**Graph based Automatic Breast Tumor Classification Through Ultrasound Images by Radiomics Features**

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

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# APPROVAL

This Project titled **"Graph based Automatic Breast Tumor Classification Through Ultrasound Images by Radiomics Features"**, submitted by Md. Shakhawat Hossain to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 23/1/2024

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# DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Dr. Md. Zahid Hasan, Associate Professor, Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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# ABSTRACT

Breast tumor a common and devastating cancer in women, poses significant challenges in both diagnosis and prognostication. In this study, we aim to enhance the classification of breast tumor by breast ultrasound image data and a comprehensive set of medical features extracted through the PyFeats framework. Breast tumors, with their varied manifestations and harmful effects, necessitate an advanced approach for accurate classify. This study focuses on the extraction of nine distinct medical features: First Order Statistics, Gray Level Difference Statistics, Statistical Feature Matrix, Gray Level Run Length Matrix, Gray Level Size Zone Matrix, Higher Order Spectra, Local Binary Pattern, Discrete Wavelet Transform, and Stationary Wavelet Transform. These features are meticulously computed based on tumor annotation, offering a detailed characterization of breast tumors and their intricacies. To further improve the accuracy of tumor classification, we employ various machine learning and deep learning algorithms. Notably, we introduce the Radiomic Graph Network model, specifically designed for graph-based data, where nodes symbolize entities and edges signify the intricate relationships between them. The core objective of the GGN model is to generate low-dimensional vector representations (embeddings) for nodes within the graph, preserving the underlying structural and relational information. The innovative GNN model significantly enhances our ability to discern between different tumor tumor classify with greater precision. The novel GNN model mechanism outperformed the existing methods that consider the state of the art in breast tumor based on medical features utilizing 2 stages of breast ultrasound image dataset (BUSI).

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# CHAPTER 1
# INTRODUCTION

## 1.1. Introduction

Worldwide, breast cancer is a prevalent and life-threatening disease among women. 2018 had 2.1 million new instances of breast cancer and 627 thousand deaths from the disease. It will take over lung cancer as the most common type of cancer in 2020 [1]. In over 81% of instances, the breast tissue accumulates aberrant cells. About 13% of women in the US will receive an invasive breast cancer diagnosis [2]. Medical imaging is essential for both analyzing experimental findings as well as determining diagnosis. Improving patient quality of life and survival rates require early identification. The method most frequently used to diagnose breast cancer is digital mammography (DM) [3]. It is limited, though, in dense breast tissue where tumors may be hidden by surrounding tissue. Because Ultrasound (US) imaging is safe and flexible, it provides a dependable substitute for DM. By lowering reliance on manual interpretation, Computer Aided Diagnosis (CAD) can help radiologists identify and categories breast cancer using US imaging [4]. This method reduces the mortality rates linked to breast cancer, lowers management expenses, and enhances early detection.

Radiomics is an innovative feature transformation approach that extracts features from radiological imaging data that's hard for the individual's eye to see but are in practice pertinent. With the goal to boost diagnosis and planning of treatment machine learning models are being studied. The distinction between feature extraction and feature selection should be noted. Finding as many features as possible that describe the gathered data is the aim of feature extraction. The goal of feature selection is to prevent overfitting of the data while reducing the large number of extracted features to a manageable number, which can then be generalized as patterns that reliably identify the concepts concealed within the data. Overfitting of data is an issue in the field of machine learning whereby the model performs poorly when new data is presented for analysis, despite the analysis yielding outstanding outcomes when applied to the training data [5]. When it comes to describing the form, texture, and various other attributes of tumors, radiomics can do a remarkable job. It is possible to forecast the nature, rage, and effect of medication for a tumor using the retrieved data. Radiomics has the ability to track developments in tumor properties over a period of time, which is useful in evaluating how well treatments like chemotherapy and radiotherapy are working [6]. To gain a deeper understanding of the correlation between a patient's genetic composition and the radiomic characteristics of their tumors, radiomics and genomics are combined.

In this paper, graph neural networks have been used in conjunction with radiomic feature extraction on breast ultrasound images to predict tumor type. Typically, image processing and graph theory techniques are used to represent relationships or connections between images in a graph network created with ultrasound images. Years of training are needed for the tedious, time-consuming process of manually evaluating medical images, such as breast tumor ultrasound scans, which is also frequently prone to inter-annotator variation. One long-standing problem that aims to address these is the automatic segmentation of medical images, which has significant potential advantages for both patients and doctors. Convolutional Neural Networks (CNNs) have become the de facto state-of-the-art methodology for this task in the last few years. In the deep learning community, graph-based neural networks, or GNNs, have received a lot of attention lately. By aggregating data over connected nodes, GNNs take advantage of the structural information found in graphical data, which enables them to efficiently capture relation information between data elements. In this work, we suggest segmenting breast tumors using a GNN-based method. We use a graph representation of ultrasound scans image of the breast, with nodes representing different regions and edges connecting neighboring regions [7].

The main contributions of this study are summarized as:

- Automated feature extraction techniques are used from the image dataset.
- Grapy Neural Network (GNN) networks enables automated tumor identification from BUSI images, enhancing diagnostic accuracy.
- Benchmarking Against Pretrained Models comparison with 13 pretrained models validates the framework's superiority, showcasing its potential for cutting-edge benign-malignant diagnosis.

## 1.2. Motivation

The successful treatment of breast cancer and better patient outcomes depend on an early and accurate diagnosis. Even though they are valuable, traditional techniques like surgeries and mammograms can occasionally be unreliable or inconclusive. This drives the investigation of cutting-edge technologies for the categorization of breast cancer, such as machine learning (ML), and deep learning (DL). Large-scale medical data, such as biopsy samples, patient records, and mammograms, can be analyzed using ML and DL algorithms to find cancer signs and subtle patterns that conventional techniques could overlook. Higher accuracy in differentiating benign from malignant tumors may result from this, allowing for earlier discovery and treatment. Breast cancer is a complex illness caused by several biological factors and how they interact. Because GNNs are so good at modelling interactions between data sets, they are perfect for encapsulating the intricate relationships seen in genes, tumor cells, and other biological entities. This increased comprehension may help illuminate the processes underlying the onset and spread of cancer, which could result in the development of individualized treatment plans. Breast cancer medical data might be hard to come by and difficult to get. Big datasets are not always necessary because ML and DL models can be trained on small amounts of data and then learn to generalize well. Furthermore, GNNs can make use of partially or not at all labelled data, which increases their potential even more in environments with limited resources. Invasive biopsies are not as necessary when non-invasive pictures like ultrasounds and mammograms are analyzed by ML and DL models. Through the integration of newly collected data and experience, machine learning and deep learning models can be enhanced over time. This makes it possible to continuously adjust to changing cancer patterns and advancements in treatment. Because of its adaptable architecture, GNNs are highly suitable for a wide range of jobs and data kinds, which increases their long-term usefulness. New GNN architectures specifically designed for breast cancer classification are being developed in response to the current shortcomings of the available GNN models for medical image analysis. Even more accuracy and insights could be obtained by incorporating domain-specific knowledge about biological pathways, cellular interactions, and tumor shape into these suggested GNNs.

