Machine Learning in Healthcare: Breast Cancer Detection Using Graph Convolutional Network

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Abstract: **Machine learning is a vast field of research. The idea is to build a machine learning-based cad system for breast cancer detection using mammogram image data. At first, we use supervised classification techniques in our mammogram image data and then feed the classified data into the GCN model for detection. We investigated that the GCN model can give better accuracy than traditional machine learning models. Breast cancer is one of the most common cancers that women suffer the most. But breast cancer can be detected early. The vast amount of research shows that if breast cancer is successfully detected early, the patient life can be 99% saved early. A screening mammogram is the other most useful thing in the detection of breast cancer. According to researchers, with the help of mammograms breast cancer can be detected three years earlier before the start of cancer symptoms. Graph Convolutional Neural Network (GCN) is a new field of convolutional machine learning. Unlike CNN, GCN follows a non-Euclidian approach which can show better results in image classification. We aim to investigate the GCN model into breast cancer mammogram image data, that it can give better accuracy than traditional machine learning models. After evaluating our proposed GCN algorithm to four others, we discovered that GCN achieved the accuracy of 81 percent.**

Keywords: **Graph Convolutional Network Graph (GCN), Machine Learning, Breast Cancer, Mammogram, Graph Neural Network, Classification, Morphological Operation, Contrast limited adaptive histogram equalization**

I. INTRODUCTION

For centuries, cancer has afflicted us. According to the International Agency for Research on Cancer (IARC), a part of the World Health Organization (WHO), there were 4.5 million deaths caused by cancer in 2016 [1]. Among the cancer types, Breast Cancer is the most common cancer type in women. It is the second leading cause of cancer death excluding lung cancer. Early detection of breast cancer can reduce its death rate. For the past few decades, Machine learning techniques have been used in various fields of healthcare worldwide. Afterward advances in picture handling and machine learning techniques allow building Computer-Aided Detection/Diagnosis (CAD / CAD) frameworks that can offer assistance specialists to be more productive, objective, and unfaltering within the assurance [2]. The mammogram is broadly utilized inside the early screening of breast cancer due to its by and large fetched and tall affectability to minor tumors. Within the real determination handle, be that as it may, the exactness can be contrarily influenced by numerous components, such as radiologist weariness and diversion, the complexity of the breast structure, and the inconspicuous characteristics of the early-stage illness. The computer-aided detection/diagnosis (CAD) for breast cancer can offer assistance address this issue [3]. The utilization of a correct machine-learning calculation for an early cancerous area might verifiably save valuable lives. Machine learning (ML) is broadly recognized as the procedure of choice in breast cancer plan classification and estimate modeling [4]. By comparing a well-known and trending machine-learning procedures into a viable dataset ready to discover an appropriate arrangement of an issue which can be utilized in real-world classification issues [5]. Machine learning can solve the problem of automatic detection of breast cancer using a machine learning algorithm [6]. These days data mining have especially basic run within the assortment of portions. Data mining, which is utilized to uncover secret, vital, usable information and give vital choice back from a tremendous entirety of data. It has made an unused perspective inside the utilization of prosperity data as well as reacting to issue zones related to gigantic holes of information [7]. The application of machine learning calculations to therapeutic information is a developing point and, the adequacy of Random Forest, kNN (k-Nearest-Neighbor) and Naïve Bayes algorithm in breast cancer information classification gives compelling data [8]. On the other hand, profound learning can remove and organize discriminative data from the data, not requiring the arrangement of incorporate extractors by a space ace (age? Or game “Space Ace”?). Convolutional Neural Frameworks (CNNs) is a specific sort of significant, feedforward network that have picked up consideration from peer community and industry, accomplishing observational triumphs in errands such as talk affirmation, flag preparing, dissent affirmation, characteristic tongue dealing with an exchange learning [2]. Graph convolutional neural organize (GCN) was created as of late to appear data characterized in non-Euclidean spaces such as charts. GCNs perform convolution on the input chart through the chart Laplacian instead of on the settled arrange of 1-D or 2-D Euclidean-structured data [10]. Currently, GCN models have been used to predict metastatic breast cancer events and empower the protein-protein interaction database (STRING) into breast cancer (models). This prompted us to see GCN models for expression-based cancer sort classification [16]. This persuaded us to construct a GCN model to demonstrate breast cancer detection.

The idea is to utilize a directed classification calculation in a mammogram dataset and after that apply the GCN strategy to it to recognize breast cancer.

1.1 Problem Statement

Breast cancer is the preeminent commonly analyzed cancer in women. According to International Agency for Research on Cancer (IARC), there are about 2.1 million new cases identified as breast cancer and around 627 000 deaths in 2018 [1]. But breast cancer can be detected and treated early using a mammogram. Although there are many existing systems that use CNN and many other algorithms to detect breast cancer, its detection accuracy can be improved by using GCN. Finding or making an appropriate mammogram dataset and using it in our system is the main problem of our system.

