading to improved patient outcomes. By developing automated tool with the machine learning model can improve better outcome. Environmentally, its efficiency contributes to resource optimization in medical imaging, aligning with sustainability goals.
Familiarity	A5	The thesis work requires familiarity with medical imaging, image processing, and deep learning techniques. Understanding histopathology features, cancer classification, image processing techniques and neural network architectures is crucial for effective implementation.

In conclusion, breast cancer detection is undoubtedly a challenging domain that integrates machine learning and image processing. In this chapter the current problems and complex activities that are associated with the field has been discussed. Some of the problem still needs to be addressed, and could be solved with a complex model and more computational resources.

CHAPTER VII

Conclusions

This chapter includes the summary, limitations and the work plan that might be executed in near future**.**

7.2 Summary

This thesis work is about detecting breast cancer from histopathology images using Machine Learning. A pre-trained CNN model was used to classify whole slide breast cancer histopathology images into benign and malignant (binary classification). The result obtained by the segmented image was better than the other. This will have a great impact by helping pathologists, especially in those low resource settings where both the expertise and the means is in scarce.

7.2 Limitations

- Some technical errors caused failure in model training.
- Some of the image quality was low.
- Duplicate image caused problem.
- Fitting the dataset into the model.

7.3 Recommendation and Future Work

Instead of manually shrinking images, the proposed method can be improved by using an auto encoder. Data can be compressed without losing important details because to auto encoders' ability to recreate up to 90% of the original image. I can add spectrum imaging from the standpoint of technique improvement. In contrast to the simple RGB image with three channels, spectral imaging produces images with varied wavelengths. Additionally, I can mix several imaging techniques like MRI, CT scan, ultrasound, and mammographic images to get the results of the combination. The term "multi model fusion" refers to this method. Deep learning may easily fix the aforementioned issues and be utilized to conduct high-caliber research that could result in even better outcomes.

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