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A Review of Breast Cancer Classification and Detection Techniques

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ABSTRACT

Cancer is a very serious disease. Deadly and very hard if you lived with. Cancer is caused when abnormal changes happens on cells that are out of control. Cancer cells often form a lump or mass called a tumor and are named after the part of the body in which they originated. When Happens at breast organ it is called Breas Cancer. Deadly as any other type of cancer. Also as any other type, it has a life cycle consist of stages. usually does not produce any pain in the early stages in which it is easy to treat on. Cancer main problem is when to find out that the patient had cancer cell inside his body. Early stages always it better timing to start treating the cancer tumors. All old researchers and doctors always tried to improve the medical process in which we try to find cancer cells also the other medical checkups to help us detect or even predict that this person had or will have a cancer disease in the future. CAD systems and Medical Screening was the main ways to think about. Medical Images processing technologies and finding best features of cells was the right way and using CNN, Deep CNN, Convoltion Matricese, SVM Technique and many of Machine Learning algorithms used before, the main challenge was to make it easy and also more accurate to complete these tests. Many improvements made at this track of work. The results always was More and more of accuracy improvements and time reduction and resources usage improvements too.

1. Introduction

In Breast cancer is referring to cells which grow at a rate of more than normal rate every several months and multiply out more and more without any control and spread to many parts of human body. BT (Breast tumor) is the top first kind of cancer and the number two component of death of women gender. Because the reason of appearing and happening of breast cancer is not known, ways to prevent the disease have not been identified. Recognizing it as a tumor and the type of cancer will play a role in helping the doctors to take the decision to implement real treatment methods and thus restore people's lives (more than 40%). Cancer is a group of cells that grow abnormally. It can begin in any trillions cells in the body. Cancer differently behave and grow, that is whether they are malignant (cancerous), benign (noncancerous), or might be precancerous too. In carcinoid, the cells of cancer start at any cell of body. Calling them carcinomas after they formation or growth, [7].

A cancerous tumor is: 1- Growing in adjacent cells or tissues. 2- It has breaking down cells that can travel through the lymph system and blood then spread to distant parts and lymph nodes.

Cancer which spreads at the beginning of the life cycle of cells (called a primary tumor). When cells spreads out and be developed into new tumors can be called metastases.

In tumors which are non-cancerous, these tumors are called like that because: 1- Do not spread and stay in one place. 2- It does not usually return after removal. 3- It tends to have a regular and smooth shape and has a covering called a capsule;

Currently, the early diagnosis of breast cancer is usually made by biopsy. In clinical practice, biopsy consists of three main steps. First, breast cancer biopsy material is obtained by drilling a biopsy. Second, histopathological images are stained with hematoxylin and eosin (H&e). Third, pathologists make an early diagnosis of breast cancer by observing images of tissue.

Specialists made awesome steps in the early detection and treatment of breast cancer, which led to a promising reduction in breast cancer mortality using medical diagnostic tools such as computer aided detection, digital mammography, resonance imaging and ultrasound. Mammography is one of the best and most accurate detection methods, mammography, which indicates changes in breast cells that can lead to cancer. It helps detect masses so tiny that they are rarely seen by the human eye. Researchers have attempted to make this procedure automatic by reducing task of the radiologist due to the large volume of images due to the increase in cancer cases worldwide. However, modern studies viewed that using deep learning, (CNN) can automatically find and extract features from mammography and predict the likelihood of cancer creation.

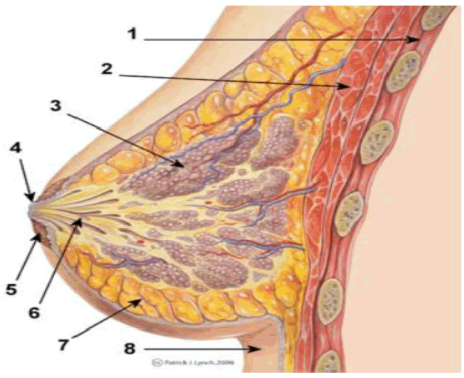

Figure 1. Schematic diagram of the anatomy of the breast. (1-Chest wall, 2-Pectoralis major, 3-Lobules, 4-Nipple, 5-Areola, 6-Mammary ducts, 7-Fatty tissue, 8-Skin) with permission

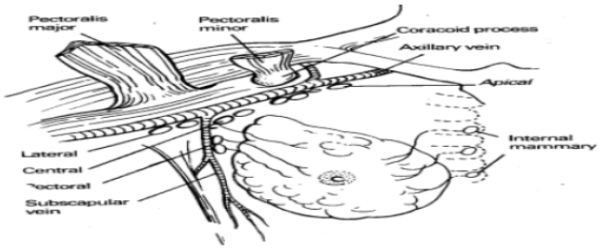

Figure 2. Lymphatic drainage of the breast (Axillary and Internal mammary nodes)