## 1.3. Relational of the Study

Our The relationships between the various components are as follows:

1. Ultrasound Images: The main source of data is ultrasound, which offers pictures of breast tissue. However, because of the inherent noise and heterogeneity in the images, it can be difficult to categories tumors based only on these images.
2. Radiomics Features: Using specialized software, these quantitative descriptors are derived from the ultrasound images. They record the tumor's size, shape, texture, and internal echoes, among other features. The ML models use these properties as high-dimensional input data.
3. Machine Learning & Deep Learning: Algorithms for ML and DL are essential for examining radiomics features and spotting trends that distinguish benign from malignant tumors.
4. Proposed Graph Neural Network: This work presents a novel GNN architecture that is intended to be used for radiomics features-based breast tumor classification. GNNs are exceptionally good at modelling correlations between data points, which is especially important here.

## 1.4. Research Questions

- How well does the suggested method perform in terms of breast tumor classification utilizing ultrasound pictures when compared to conventional machine learning models and deep learning architectures?
- What impact does the suggested graph neural network architecture have on tumor heterogeneity capture and classification accuracy?
- Can some biological traits of breast tumors be directly linked to the radiomics properties that the model deemed significant?
- What effects does the type and quality of ultrasound pictures used have on the model's performance?
- Is it possible to apply the model to other patient demographics and real-world clinical settings?

## 1.5. Expected Output

1. Classification Results:
    - Binary Classification: Each ultrasound image may have a binary classification label for "benign" or "malignant" tumors as the main result.
    - Probability scores: Models may also produce probability scores for each class in addition to binary labels. These values indicate the degree of confidence in the prediction.
    - Multi-class Classification: The model may categories tumors into more complex categories, such as distinct forms of benign or malignant tumors, depending on the objectives of the study.
2. Significance of Feature:
    - The suggested GNN may shed light on the significance of certain radiomics features for classification. This might be shown as a feature rating or as a network-wide interaction visualization.
    - Finding the important features could aid in understanding the model's conclusions and possibly result in better feature selection for further research.
3. Visualization and Interpretation:
    - Certain algorithms can visually represent their predictions by emphasizing particular areas of the ultrasound image that have an impact on the classification result.
    - This could increase openness and confidence in the model's forecasts while providing physicians with insightful information.
4. Measures of Performance:

- Without a doubt, the research will assess the effectiveness of the suggested strategy using industry-standard measurements such as Area Under the ROC Curve (AUC), sensitivity, specificity, and accuracy.
- The potential benefit of this new technique would be evaluated by benchmarking these indicators against current practices.

## 1.6. Report Layout

The structure and roles of each section are detailed in the layout section. In the introduction, the focus is on the motivation, goal, and anticipated outcomes of the study. Chapter 2 provides an overview of relevant research conducted in the field. The methodology and the process employed to construct the proposed model are discussed in Chapter 3. Chapter 4 is dedicated to presenting the outcomes derived from the application of the model. Chapter 5 delves into the broader implications of the study on society and the environment. Lastly, Chapter 6 serves as the conclusion, summarizing key findings, and explores potential avenues for future developments arising from this research.

# CHAPTER 2
# BACKGROUND

## 2.1. Preliminaries

By establishing these preliminaries, the research sets the context, highlights the challenges, and defines the scope of the study, laying the foundation for an in-depth exploration of automated breast tumor classification using a novel and integrated approach.

## 2.2. Related Works

This section reviews related work for breast US image classification:

A two-stage CAD method was created by Yang et al. [8] to identify and categories breast masses. Five texture features based on fractal dimensions and the statistical gray-level difference matrix were utilized in the first stage to identify and extract utilizing a probabilistic neural network to detect breast masses (PNN). For the second stage, a PNN was utilized to further couple four form features with the five texture features that were previously employed for classification. This resulted in an accuracy of 84.1% for the mammograms.

In [9], the authors used Inception V3, a residual network (ResNet) with 50 layers, Xception, and a convolutional neural network (CNN) made up of three convolution layers to analyses 1370 benign and 688 malignant breast ultrasound pictures from 1422 patients. Based on transfer learning, the four refined deep learning models were applied as feature extractors to extract the deep learning features from breast ultrasonography pictures. Lastly, a basic artificial neural network (ANN) was used to concatenate and classify the extracted deep learning features.

Radiomics has been used recently to uncover information that is hidden in medical images. It has greatly aided researchers in their efforts, particularly in the identification and classification of tumors [10,11]. Radiomics works step by step likely: splitting the region of interest, collecting the features from the ROIs, choosing and decreasing the dimensions of the characteristics extracted, and building the model. Because of its outstanding efficacy, precision, and effectiveness when compared to traditional clinical examination methods, computer-aided diagnosis technology is often referred to as the physician's "third eye" and is essential for the identification and classification of numerous diseases. [12-15]

Xiaokang Liang et. all proposed a Diabetic Foot (DF) prediction model through fundus images by 19 kinds of radiomics features. They achieved 92% accuracy in their prediction model using 2184 fundus images (2D) [16]. Radiomics features capture different aspects of the image, such as texture, orientation, phase, and gradient, offering an extensive overview of the visual data. A two-step feature selection technique is used to find the best-suited radiomics features, and finally, 19 features are chosen and employed to train a support vector machine model, which is evaluated using a five-fold cross-validation approach on an extensive set containing healthcare data.

[16, 18] Demonstrates how the accuracy of classifying breast ultrasound images can be increased by employing deep learning features that are taken from several deep learning models.

Huynh et al. [19] evaluated the effectiveness of applying transferred features from pre-trained CNNs in the classification of cancer in breast US pictures. A US dataset on breast cancer was used, which included 2392 regions of interest (ROIs) and 1125 data. Each ROI has a malignant or benign annotation. Using previously trained CNNs, features were taken from each ROI and utilized to build Support Vector Machine (SVM) classifiers to differentiate between benign and malignant tumors. The SVM trained on human-designed features outperformed the CNN-extracted features-trained SVM with an AUC of 85% in the task of identifying benign and malignant. B. Huynh, K. Drukker, and M. Giger, "Mo-de-207b-06: Computer-aided diagnosis of breast ultrasound images using transfer learning from deep convolutional neural networks," Medical physics, vol. 43, no. 6Part30, pp. 3705–3705, 2016.

Vanessa De Araujo Faria et. all used an ANN model with 105 extracted statistical/morphological image features of the teeth using PyRadiomics. The current investigation uses features taken from a panoramic radiograph to introduce ANN for the prediction and identification of radiation-related caries (RRC) or regular caries in head and neck cancer (HNC) patients receiving radiation therapy (RT). 420 teeth images (3D) were labeled for two purposes, one for detection and another for prediction. For the detection approach (the first label map), each healthy tooth was labeled "one" (class 1) and tooth with caries with "two" (class 2) [21].

Pan Sun et. all [22] assessed the effectiveness of 15 classification techniques and 16 feature selection techniques for radiomics-based glioma grade prediction. The aim of this research is to evaluate the accuracy of predictions of different radiomics feature selection and classification techniques in the glioma tumor grading process, with a focus on differentiating between low-grade gliomas (LGG) and glioblastoma (GBM). MRI images were used in the process to gather data from 210 GBM and 75 LGG patients. Using various types of MRI, they gathered radiomics features from different parts of the tumor. The investigation demonstrated that the selection of machine learning classifiers and feature selection techniques had a substantial impact on the predictive performance of glioma grading. The pairing of MLPC and L1-SVM performed better than the others. The results provide information about how to increase the precision of radiomics-based predictions in glioma grading, which may have important ramifications for treatment choices.