1.2 Problem Background

The breast cancer location framework has used numerous existing frameworks like CNN, GCN, SVM, Classification strategies, administered, unsupervised, and numerous other models. But there is no existing execution on mammogram picture dataset in GCN to show it identifies breast cancer. We emphatically accept that GCN demonstrates can give way better precision on mammogram picture dataset in arrange to distinguish breast cancer. But to do that we require a mammogram picture dataset that has adequate pictures with legitimate resolution. Tall determination picture information can be a cause of system fault. We are looking forward to executing the breast cancer discovery framework with picture information on the GCN. This will give better exactness than the existing models.

1.3 Research objectives

- Classifying mammogram image by Supervised Classification technique.
- Detecting breast cancer by comparing normal cases with Benign or Malignant cases.
- Improving the detection accuracy by using Graph Convolutional Network.
- Comparing GCN, and numerous other models to find out which is better.

1.4 Motivation

Breast cancer is one of the common cancers all over the world. Women are at higher risk for breast cancer. Breast cancer is 69% of the women's diagnosis in Bangladesh. In Bangladesh, around 22.5 per 100000 have breast cancer of all ages. Early detection is the key in the treatment of Breast cancer. In case early detection and treatment are possible, breast cancer can be cured by nearly 99%. It can be done accurately by utilizing machine learning procedures. Machine Learning for healthcare gives calculations with self-learning neural frameworks that can increase the quality of treatment by analyzing. This paper describes how to distinguish breast cancer utilizing Graph Convolution Network, which is the basic variety of Graph Neural network.

1.5 Flow of Research

This research work involved a few steps. To begin with, we analyzed the inquiry about the point considered the essential hypothesis of picture classification. We examine the breast cancer discovery issue and an arrangement inside GCN and propelled them to construct unused engineering based on GCN. Figure 1.1 illustrates the overall steps to the research procedure in the following diagram.

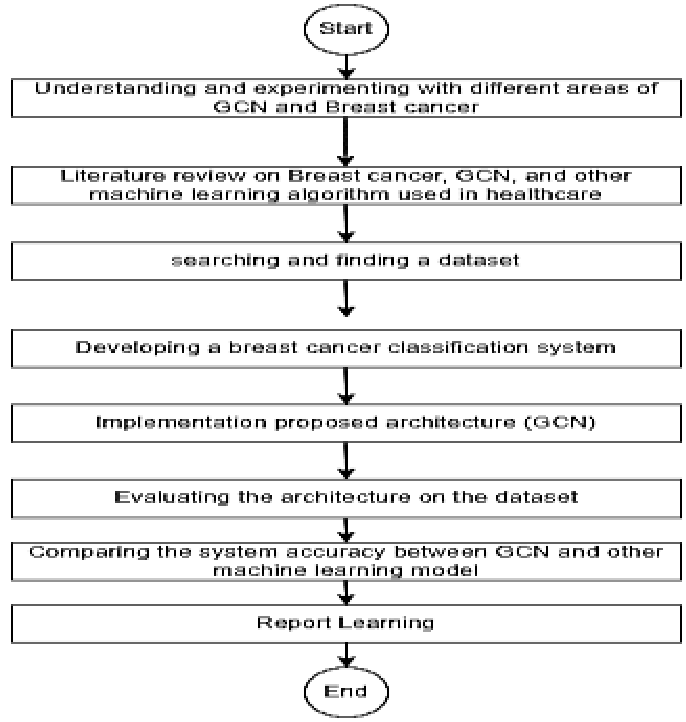


Figure 1.1: The figure illustrates the flow of work we do through our research.

1.6 Significance of Research

We take note that the larger part of mammogram image datasets for breast cancer detection on the internet are unstructured and image resolution is exceptionally high or low. In any case, to consider the accuracy of breast cancer, we required a dataset classified into the same resolution and same measure. In expansion, we proposed a Supervised Classification method with a GCN-based design that produces the most noteworthy results. This system categorization challenge advances into a cutting-edge design for evaluating the detection of breast cancer.

1.7 Research Contribution

The overall contributions are:

- We are using the GCN model in our system as it uses a non-Euclidean method which will improve accuracy for image classification.
- We have collected the breast cancer mammogram image dataset.
- We have communicated in different medical centers, hospitals, doctors, and some of the researchers about breast cancer diagnostic system.

- We have analyzed about different implementation on this topic like, KNN, GCN, Logistic, etc. Among of them GCN brings comparatively better outcome.

II. MATERIAL AND METHODS

In this section, we examined the strategy utilized in our exploration. We utilized a breast cancer mammogram dataset and Graph Convolutional Network (GCN) to group harmless (benign) and dangerous (malignant) cancers. Picture handling is expected to guarantee picture quality and to work on the exactness of the framework. We first eliminate the clear space of every mammogram picture. Then, at that point, we involved the morphological tasks to eliminate the flaws in the design of the picture and utilized the different upgrade (CLAHE) to further develop the perceivability level. We utilized the histogram correlation calculation to analyze the contrast between the genuine picture and our handled picture.