1.1 Breast cancer types

The World Health Organization classified cancer of breast into several types Noninvasive DCIS epithelial, invasive DC (85%), (1%) lobular, (5) mucinous), (<5%), papillary, (<5%) medulla , miscellaneous epithelial tissue and mixed connective tissue. The majority of breast cancers are adenocarcinomas that arise from the epithelium of the ducts and lobules (ductal and lobular types) [2,3]. Histological types of invasive breast cancer are summarized in Table 1. Ductal with productive fibrosis are the most common form. Lobular carcinomas are characterized by a high tendency to be bilateral, multicentric and multilocular and have a special tendency to spread to membranous structures, such as the peritoneum, pleura and meninges.[7]

Table 1. Relative frequency of histological types of breast cancer

Type	Frequency (%)
Ductal	80 (non-specific 50%)
Lobular/ductal combined	5
Medullary	6
Colloid	2
Other less common specific types (tubular, papillary)	2
Sarcoma and lymphoma	0,5

1.2 Problem Statement

About 232,670 cases of breast cancer in women, about 40,000 from them dies from this disease and more and more, so this is considered as the second reason of death with cancer in women. Prevention of it is still only available with applying extreme measures for women at high genetic risk profile, so a woman must know that she will develop cancer one day and really start taking action to prevent it in high-cost ways. Early detection remains the main focus in the fight against this disease. Early detection help with the diagnose and treat patients with this disease at an early stage [8]. Generally is more and more preferred for women in early stages of the disease. As detection in early time is associated with lower risk of death, we should reduce the detection and treatment time [9].

1.3 Objective

We should improve the process of screening to reduce the number of females not covered by these programs and to have more numbers of early detected cases. This improvement could be by any of the following: determination of the list of women having to do regular examination for prevention efficiently, introducing programs for screening many types of images and work as a method for diagnosis before screening stages, increase the efficiency of the mammograms analysis and always monitoring the patients.

Finding a new criteria for finding the target women for examination not just by the age. Improving the early diagnosis process in an efficient identification of the whose women based on many factors influenced to the happening of cancer [8]. Including a stage before screening which we can examine thermal images and radiological tumor with multi software in detection phase can be very useful.

Using Manual Hashing and computer algorithms. Identification of structures of tumors or other ROIs, including axillary tissues and lymph nodes, was important for finding the best method for the detecting process and that happens on early stages. The first aim of the research was to make a comparison manually and automatically make segmentation for each image getting 3D nodes for determining the most reliable computerized method.

Already configuring manual hash on every node. Then working on same nodes but using more complicated automated computer software to split them all. Comparing the results for the determination of the reliability of the volumes which were calculated and finding the differences and bet oof manual and automatic methods [9].

2. Related Work

Multiple work had made before to improve many thigs including time problem, resources usage, accuracy and ease of use problems. Using the following methods we made a lot.

1. Method of Sparse Representation
2. Support Vector Machine [SVM]
3. K-nearest neighbor [KNN]
4. Convolution Neural Network

5. Deep Convolution Neural Network
6. Adaptive Fuzzy Means Algorithm For Segmentation (Mass Detection)
7. LeNet using Patch-based
8. U-Network
9. Pretrained FCN-AlexNet
10. Classification using utilized ELM
11. Discrete Wavelet Transform (DWT)
12. Probabilistic Neural Network (PNN)

2.1 Based on Sparse Representation, Support Vector Machine and K-nearest neighbor

The authors proposed a model using SVM for breast cancer detection in which two types of SVM models were used, C-SVM and V-SVM. To hybridize the model, the WAUCE, method was used. The model performed better than other studies proposed using a single SVM architecture. This study proposed Bayesian networks for the classification of mammography[6] Images with each view and then using logistic regression to make final decisions on the results generated by Bayesian networks. Analyzing each mammogram view separately while the radiologist has to analyze two views each time to find the difference by comparison. An expert system for breast cancer screening (Ex-DBC) has been proposed.[6] The neural obfuscation method is used to find ambiguous rules. The proposed system predicts high positive values that help to avoid erroneous interpretive results that lead to biopsies. A rule-based system is very useful because it contains specific, unambiguous information. The rules can be easily changed and updated whenever the need arises. Mammograms are usually obtained from the same breast in two views: a side view called a tilted medial view (MLO) and a top-to-toe view called a cranial view (CC).[6] In the proposed method, geometry-based area matching method is used to extract breast lumps from double-width CC and MLO mammograms and then use a multi-view classifier to classify breast lumps.

For feature selection and dimensionality reduction, a genetic algorithm is used where SVM is used for classification. The experiments achieved better accuracy compared to previous approaches. A technique based on MAD normalization for grading breast cancer where the model consists of three stages. The procedure for weighting the data measured using K-mean clustering (KMC) involves AdaBoostM1 classifier used at the end of the last classification. Using a multilayer neural network (MLP). A non-dominant genetic sorting algorithm is used to aggregate the network but the local minimum is a problem for MLP.[6] Feature extraction from mammograms with two presentations MLO and CC, ANNs are used and then features of the resulting mammograms from the ANN are combined to classify the two types of cells, benign and malignant.

Some of the limitations of this work are:

1. Is that it takes a lot of time and cost
2. The lack of experimental data, which led to the high cost of the experiment.
3. Save the images in equal sizes.