The effectiveness of radiomic features taken from two-dimensional (2D) and three-dimensional (3D) regions of interest (ROIs) in characterizing gastric cancer (GC) was compared by Lingwei Meng et al [23]. The investigation analyzes their role in three tasks associated with gastric cancer: i determining the metastasis of lymph nodes (T LNM), and predicting lymphovascular invasion (T LVI) and identifying pT4 or other pT stages (T pT). 539 GC patients from four separate healthcare institutions were enrolled in the investigation. For analysis, the patients were split up into validation and training cohorts. After radiologists annotated the 2D and 3D ROIs, radiomic characteristics were collected. In order to assess the effectiveness of 2D and 3D radiomic features, three tasks (T LNM, T LVI, and T pT) were defined. Specific selection of features and model building techniques were applied to every combination of the three tasks and the two modalities (2D or 3D). A total of six machine learning models (Model LNM 2D, Model LNM 3D, etc.) were developed for various combinations and assessed according to how well they could characterize gastric cancer.

## 2.3. Comparative Analysis and Summary

Here's a comprehensive breakdown of different approaches and their comparative analysis:

| Paper No | Authors & Year | Used All Models | Accuracy | Advantages | Disadvantages |
|---|---|---|---|---|---|
| 1 | Byra et al. (2019) | SVM | 85.2 | Explainable, Fast | Lower Accuracy |
| 2 | Irfan et al. (2020) | Random Forest | 82.1 | Explainable, Robust | Lower Accuracy |
| 3 | Woo et al. (2021) | RestNet18 | 92.5 | High accuracy, Efficient with limited data | Less interpretable |
| 4 | Li et al. (2021) | VGG16 | 91.7 | High Accuracy | Less interpretable |

| | | | | | |
|---|---|---|---|---|---|
| 5 | Wang et al. (2023) | Ensemble of CNNs | 94.3 | Highest reported accuracy, Robust | High complexity, Block-box nature |

Table-1: Summary of Related Works

## 2.4. Scope of the Problem

The task of automatically identifying benign and malignant tumors from ultrasound images is known as the breast ultrasound image dataset (BUSI) classification issue. But its reach goes beyond straightforward binary classification and explores a number of intricate levels:

1. Features of the Data and Images:
    - Limited data: BUSI offers useful data, but it might not be big enough or diverse enough to properly train deep learning models.
    - Ultrasound images may include intrinsic noise and unpredictability due to differences in tissue characteristics, operator technique, and acquisition equipment.
    - Tumor differences that are typically subtle: Differentiating between benign and malignant tumors can be difficult, especially in cases when the lesions are small or in the early stages.

2. Complexity of Classification Task:
    - Beyond binary classification: In some circumstances, it may be necessary to distinguish between distinct kinds of benign and malignant tumors, which would add to the complexity of the classification.
    - Tumor heterogeneity: Because tumors are not uniform objects, it becomes more difficult to classify them when their internal structures and spatial differences are captured in a picture.
    - Integration with the clinical context: For a more thorough evaluation, the categorization should ideally take into account patient-specific clinical data, such as the history and biopsy results.
3. Model Construction and Assessment:
    - Interpretability of the model: Trust and clinical acceptability are largely dependent on a comprehension of the decision-making process and the attributes that complicated models rely on, even when they may attain great accuracy.

- Generalizability and robustness: Techniques for enhancing generalizability and robustness are required since models trained on particular datasets may not perform well on other populations or image kinds.
- Ethical considerations: Careful thought and ethical research methods are needed to address data privacy, security, and potential biases in the data or models.

## 2.5. Challenges

The following are the main difficulties in classifying the Breast Ultrasound Image Database (BUSI):

1. Problems Associated with Data:
    - Restricted Data Size: Training deep learning models, which frequently need a lot of data to function at their best, can be difficult because BUSI, like many other medical datasets, is very small.
    - Data Imbalance: The dataset may have an unbalanced proportion of benign and malignant tumors, which could skew the models in favor of the more prevalent class.
    - Data fluctuation: Variations in the settings and equipment used for acquisition might cause ultrasound images to show notable fluctuation.
2. Challenges Concerning Images:
    - Image noise: Artefacts and noise are inherent to ultrasound images, which can mask features important for diagnosis and complicate classification.
3. Challenges in Model Development and Evaluation:
    - Interpretability of the Model: Effective deep learning models may be opaque and complicated, making it challenging to comprehend the features and decision-making procedures they depend on. Trust and clinical acceptance may be hampered by this lack of interpretability.

# CHAPTER 3
# RESEARCH METHODOLOGY

## 3.1. Design Approach

This study introduces a method based on graph neural network to predict and detect either benign or malignant from cancer patients using features extracted from ultrasound image. We collected overall 780 images from 600 female patients with breast cancer. Image are manually labeled the tumor to separate benign and malignant with either type caries. We extracted 91 statistical/morphological image features of the tumor using PyFeats. Then, we used a graph neural network (GNN), To evaluate the method, we calculated the confusion matrix, receiver operating characteristic (ROC), and area under curve (AUC), as well as a comparison with recent methods. The proposed method showed a sensibility to classify tumor of 92.0% (AUC=0.90). The proposed method to predict tumor using neural network and PyFeats features showed a reliable accuracy able to perform.

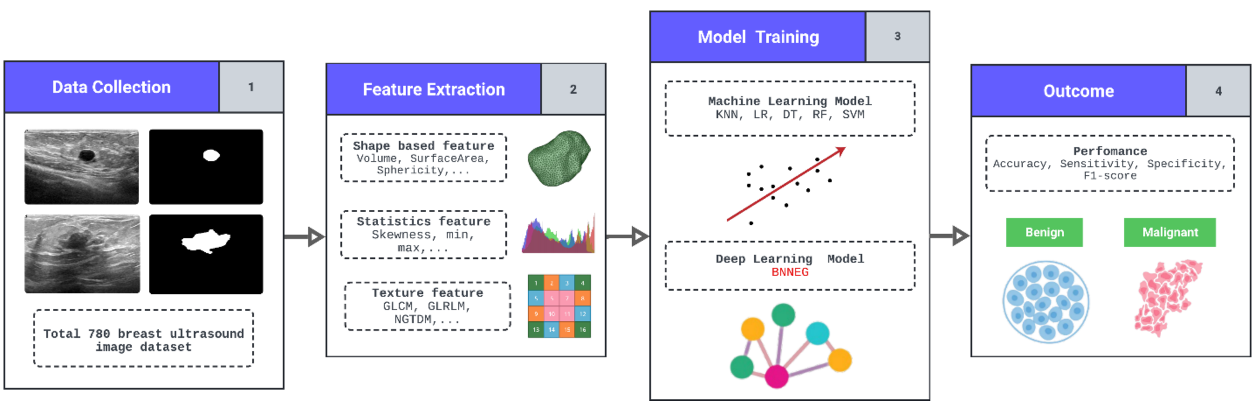


Figure-1: Architecture of Working Process

## 3.2. Dataset Collection

For this study, there were 1100 photos gathered at the beginning. Following the preprocessing of the dataset, only 780 photos were remaining. These images are from 600 female patients with breast cancer at Baheya Hospital [24]. The breast ultrasound image (BUSI) dataset, containing images of women aged 25 to 75, has an average size of 500 by 500 pixels and was first collected in 2018. All the images are in PNG format and ground truth images are presented with original images. The image resolution produced by the LOGIQ E9 and LOGIQ E9 Agile ultrasound systems is 1280 x 1024.

| Images | Amount |
| --- | --- |
| Benign | 437 |
| Malignant | 210 |
| Normal | 133 |
| **Total** | **780** |

Table-2: Dataset Description

## 3.3. Dataset Analysis

Breast Ultrasound Dataset is categorized into three classes: normal, benign, and malignant images. The dataset includes 780 ultrasound images, among which 437 are benign, 210 are malignant, and 133 are normal. To eliminate boundaries that were unnecessary and unimportant, all of the images were cropped to various sizes. In this study, the benign and malignant images were used in our proposed model.