Picture pixel point is really significant in our analysis/examination. We utilize the Regions of Interest (ROI) calculation to distinguish the thickness of the picture and gain the pixel worth of that specific point. The chart is the really central issue of our examination. We utilized the picture pixel point as a chart hub and edges and make a diagram. Then utilized the Graph installing calculation to standardize the chart hub. In the wake of handling and making the diagram, we were prepared to apply the calculation to our important information.

We utilized the Graph Convolutional Network (GCN) as our essential algorithm in our information. To consider that the GCN algorithm was better and gives a superior outcome we contrasted our proposed algorithm and undirected algorithm. We utilize KNN, K-implies, Canopy, and Logistic and contrasted them and compare them with our proposed algorithm. Our proposed calculation gives better results over others.

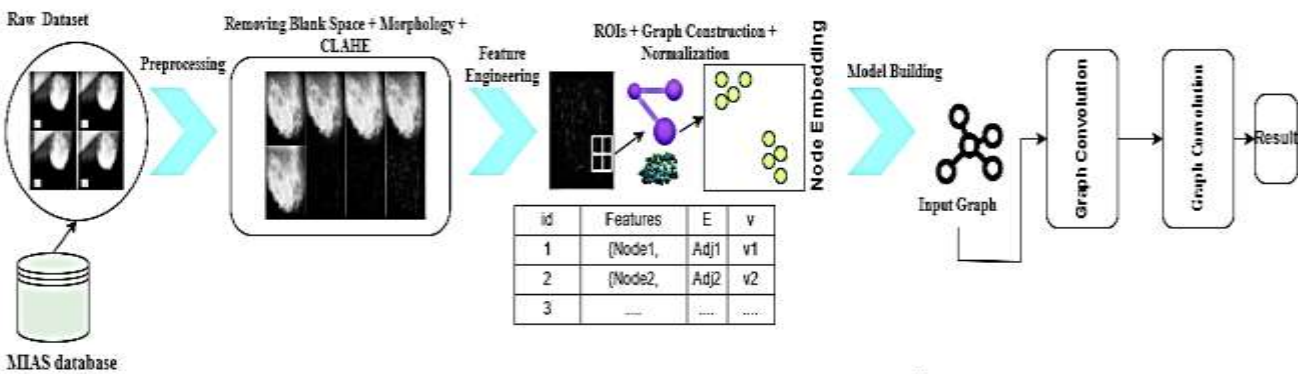


Figure 2.1: Proposed methodology

2.1 Dataset

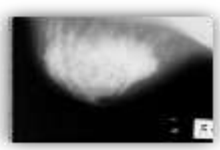
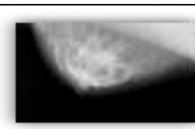
We involved pictures from the Mini-MIAS data set in our proposed algorithm to do all necessary investigation. MIAS is an exploration association in the UK that concentrates on mammography. This foundation holds the mammogram information. The information base has 322 cases with a picture goal of 1024×1024 pixels. Examined film mammographic pictures lessen the goal from 50 μm to a limit of 200 μm. Each case is made out of a solitary picture without the information on the four perspectives (LMLO, RMLO, LCC, and RCC).

2.2 Preprocessing and Feature Extraction

2.2.1 Removing the Blank Space

In MIAS pictures, they have conflicting edges on the left and right edges. This happens because of digitized film mammography. It should be preprocessed for our goal/strategy. We utilized a line profile strategy to eliminate the clear space to preprocess the picture. The technique utilized the amount of the pixel values relating to every pixel segment and it tracks down the two quickly evolving focuses. This technique eliminates the clear space which didn't compare to the two places. Curios/Artifacts were normal for certain pictures in the dataset. The proposed strategy eliminates the curio utilizing a marking calculation. With the exception of the biggest locale, all curios were taken out after the naming system.

Table 1: Mini-MIAS Mammography Image Database Image types (Normal, Benign, Malignant)

Type of Images	Sample Image 1	Sample Image 2
Normal		
Benign		
Malignant		

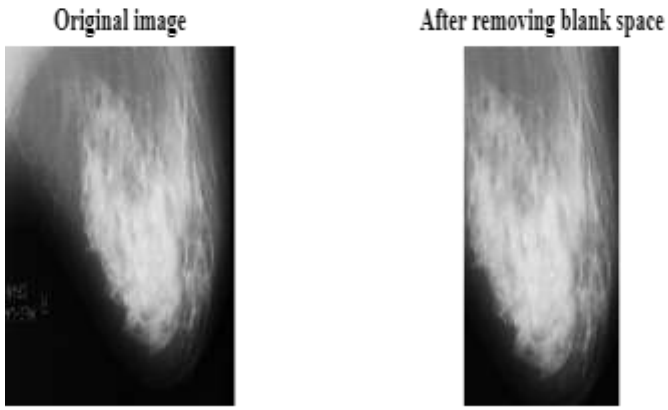


Figure 2.2: Removing Blank space in Mammography Images

2.2.2 Morphological Operation

In the morphological handling of pictures, pixels are added or eliminated from the pictures. The proposed strategy broke down the design and the state of the item to recognize them. It utilized parallel convolution and connection which depended on the consistent activity. The proposed strategy involved Dilation and disintegration as essential activity.