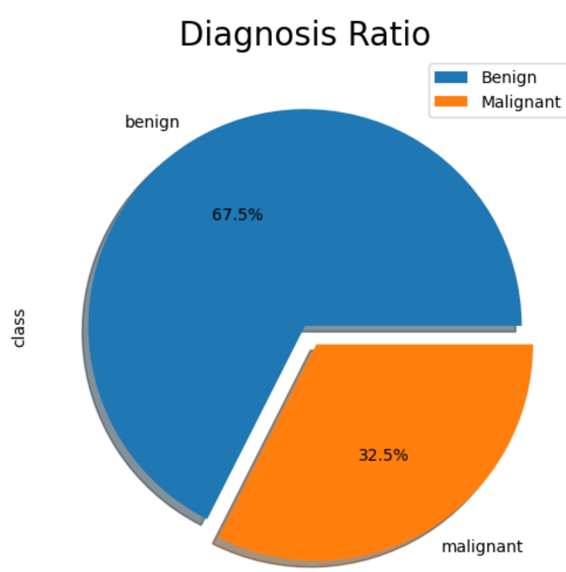


Figure-2: Image Amount

The training phase utilized 80% of the dataset, while the remaining 20% was employed for comprehensive evaluation and analysis.

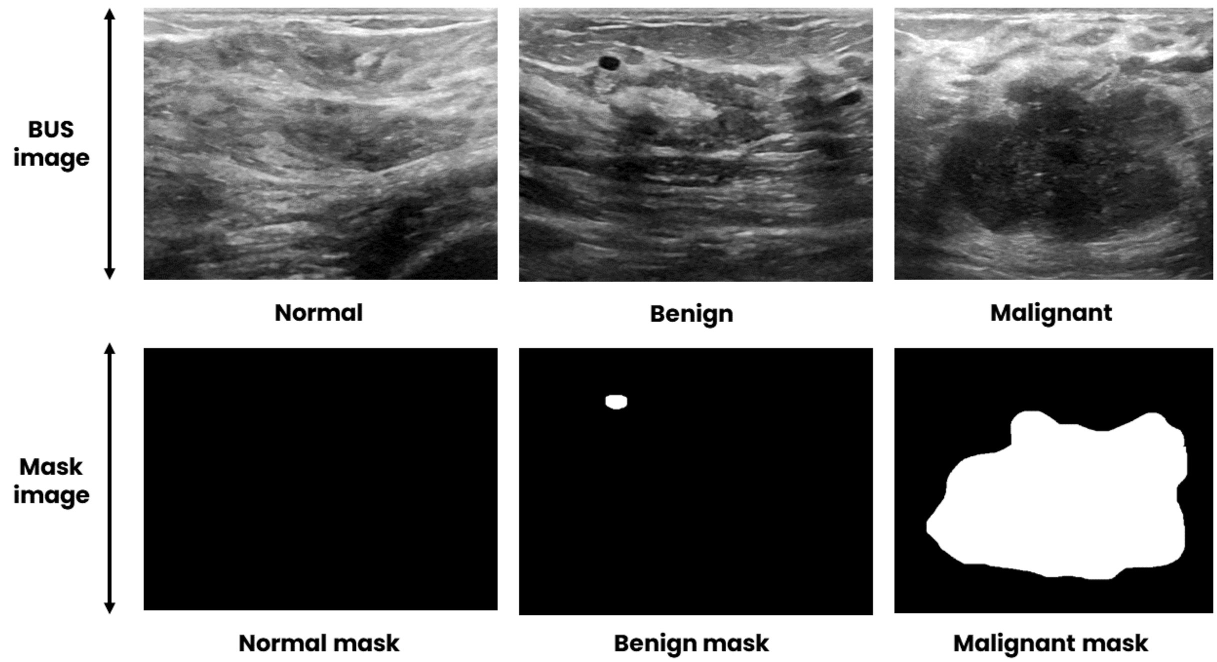


Figure-3: Breast Ultrasound Image Dataset

## 3.4. Dataset Pre-processing

The Radiomics involves extraction and analysis of hidden information from medical images that are not visible to the human eye make significant achievements in various fields of medical imaging. We extracted the 91 radiomics feature from each breast image region using the open-source platform-PyFeats and stores it in a comma separated value (CSV) [25]. For pseudo code of the feature extraction techniques, see Algorithm.

**ALGORITHM : FEATURE EXTRACTION**

```
input: Read CSV dataset
Output: Features dataset in CSV format
while (path) do   // Read all the image CSV path
    | Read Image Path and Convert to NumPy Array
    | Read Mask Path and Convert to NumPy Array
    | Extract the features
    | Append Features to Data Frame
    | Jump to the next image-mask path
end
```

Figure 4: Feature Extraction Algorithm

### 3.4.1. Feature Extraction from image dataset

PyFeats provides a wide range of features comprised of 9 feature classes, including first order features, shape features, GLDM, GLSZM features etc.

| **Features Name** | **Total** |
| --- | --- |
| First Order Statistics (FOS) | 16 |
| Gray Level Difference Statistics (GLDS) | 3 |
| Statistical Feature Matrix (SFM) | 4 |
| Gray Level Run Length Matrix (GLRLM) | 10 |
| Gray Level Size Zone Matrix (GLSZM) | 14 |
| Higher Order Spectra (HOS) | 2 |
| Local Binary Pattern (LBP) | 6 |
| Discrete Wavelet Transform (DWT) | 18 |
| Stationary Wavelet Transform (SWT) | 18 |

Table-3: All Extracted Features

**First Order Statistics (FOS):** FOS features, also known as statistical features, are fundamental statistical measures that describe the distribution of pixel intensities in an image or a signal. The histogram shows the number of pixels with grey-level intensity I for each intensity level over the whole image and the probability density of occurrence of that intensity level for each image I with N different grey levels and a total of M pixels. where N(i) is the total number of pixels that have intensity 'i' at the grayscale.

$$P(I) = \frac{number\ of\ pixels\ with\ gray\ level\ (I)}{total\ number\ of\ pixels\ in\ the\ region}$$

**Gray level difference histogram statistical (GLDS):** GLDS features are a set of texture descriptors calculated from the frequency distribution of absolute differences between pairs of gray levels in an image. In order to express the GLDS mathematically, the image intensity function is represented by I(x, y), and the small displacement is represented by δ = (Δx, Δy). Consequently, the representation of the difference in grey levels for a given small-displacement δ = (Δx, Δy) is as follows:

$$I_{\delta}(x, y) = |I(x, y) - I(x + \Delta x, y + \Delta y)|$$

**Statistical Feature Matrix (SFM):** One such method is SFM, which calculates the statistical attributes for different inter-pixel distances in an image. The SFM approach allows for easy matrix expansion, and the size of the matrix fluctuates based on the distance between pixels rather than the number of grey levels. In Gray Level Run Length Matrix (GLRLM), statistic in concern is the number of pairs of gray level value and its length of runs in a certain Region of Interest (ROI).