2.2.3 Contrast Enhancement

Contrast Enhancement Algorithms intend to work on the impression of the picture by the natural eye. The proposed calculation utilizes the greatest and least pixel values inside the bosom. The strategy is applied to the differentiation restricted versatile histogram balance (CLAHE) channel and with a middle channel, the clamor is taken out. The CLAHE channel in the proposed strategy smoothed the picture with bilinear addition separated by the quantity of blocks by blending the outcomes. The histogram leveling was done autonomously in each block.

2.2.4 Histogram Comparison

A picture histogram is a kind of histogram that goes about as a graphical portrayal of the apparent dissemination in a computerized picture. It plots the quantity of pixels for each apparent worth. The proposed strategy looks at the genuine pictures in the MIAS dataset with our preprocessed picture. We additionally utilized the technique to distinguish the distinctions among harmless and dangerous pictures. It utilized the accompanying condition.

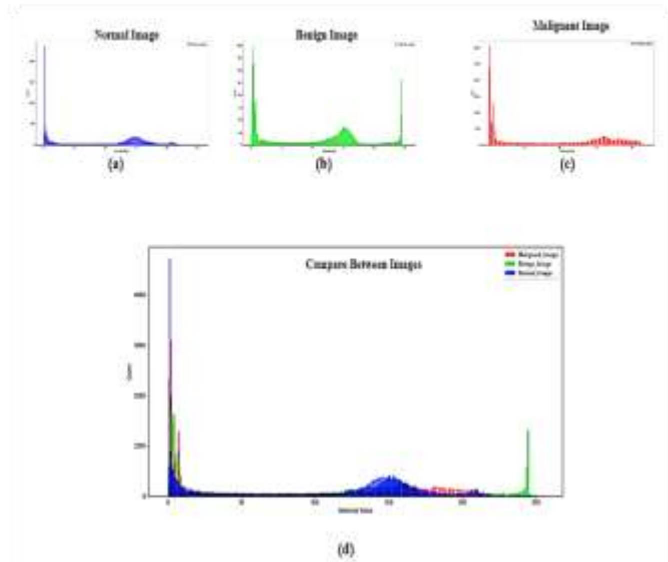


Figure 2.3: (a), (b), (c) Histogram representation of Mammogram image (Normal, Benign, and Malignant), and (d) Histogram Comparison between Mammogram Images (Normal, Benign, and Malignant)

2.2.5 Region of Interest (ROI)

Region of Interest (ROI) is a console controlled distinguishing proof of a given region of a picture for mathematical examination and the area of life structures being filtered that is of specific significance in the picture. The proposed technique can keep away from the handling of superfluous picture focuses and speed up the handling. By utilizing the ROI, we crop the picture on the injury part and store the picture pixel an incentive for research purposes. This cycle was directed physically.

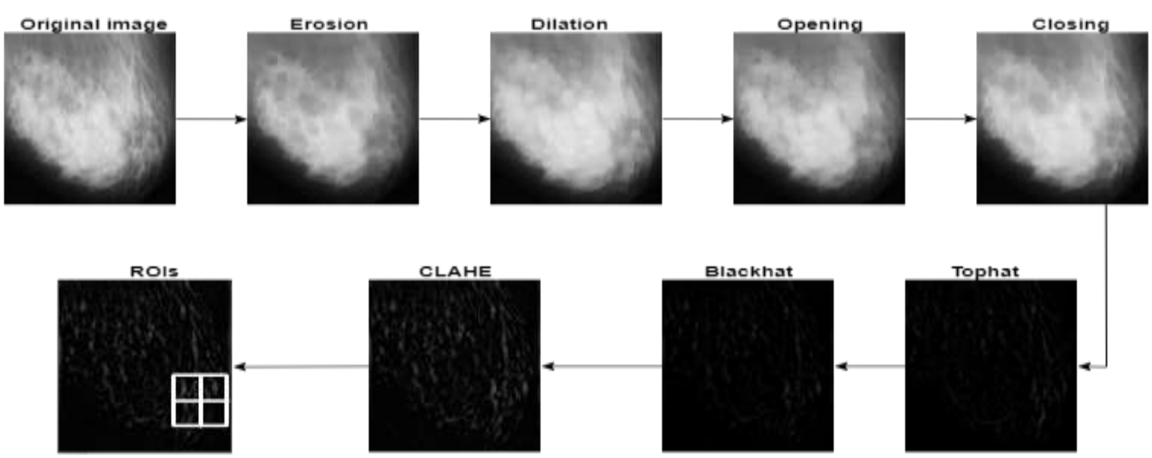


Figure 2.4: Data Pre-processing and Feature extraction, Morphological Operations (six step: erosion, dilation, opening, closing, tophat, blackhat), Contrast Enhancement (CLAHE), Regions of Interest (ROIs) crop

2.3 Graph Construction

The development of a Graph is essential to display the collaborations among the subjects precisely. We developed a directed graph on the picture pixel information which we removed from ROIs trimming.