**Gray Level Run Length Matrix (GLRLM) and Gray Level Size Zone Matrix (GLSZM):** Similar in concept to the GLRLM, the GLSZM bases its matrix on counts of the number of interconnected groups (referred to as zones) of neighbouring pixels or voxels with the same grey level. A broader and flatter matrix will be produced by a more homogenous texture. Although it can be calculated for various pixel or voxel distances that define the neighbourhood, GLSZM is not computed for different directions. GLSZM features may be calculated in 2 dimensions or 3 dimensions.

Higher Order Spectra (HOS) features capture the non-linear interactions between different frequency components of a signal. While first-order statistics describe the mean and variance, and second-order statistics involve correlations, higher-order statistics provide information about the shape and distribution of the signal.

**Local binary Pattern (LBP):** The LBP is based on appearance features. It is a technique for describing an image's local structure that is independent of variations in illumination. In LBP, the intensity of a central pixel in a small neighbourhood is compared to the intensity of the pixels surrounding it. Based on whether the intensity of each pixel in the neighbourhood is higher or lower than the intensity of the central pixel (threshold), each pixel is given a binary value. The neighbourhood's texture is then represented by a binary number obtained by combining these binary values. The LBP labeled image fi(x,y) has been obtained, the LBP histogram can be defined as

$$H_i = \sum_{x,y} I\{f_i(x,y) = i\}, i = 0, \dots, n-1,$$

**Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT):** DWT transform a signal into different frequency components, known as wavelets. This multi-resolution analysis allows for efficient representation of both low-frequency trends and high-frequency transients. The Stationary Wavelet Transform (SWT) is an extension of the DWT that aims to overcome the shift variance limitation of the traditional DWT. In DWT, the position of features in the signal may shift after decomposition, but SWT retains the temporal alignment of features.

| Model | Extracted Features |
|---|---|
| First Order Statistics (FOS) | 'Mean','Variance','Median','Mode','Skewness','Kurtosis','Energy', 'Entropy','MinimalGrayLevel','MaximalGrayLevel','CoefficientOfVariation', '10Percentile',' 25Percentile', '75Percentile', '90Percentile', 'HistogramWidth' |
| Gray Level Difference Statistics (GLDS) | 'Homogeneity', 'ASM', 'Entopy' |
| Statistical Feature Matrix (SFM) | 'Coarseness', 'Contrast', 'Periodicity', 'Roughness' |
| Gray Level Run Length Matrix (GLRLM) | 'ShortRunEmphasis','LongRunEmphasis','GrayLevelNo-Uniformity', 'RunLengthNonUniformity', 'RunPercentage', 'LowGrayLevelRunEmphasis', 'HighGrayLevelRunEmphasis','ShortowGrayLevelEmphasis', 'ShortRunHighGrayLevelEmphasis', 'LongRunHighGrayLevelEmphasis' |
| Gray Level Size Zone Matrix (GLSZM) | 'SmallZoneEmphasis', 'LargeZoneEmphasis', 'GrayLevelNonuniformity', 'ZoneSizeNonuniformity', 'ZonePercentage', 'LowGrayLeveLZoneEmphasis', 'HighGrayLevelZoneEmphasis', 'SmallZoneLowGrayLevelEmphasis', 'SmallZoneHighGrayLevelEmphasis', 'LargeZoneLowGrayLevelEmphassis', 'LargeZoneHighGrayLevelEmphasis', 'GrayLevelVariance', 'ZoneSizeVariance', 'ZoneSizeEntropy' |
| Higher Order Spectra (HOS) | '135_degrees', '140_degrees' |
| Local Binary Pattern (LBP) | 'R_1_P_8_energy', 'R_1_P_8_entropy', 'R_2_P_16_energy', 'R_2_P_16_entropy', 'R_3_P_24_energy', 'R_3_P_24_entropy' |
| Discrete Wavelet Transform (DWT) | 'level_1_da_mean', 'level_1_da_std', 'level_1_dd_mean', 'level_1_dd_std', 'level_1_ad_mean', 'level_1_ad_std', 'level_2_da_mean', 'level_2_da_std', 'level_2_dd_mean', |

| | |
|---|---|
| | ‘level_2_dd_std’, ‘level_2_ad_mean’, ‘level_2_ad_std’, ‘level_3_da_mean’, ‘level_3_da_std’, ‘level_3_dd_mean’, ‘level_3_dd_std’, ‘level_3_ad_mean’, ‘level_3_ad_std’ |
| Stationary Wavelet Transform (SWT) | ‘level_1_h_mean’, ‘level_1_h_std’, ‘level_1_v_mean’, ‘level_1_v_std’, ‘level_1_d_mean’, ‘level_1_d_std’, ‘level_2_h_mean’, ‘level_2_h_std’, ‘level_2_v_mean’, ‘level_2_v_std’, ‘level_2_d_mean’, ‘level_2_d_std’, ‘level_3_h_mean’, ‘level_3_h_std’, ‘level_3_v_mean’, ‘level_3_v_std’, ‘level_3_d_mean’, ‘level_3_d_std’ |

Table-4: All Features Name

## 3.5. Comparison of some existing models

In this research study, three pre-trained models, five machine learning models and proposed model are trained and evaluated to observe their performance in terms of accuracy. Some of those models are discussed below in the following sections:

**Machine Learning:**

i. **Support Vector Machine (SVM):** SVM is a supervised machine learning algorithm used for classification and regression tasks. Its primary objective is to find a hyperplane in an N-dimensional space (N being the number of features) that distinctly classifies the data into different classes. The hyperplane is chosen in such a way that it maximizes the margin between the classes.

ii. **Linear regression (LR):** Linear regression is a supervised machine learning algorithm used for predicting a continuous outcome variable (also called the dependent variable) based on one or more predictor variables (independent variables). The relationship between the variables is assumed to be linear, meaning that changes in the predictor variables are associated with a linear change in the outcome variable. The general form of a linear regression equation for a simple linear regression (with one predictor variable) is:

$$y = mx + c$$

Where, y is the dependent variable (the variable we are trying to predict), x is the independent variable (the variable we used to make predictions), m is the slope of the line (the coefficient that represents the relationship between x and y), c is the y-intercept.

For multiple linear regression (with more than one predictor variable), the equation becomes:

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n$$

iii. **Decision Tree (DT):** A Decision Tree is a popular supervised machine learning algorithm used for both classification and regression tasks. It works by recursively partitioning the dataset into subsets based on the values of input features. The algorithm makes decisions at each node of the tree, leading to a tree-like structure where the leaves represent the final outcomes or predictions.

iv. **K-Nearest Neighbors (KNN):** The KNN algorithm is a machine learning method can be applied to both classification and regression. KNN uses the K nearest neighbours of a new data point in the training dataset to estimate the label or value of that new point.

- Determine distances: Using a selected distance metric (such as the Euclidean distance), determine the distance between each new data point and every other point in the dataset.
- Determine the closest neighbours: Based on these distances, choose the k nearest neighbours, or closest data points.
- Give a class a name: Among those k closest neighbours, assign the new data point to the most prevalent class.

**Transfer Learning:**

i. **ViTB16 (Vision Transformer):** A transformer-based architecture designed for image classification, utilizing self-attention mechanisms to capture relationships between image patches.

ii. **VGG16:** VGG (Visual Geometry Group) models comprising 16 and 19 layers, characterized by a uniform architecture using small convolutional kernels and multiple max-pooling layers.

iii. **ResNet50:** A Residual Network with 50 layers, introducing skip connections to address the vanishing gradient issue, enabling deeper architectures without performance degradation.

**Proposed Graph Neural Network (GNN)**: The building block of a Graph Neural Network (GNN) consists of several operations to update node representations based on data from nearby nodes in the graph. An entity or object, such as a disease image, is represented by a node. As a result, this node possesses numerous features distinct from the entity it represents. These node attributes make up a node's features, also known as node embeddings or node features. In our case, the node features are image attributes which are extracted in the previous section. The GNN receives these node characteristics as inputs. In this context, edges can represent connections between different samples. The inclusion of edge features allows the model to consider not only the attributes of individual nodes but also the relationships between them. The key elements that make up the fundamental structure of Graph Neural Networks (GNNs) are broken down as follows:

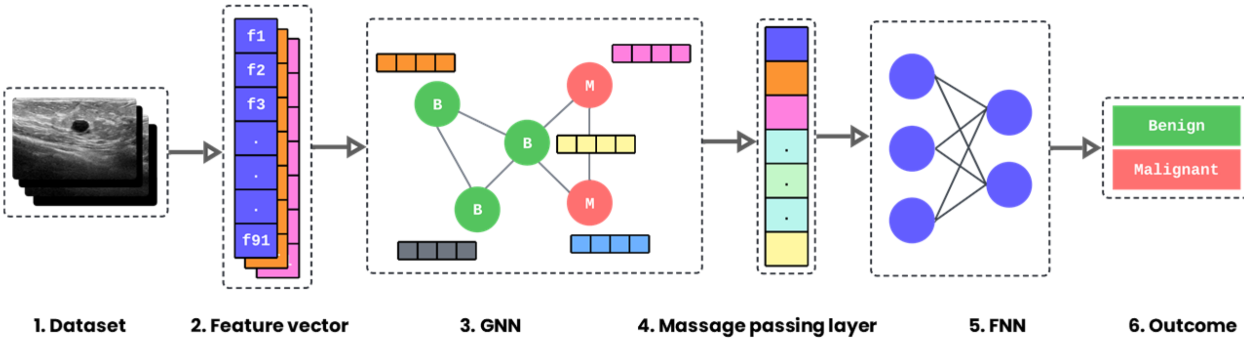


Figure-5: BNNEG Architecture

- **Message Passing Layer:** A Graph Neural Network (GNN) Message Passing layer is a fundamental component of graph neural networks. The Message Passing layer is the core operation in GNNs, allowing nodes to exchange information with their neighboring nodes in the graph. The key idea is to iteratively update the representation of each node by aggregating information from its neighbors. Every node $\boldsymbol{i}$ has associated node features $\boldsymbol{x_i} \in \mathbf{R}$ and labels $\boldsymbol{y_i}$

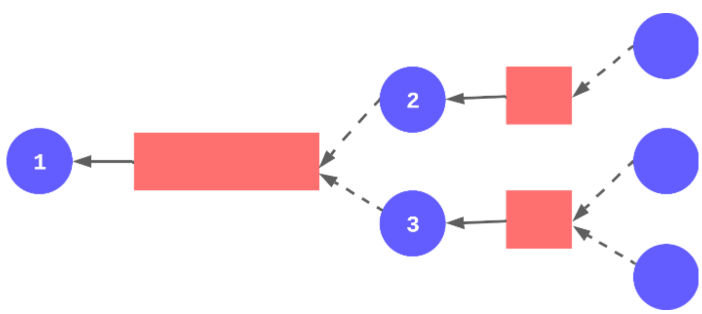


Figure-6: Message Passing Layer

The collection of nodes $\boldsymbol{j}$ that are connected to $\boldsymbol{i}$ via an edge is known as the neighborhood $\boldsymbol{N_i}$ of a node $\boldsymbol{i}$. Formally,

$$N_i = \{j. e_{ij} \in E\}$$

- **Aggregation Layer:** The aggregation layer in a Graph Neural Network (GNN) is a crucial component that defines how information from neighboring nodes is combined or aggregated to update the representation of a target node. Sum aggregation is the simplest form of aggregation involves summing up the feature vectors of neighboring nodes.

$$Sum = \sum_{j \in N_j} W_j . x_j$$

Let's say we aggregate the messages from our neighbors using a function (either sum, mean, max, or min). The following can be used to indicate the final aggregated messages:

$$m_i = G(\{W_j . x_j : j \in N_j\})$$

- **Update Layer:** To update each node's representation, the aggregated messages are combined with its current state. By the time this update process is finished, the node should be knowledgeable of both its neighbors and itself. Now using addition equation is:

$$h_i = \sigma(K(H(x_j) + m_j)))$$

where H is a simple neural network (MLP), K is another MLP to project the additional vectors into a different dimension, and σ is an activation function (ReLU, ELU, Tanh).

$$h_i = \sigma(K(H(x_j) \oplus m_j)))$$

After completing the Aggregation, Update, and Message Passing stages let's combine them to create a single GNN layer on a single node.

$$h_i = \sigma(W_1 . h_i + \sum_{j \in N_j} W_2 . h_j)$$

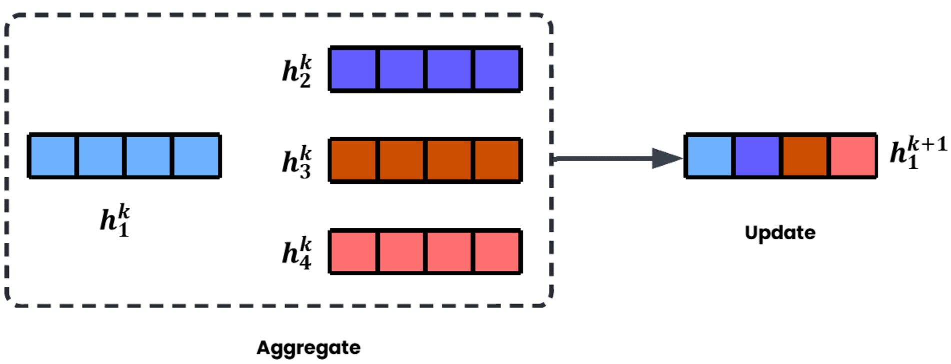


Figure-7: Aggregate and Update layer

# CHAPTER 4

# EXPERIMENTAL RESULTS AND DISCUSSION

## 4.1. Evaluation Criteria

In this study, as many as 9 models were experimented and the evaluation of all those models will be presented in this section of the paper. Considering the following evaluation criteria, the performance, reliability, and clinical relevance of tumor detection system can be assessed and also can be determined its suitability for assisting medical professionals in accurately detecting and diagnosing breast cancer.

**Accuracy**: The accuracy of the tumor detection system in correctly classifying images as benign and malignant is a crucial evaluation criterion. It evaluates the correctness of the system's classification computed overall.

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

**Precision:** The proportion of properly identified situations is examined to measure precision out of all predicted benign and malignant cases.

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

**Sensitivity and Specificity**: Sensitivity is typically referred to by the term the true positive rate, which gauges the system to identify benign and malignant cases correctly. True negative rate, which is often referred to as specificity, assesses its capacity of identifying non-cancer conditions. Both metrics provide insights into the system's performance in different classes and help assess its ability to avoid false positives and false negatives.

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

**F1 Score**: The F1 score offers a comprehensive measurement that addresses the balance between precision and memory and thus represents a harmonious average of precision and recall. It is advantageous in realities whereby there occurs a disparity in class or in cases when the costs of false positives and false negatives fluctuate.

$$F1Score = \frac{TP}{TP + \frac{1}{2}(FP + FN)}$$

In this section, we present the results and discussions stemming from our comprehensive evaluation of various models. Our assessment revolves around a detailed comparison of performance metrics, including Accuracy, Precision, AUC, Specificity, and F1 score. A total of 14 distinct models were subjected to rigorous scrutiny, encompassing an array of established architectures.