$Graph: G(V, E) \qquad where,$

V *is Nodes, pixel value of images and* E *is the relation between nodes*

$V \in v(n) \quad where, v(n)\ is\ a\ vertex\ set, n = 1,2,3, \ldots\ldots, N$

$E \in (v_n, v_m)$ *, where* (v_n, v_m) *is a edges set and* v_n *signifies a node from pixel data*

$A \in (v_n, v_m) = a_{nm} = a_{nm}, a_{mn}$ *where, A is the adjacency matix that describe connectivity*

2.3.1 Normalization

Standardization in graph implies reducing the size of information by decreasing or dispensing with redundancies. It changes values estimated on various scales to a notionally normal scale, frequently before averaging. The proposed strategy further develops the information respectability and diagram question, execution in list free nearness chart. The proposed strategy utilized the graph embedding calculation to standardize the diagram. Diagram inserting calculation changed hubs, edges, and the component into vector space (a lower aspect) which maximally protects the chart information construction and data.

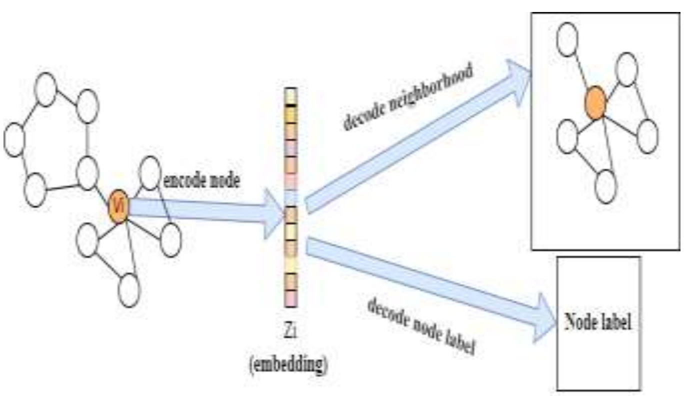


Figure 2.5: Graph Node Normalization using Graph Embedding method

2.4 Algorithms

2.4.1 Graph Convolutional Network (GCN)

Graph convolutional network (GCN) sums up customary convolutional brain network from Euclidean information (e.g., 2D or 3D pictures) to the non-Euclidean space (e.g., diagrams and manifolds), and has been arising as a promising technique for diagram mining. Indicate a graph as $X = (V, E)$, where V is the arrangement of vertices and E is the arrangement of edges. Likewise, a contiguousness lattice $A = [a_{ij}] \in R_n * n$, encodes the network among vertices, with the component a_{ij} demonstrating whether the i-th and j-th vertices are associated $(a_{ij} = 1)$ or not $(a_{ij=} 0)$. Mean$D = diag(d_1, d_2, \ldots, d_n)$ as a degree network, with every component $d_i = j \,.\, a_{ij}$ signifying the quantity of edges associated with the I-th vertex. Other researchers, characterizes GCN, as the convolution by decaying a chart signal $s \in R_n$ (characterized on the vertex of diagram X) in the unearthly space. Then, at that point, the sign s will be handled by a ghastly channel δ_θ with the primary request polynomial of ChebyNet, rather than unequivocally figuring the Laplacian eigenvectors. To decrease the quantity of boundaries (i.e., θ_0 and θ_1), the ghostly GCN model expects to be that $\theta = \theta_0 - \theta_1$, and the chart convolution is correspondingly characterized as:

$$H^{(l+1)} = \sigma(\breve{D}^{-\frac{1}{2}} \breve{A} \breve{D}^{-\frac{1}{2}} H^{(l)} W^{(l)}) \qquad (1)$$

where,

l = layer in the Graph Convolutional Network

σ = activation function

$\breve{A} = A + I_N$ is the adjacency matrix of the graph G with added self-connection

I_N = identity matrix

$H^{(l)} W^{(l)}$ = accumulate or aggregates,

where H is a matrix of feature vector of every single vector and W is the linear projection layer

$H^{(l+1)}$ = Graph Convolutional Network feature vector for l+1 layer

2.4.2 K-means

The K-implies grouping calculation figures centroids and rehashes until the ideal centroid is found. It is possibly known the number of groups that are right there. The quantity of bunches found from information by the technique is signified by the letter 'K' in K-implies. K-implies grouping utilizes "centroids", K different arbitrarily started focuses in the information, and relegates each datum highlight the closest centroid. After each point has been relegated, the centroid is moved to the normal of every one of the focuses allocated to it. This calculation targets limiting a goal work know as squared mistake work given by:

$$J(V) = \sum_{i=0}^{c} \sum_{j=0}^{c_i} (||x_i - v_j||)^2 \qquad (2)$$

where,

'$||x_i - v_j||$' is the Euclidean distance between x_i and v_j.
'c_i' is the number of data points in i^{th} cluster.
'c' is the number of cluster centers.

One of the advantages of this algorithm is that it is relatively simple to implement and it also scales to large data sets.

2.4.3 KNN

K-NN is a non-parametric calculation, and that implies it makes no presumption on fundamental information. It is likewise called a languid student calculation since it doesn't gain from the preparation set quickly rather it stores the dataset and at the hour of order, it plays out an activity on the dataset. KNN works by tracking down the distances between a question and every one of the models in the information, choosing the predetermined number models (K) nearest to the inquiry, then, at that point, votes in favor of the most regular mark (on account of characterization) or midpoints the names (on account of relapse).

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3}$$

KNN is one of the simplest supervised learning techniques and it makes no assumption of underlying data.

2.4.4 Logistic Regression

Logistic regression is a course of displaying the likelihood of a discrete result given an info variable. The most widely recognized strategic relapse models a parallel result; something that can take two qualities like valid/bogus, yes/no, etc.

The simple logistic model has the form,

$$logit(Y) = natural\log(odds) = \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta X \tag{4}$$

This algorithm is of the simplest to train and implement.

2.4.5 Canopy

Canopy clustering is a fast and simple method for grouping objects into cluster. In this algorithm objects are represented as a point in multidimensional space. It has two distance thresholds for processing, T_1 *and* T_2, where $T_1 > T_2$. The algorithm works by creating a set of point and randomly removing one of the two point. Then it creates a canopy around the remaining point until all the initial value is empty. In this algorithm same point may belong to a different canopy cluster.

The advantage of this algorithm is it is very simple and it can be combined with other neural network for better result.

This section was a discussion about our dataset, preprocessing the dataset, proposed approach, and various kinds of calculations we used to work on our strategy. The analysis/examination and the implementation/execution section are addressed below for our exploration.

III. IMPLEMENTATION AND RESULT ANALYSIS

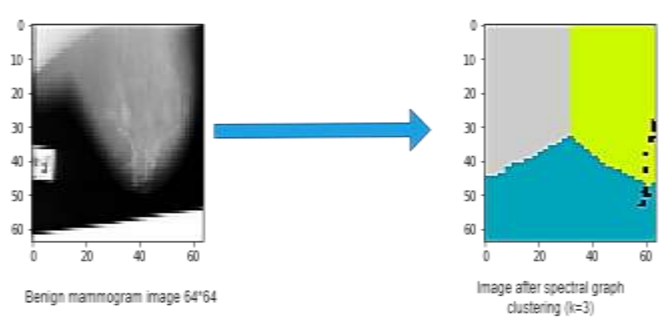
3.1. Introduction

In this chapter, we discuss about proposed model and analyzing the result. Also, discuss the comparative analysis of our proposed model and KNN, K-Means, Logistic, and Canopy algorithm. This chapter summaries the overall result and show the result efficiency about our classification system.

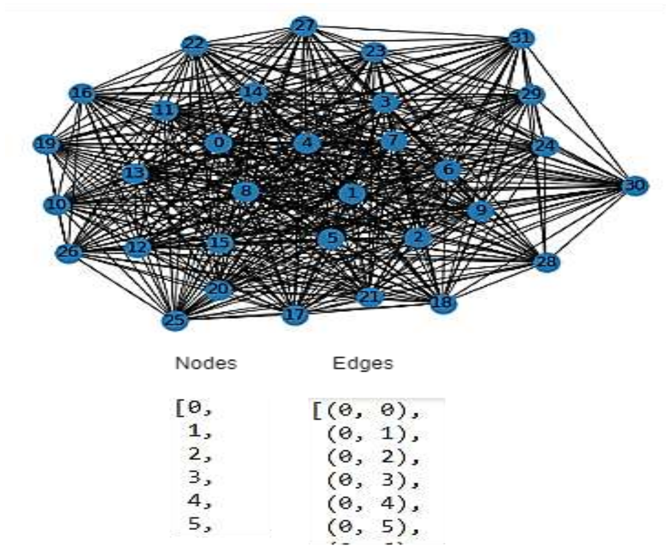
3.2. Implementation

To develop our proposed method, first we preprocess the data. The mammogram image of MIAS dataset contains blank space in the image file. Which can reduce the accuracy in our proposed method. After remove the blank space we then filter our image with Morphological operation and Image Contrast Enhancement (CLAHE). This gives us more valuable data about the tumor size and the bright side of mammogram image. CLAHE return the image with more smoothness and we can view the image more clearly. We then compare between normal breast, benign breast, and malignant breast with histogram and see the difference of pixel value within the images. Then we construct graph from benign and malignant image using spectral graph clustering to see the differences between graph and identify the graphs construction problem. We identify that directly construct graph for one image can be easy but it become problematic when construct a graph for multiple images, though all the image nodes are same.