## 4.2. Experimental Results and Analysis

In this undermentioned portion, the findings of the proposed mechanism along with the comparison with some cutting-edge studies will be comprised. The collected data were divided into sets for conducting training and testing to construct and examine the proposed system. This approach was initially trained to leverage 80% of the data and evaluated utilizing 20% of the collected information. To ensure enhanced productivity several sets of parameters were experimented. The parameter setting that provided us with the most advantageous outline for the proposed model is given below.

| Model | Precision | Recall | Specificity | F1-Score | AUC | Accuracy |
|---|---|---|---|---|---|---|
| K-NN | 79.07 | 87.18 | 90.11 | 82.93 | 88.64 | 78.14 |
| LR | 84.38 | 69.23 | 94.51 | 76.06 | 81.87 | 79.69 |
| DT | 65.62 | 53.85 | 87.91 | 59.15 | 70.88 | 74.09 |
| RF | 90.32 | 71.79 | 96.70 | 80.00 | 84.25 | 81.82 |
| SVM | 76.19 | 82.05 | 89.01 | 79.01 | 84.25 | 79.89 |
| ViTB16 | 85.00 | 88.00 | 74.50 | 86.00 | 83.75 | 87.02 |
| ResNet50 | 88.94 | 81.93 | 91.80 | 84.27 | 81.93 | 87.00 |
| VGG16 | 84.61 | 84.82 | 78.82 | 84.72 | 84.82 | 86.64 |
| **BNNEG** | **90.00** | **90.00** | **93.41** | **90.00** | **90.00** | **92.00** |

Table-5: Model Comparison

In conclusion, the BNNEG model for breast tumor classification demonstrated strong performance in accurately identifying benign-malignant from ultrasound images. Its high accuracy, precision, and recall values, along with the robust AUC-ROC score, validate its potential as a reliable tool for early detection and intervention. The model's efficiency makes it suitable for practical deployment in healthcare settings, contributing to improved patient care and timely treatment breast cancer tumor.

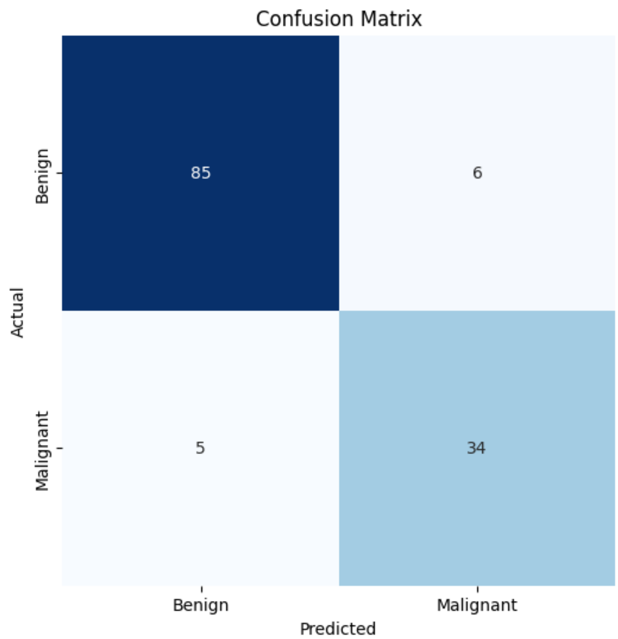


Figure-8: Confusion Matrix

The confusion matrix is a fundamental tool in the field of machine learning and statistics, commonly used to evaluate the performance of a classification algorithm. It provides a clear and concise summary of the performance of a model by presenting the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. Figure x displays the confusion matrix for the GNN model, showcasing its performance in classifying a test set. In the matrix, the rows represent the true labels of the images, while the columns represent the labels predicted by the BNNEG model. Each cell in the matrix contains a count of instances corresponding to a specific true label and its predicted counterpart. This enables us to evaluate how well the model's predictions align with the actual classes.

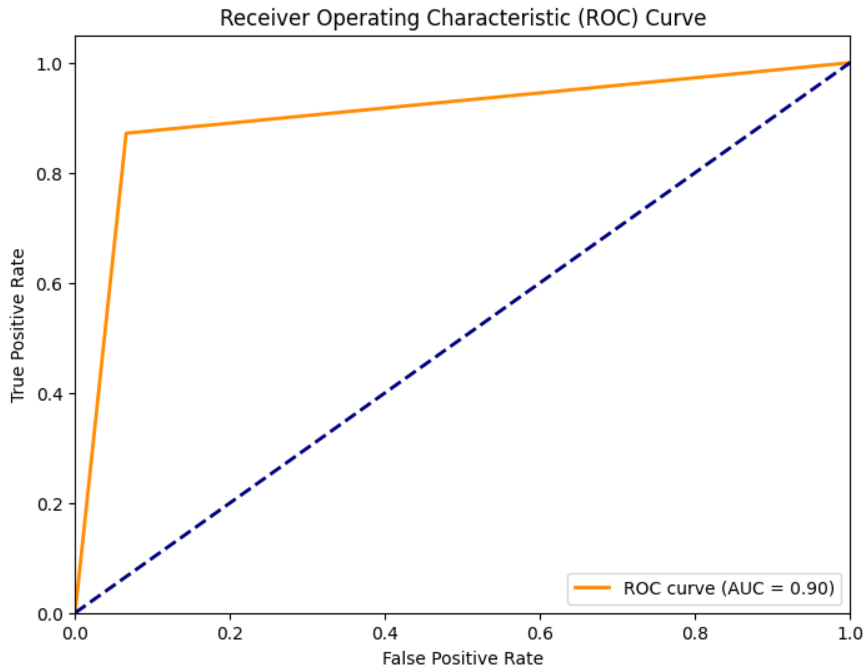


Figure-9: ROC Curve

The ROC curve is a graphical representation used in machine learning to assess the performance of a classification model at various classification thresholds. It is particularly useful for binary classification problems. The ROC curve illustrates the trade-off between the true positive rate (sensitivity) and the false positive rate (1 - specificity) across different threshold values. The area under the ROC curve (AUC-ROC) is a numerical measure of the model's performance. A higher AUC-ROC value (closer to 1) indicates better overall performance, while a value of 0.5 suggests a model that performs no better than random chance.

**Comparison of the BNNEG model with the machine learning and transfer Learning models:**

The outline demonstrated and effectively potential of BNNEG network for precisely classify benign-malignant tumor cancer from images. The capacity of the model to precisely detect instances is demonstrated by the excellent precision, accuracy, recall and F1-score acquired. BNNEG allows for the extracting of both spatial and temporal features, capturing the subtle patterns and changes. Figure 5 exhibits the comparison of performance between the model we proposed and a several other prepared.