The most important part of our data preprocessing and feature extraction is the Region of Interest (ROIs) and Graph Construction. Images are highly structured data. So, when we attamed to construct the graph with our preprocess images, we face the attamed memory overload problem. The image pixel value is so high that the graph we created id overload with a single image. To solve this problem, we use the Regions of Interest (ROIs)cropping method. With this method we crop the necessary bright section in the image that give the output of four-pixel value of that section which is nodes and edges of our graph. We manually crop the images with ROIs cropping method. After we gain the nodes and edges, we constructed our graph with Network framework. Then we use Graph Node Embedding method to normalize our nodes in our graph. The used graph node embedding method pack every node property into a vector with a smaller dimension. Thus, node similarity in the original complex irregular spaces can be easily quantifies in the embedded vector spaces using standard metrics. The we train our data with GCN algorithm. We use two GCN convolutional layer in our proposed method. After train our data with GCN we test our model with test data and gain the result. After that, we compare our proposed methodology data with the predefine Weka algorithm and dataset. We use KNN, K-Means, Logistic, and KNOP algorithms to compare our dataset. After the comparison, our proposed methodology gives the satisfactory result.

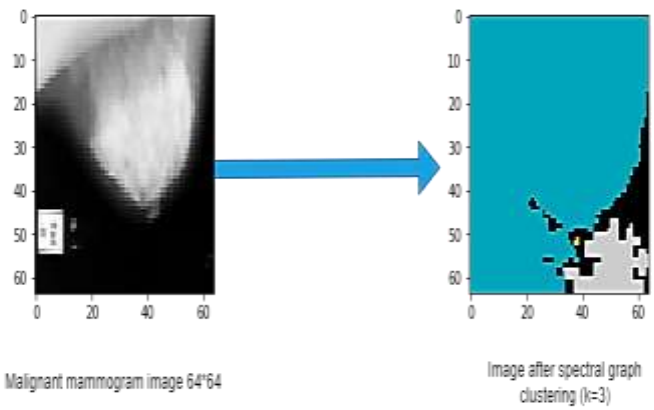


(a)

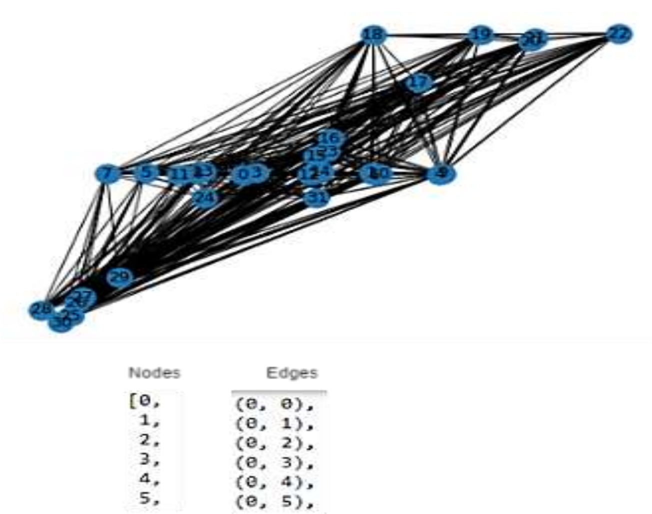


(b)

Figure 3.1: (a) Spectral clustering used in the image (benign) where k=3, (b) graph construct after clustering.



(a)



(b)

Figure 3.2: (a) Spectral clustering used in the image (malignant) where k=3, (b) graph construct after clustering.

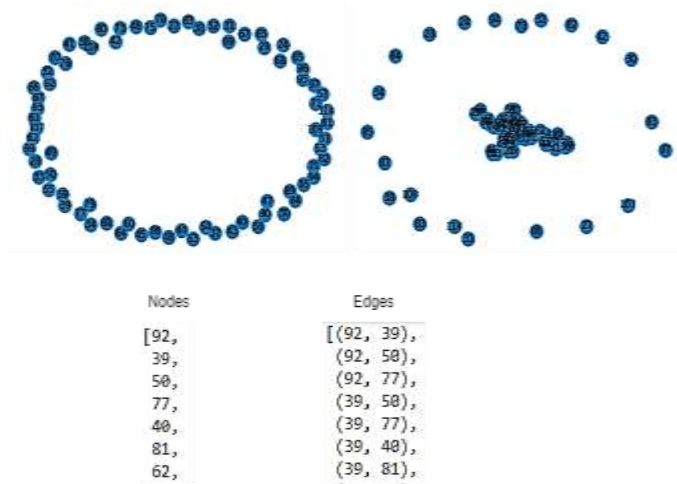


Figure 3.3: Graph used in our proposed model.

3.3 Algorithm Analysis

We utilized WEKA, a crucial tool for building models, to analyze the outcome of our suggested technique in real time. To analyze our suggested technique, we employ the KNN, Logistic, K-Means, and Canopy algorithmic models. After the analysis, the best result is produced by our suggested methodology.

3.3.1 KNN

K-NN is a non-parametric algorithm that do not make any presumption about the information. With the help of WEKA, we implemented KNN algorithm in breast cancer dataset.

Table 2: True Positive Rate, False Positive Rate, Precision, Recall and ROC Area for KNN

	TP Rate	FP Rate	Precision	Recall	ROC Area
Weighted Avg.	0.737	0.431	0.773	0.737	0.702

Table 3: Confusion Matrix of KNN

Positive	Negative
35	1
14	7

KNN with breast cancer dataset correctly classified 73.68% and incorrectly classified 26.32%. Root mean square error is 0.4669.

3.3.2 Logistic Regression

Logistic regression algorithm estimates the occurrence of an event or value to match one event or value to another.

Table 4: True Positive Rate, False Positive Rate, Precision, Recall and ROC Area for Logistic Regression

	TP Rate	FP Rate	Precision	Recall	ROC Area
Weighted Avg.	0.684	0.442	0.672	0.684	0.579

Table 5: Confusion Matrix of Logistic Regression

Positive	Negative
31	5
13	8

Logistic regression with breast cancer dataset correctly classified 68.42% and incorrectly classified 31.58%. Root mean square error is 0.5084.

3.3.3 K-Means

The K-Means algorithm groups same data in clusters until it finds the ideal central value.

Table 6: Confusion Matrix of K-Means

Positive	Negative
181	20
59	26

K-Means with breast cancer dataset, correct classified ratio is 72.38% and incorrectly classified ratio is 27.62%.

3.3.4 Canopy

Canopy is an unsupervised per clustering algorithm that performs better than another algorithm.

Table 7: Confusion Matrix of Canopy

Positive	Negative
70	25
47	3

Canopy with breast cancer dataset, correct classified ratio is 58.05% and incorrectly classified ratio is 41.95%.

3.3.5 GCN

For the classification problem, our suggested methodology utilizes a 2-layer-based GCN layer. A predictive performance of 81 percent is obtained by GCN using our dataset. After reviewing our suggested strategy with some other model, we find that it provides better results.

Table 8: Confusion Matrix of GCN

		Predicted Class	
Actual Class		Positive	Negative
	Positive	75	10
	Negative	10	11

3.4 Result analysis

After evaluating our suggested GCN algorithm to four others, we discovered that GCN achieved the highest accuracy—81 percent—and canopy the least accuracy—58 percent. Other neural networks, such as KNN, obtained accuracy of 73 percent.

Table 9: Accuracy Analysis between algorithms

References	Learning Approach	Accuracy Claimed (%)
Haskul, M., & Yaman, E. [7]	C4.5	75.87
Haskul, M., & Yaman, E. [7]	Random Forest	73.73
Haskul, M., & Yaman, E. [7]	KNN	74.83
From our investigation	KNN	73
From our investigation	Logistic Regression	68
From our investigation	K-Means	72
From our investigation	Canopy	58
Our proposed method	Graph Convolutional Network (GCN)	81

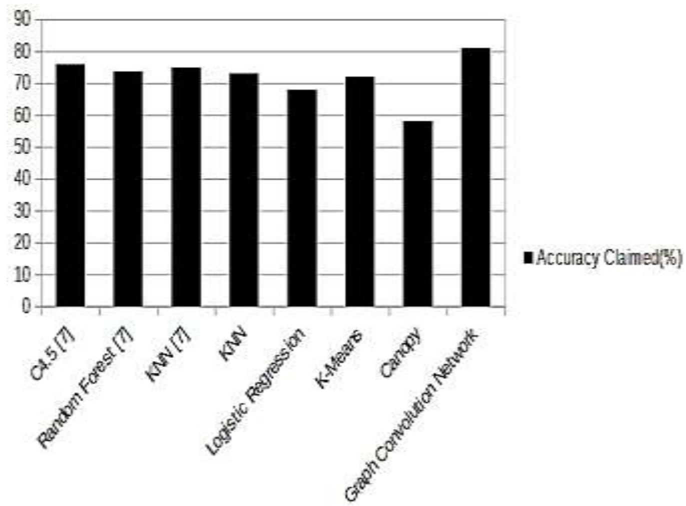


Figure 3: Accuracy analysis graph between algorithms

3.5 Summary

Analyzing the testing results and evaluation performance, our machine learning based detection system has better efficiency. This prototype can smoothly detect breast cancer. Our developed model is a unique and the smartest way to detect the breast cancer that has best efficiency, which is rigidly analyzed in this chapter.

IV. CONCLUSION

We experimented with a practical machine learning based breast cancer detection system, the Graph Convolutional Network (GCN). We use supervised classification techniques in our mammogram image data and then feed the classified data into the GCN model for detection. We investigated that the GCN model can give better accuracy than traditional machine learning models. We integrated the GCN model into breast cancer mammogram image data and conclude that it can give better accuracy than traditional machine learning models.

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