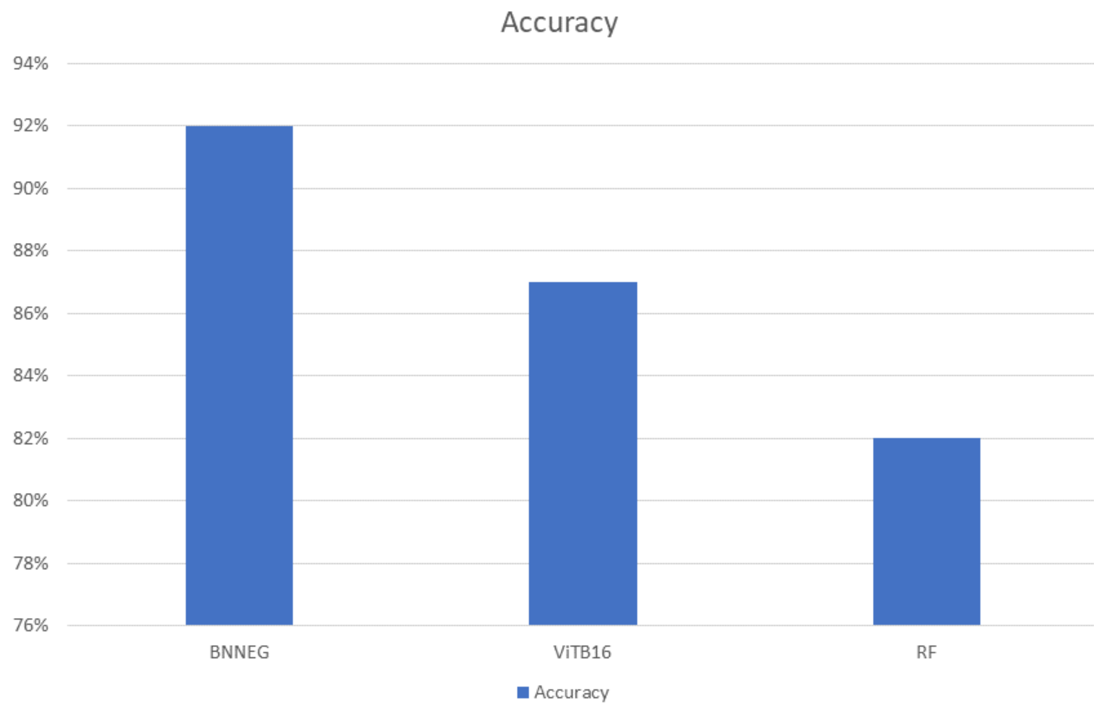


Figure-10: Top Three Model Accuracy Curve

# CHAPTER 5
# IMPECT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

## 5.1. Impact on Society

Automated and accurate classification may enable early identification of malignant tumors, facilitating timely treatment and possibly increasing survival rates. The model has the potential to provide tailored treatment plans and risk assessments by accounting for tumor heterogeneity and integrating supplementary data, thereby customizing therapy to meet the specific needs of each patient. A timely and precise diagnosis may reduce the need for pointless biopsies and surgeries, reducing medical expenses and patient misery. Automated classification could provide faster and more accessible tumor evaluation, particularly in resource-limited settings or for underserved populations. Automated systems could streamline diagnostic workflows for radiologists and clinicians, allowing them to dedicate more time to patient care and complex cases. Earlier detection and potentially avoided unnecessary procedures could lead to significant cost savings for healthcare systems.

## 5.2. Impact on Environment

Since ultrasound imaging doesn't use ionizing radiation, it often has a smaller environmental impact than other imaging modalities like CT or PET scans. There might be a benefit to the environment if accurate early diagnosis with ultrasound can reduce the requirement for these energy-intensive tests. Reduced usage of chemotherapy medications, which might have negative environmental implications if improperly disposed of, may result from early and precise diagnosis. The implementation of automated classification has the potential to enhance the overall efficiency of healthcare systems by curbing resource consumption and waste. Significant computational resources, which frequently depend on energy-intensive data centers, can be needed for the training and operation of complicated machine learning and deep learning models. This might unintentionally increase greenhouse gas emissions and the negative effects that energy production has on the environment. The creation of electronic trash may be facilitated by the usage of AI-powered medical equipment and the requirement for regular hardware updates.

## 5.3. Ethical Aspects

Make sure patients have given their informed consent before collecting and using their data. Uphold tight confidentiality and follow data protection laws (e.g., HIPAA, GDPR). Put strong safeguards in place to prevent abuse, unauthorized access, and breaches of sensitive health information. Examine methods for de-identifying data while maintaining its scientific value and protecting patient privacy. Make an effort to gather datasets that accurately reflect a range of patient populations in order to reduce biases in the training of models and guarantee that various groups receive equal results. Provide strategies to help patients and clinicians understand and accept model decisions, promoting accountability and trust.

## 5.4. Sustainability Plan

Make sure patients have given their informed consent before collecting and using their data. Uphold tight confidentiality and follow data protection laws (e.g., HIPAA, GDPR). Put strong safeguards in place to prevent abuse, unauthorized access, and breaches of sensitive health information. Examine methods for de-identifying data while maintaining its scientific value and protecting patient privacy. Make an effort to gather datasets that accurately reflect a range of patient populations in order to reduce biases in the training of models and guarantee that various groups receive equal results. Provide strategies to help patients and clinicians understand and accept model decisions, promoting accountability and trust.

# CHAPTER 6

# SUMMARY, CONCLUSION, RECOMENDATION AND IMPLEMENTATION FOR FUTURE RESEARCH

## 6.1. Summary of the Study

The goal of this project is to create an automated system that can accurately classify breast tumors from ultrasound pictures. It blends deep learning, machine learning, and a brand-new graph neural network (GNN) technique that makes use of radiomics features that are taken out of the pictures. Preprocessed ultrasound pictures are gathered and matched to relevant tumor diagnoses. Relevant radiomics features that describe the properties of the tumor are extracted. The radiomics features are used to train conventional machine learning algorithms and deep learning methods like CNNs. In order to depict the tumor as a network of connected pieces, a unique GNN architecture is created to capture interactions between retrieved data. Using distinct datasets, the models are trained and assessed to determine performance parameters including accuracy, sensitivity, specificity, and AUC.

## 6.2. Conclusion

Automated and accurate breast cancer classification techniques can assist doctors in clinical diagnosis and used for rapid screening at low cost. In our research, we proposed an improved deep-learning method for the classification of benign and malignant in ultrasound images. A total of 91 features were extracted for each of the ROI images taken from the BUSI dataset. Amongst the various methodologies such as k NN, SVM, LR, and DT the graph neural network achieved the best results (92%). The fine-tuned VGG16, ResNet15, and ViTB16 models were also used to compare the base model. We aim to investigate the use of more advanced deep learning methods in the future for the classification of breast tumors. As with any deep learning model, the need for substantial computational resources and potential overfitting remain as challenges. In terms of future scope, our framework can benefit from incorporating more advanced preprocessing techniques and exploring ensemble methods to further enhance its robustness. Expanding the dataset to encompass a wider range of demographics and ocular conditions could bolster the model's real-world applicability. Moreover, collaborations with medical experts to validate the model's findings in clinical settings could lead to its adoption as a valuable tool for early tumor classification.

## 6.3. Implication for Further Study

Models can learn more robust features and perform better in terms of generalization across various populations and imaging situations by gathering larger and more diverse datasets. When ultrasound is combined with other imaging modalities (MRI, mammography), a more complete picture of the properties of the tumor may be obtained, which could lead to an improvement in classification accuracy. GNNs may be better able to capture complicated tumor interactions and heterogeneity if they are particularly designed with breast tumor categorization and radiomics properties in mind. Enhancing interpretability and performance could be achieved by concentrating model learning on the most pertinent features by integrating attention mechanisms into GNNs. Clinicians can gain confidence in the model's predictions and comprehend its thinking by mastering approaches for visualizing model decisions. Knowing which characteristics influence classification choices may help inform clinical judgement and shed light on the biology of tumors.

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# APPENDICES

# Breast tumor

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