2.2 Using CNN & DCNN & Alex-Net Model

Mammogram detection with Convolution Neural Network accuracy is about 60% for all categories and 75% for the block category, which is too low for medical solution CNNs are generally 2D algorithms for various channel processing methods which have excellent performance in image and video process. Parameter sharing in Network is instead of learning a different parameters at each location as in the normal learning methods, it only needs to train on one set of them and apply it to

all the image.[4] This reduces computational time, thus System performance improvement. Convolution Neural Network algorithm is used to discover and classification of images by scanning of them. From abnormal tissue, tumor foundation, lumps and lumps. There are two main types of mass tumors, adenoma. Often appears as a round or oval malignant (cancerous) tumor. It is a part round and has an abnormal white outline. The goal is extracting features from the images using Various techniques: (ROI) region of interest and thresholding, and The last layer of the DeepCNN architecture has been replaced by The Truck support. The work carried out using two databases, DDSM and Coordinated Breast Screening Database Imaging Subgroup CBIS. Result was an accuracy improvement of 87.2%.

The SVM used as a classifier in combination with Deep CNN for 71.01% during feature extraction in manual way.[4] Ghongade and Wakde, our goal is to detect breast cancer tumor from mammograms using (RF) random forest and a set of Extreme Learning Machine classifier RF-ELM applied to MIAS Database. The classifiers works by sending an abnormal sample down into each tree and a vote of all trees indicated the classification at the end of the process either a benign tumor or a malignant tumor. [5] Result was that the random forest classifier works good with large DB and high dimensional data but the combination of Extreme Learning Machine gives a better result. Achieved accuracy was 89%. And the authors tried and tried more to achieve more and more even accuracy. [5]

Table 2. Summary of Reviewed Literature Accuracies

Author	Metric parameters		
	Neural Network	Database	Accuracy
Dina.et al, (2019)	DCNN classify masses	DDSM	87,2%
Jiang (2017)	DCNN classify tumors	BCDR	79,1%
Duraisamy (2017)	DCNN classify masses	MIAS	85%
Ghongade (2017)	CNN classifier	MIAS	89%
Jain et al.,	DCNN classify tumors	DDSM	66%

A more accurate way is to now tell Alex-Net DCNN that used the MIAS database of the Breast Image Analysis Community.[5]

Table 3. MIAS Database Simple Components

Specifications of MIAS Dataset and Its Division Into Train and Test Set in the Proposed System

Images		Class	
		Normal	Abnormal
	Training Samples (70%	132	93
	Test samples (30%)	57	40

Which optimizes the images for better feature segmentation and then will be assigned to a modified Alexnet CNN model for feature extraction, training, and classification. [5]

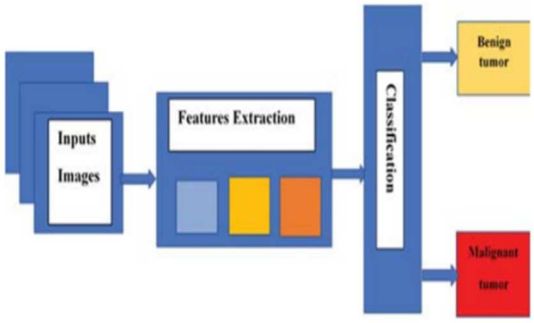

Figure 3. Basic Flowchart for The Detector And Classifier

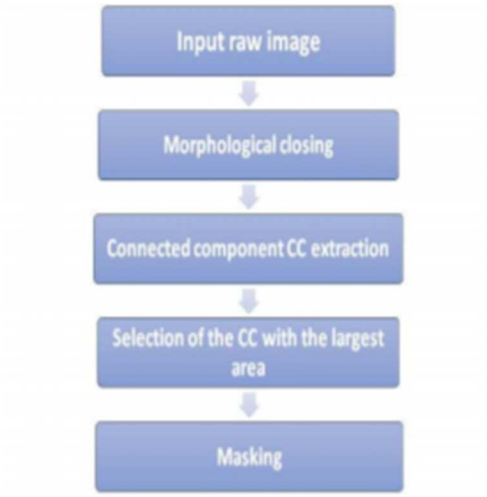

Figure 4. Segmentation Steps for Preprocessing

The processes on this method is:

1. Preprocessing
2. Increase data
3. Deep neural network convolution
4. Training the model

Table 4. Training Parameters

Sr.no	Parameters	Values
1	Minimum batch size	5
2	Maximum Epochs	50
3	Initial learn rate	0.01
4	Learn rate drop factor	0.2
5	Learn rate drop period	0.5

Table 5. Structure of The Modified Net

Input image, grayscale (64x64)		
1	Conv1	96, 5x5 convolution with Stride=2 and zero padding
2	ReLu	Rectifier linear unit
3	Cross channel normalization	Cross channel normalization with 5 channel per element
4	Max pooling layer	3x3 max pooling stride [2 2] and zero padding
5	Conv2	256, 5x5 convolution filter, with Stride=1, and Padding=2
6	ReLu	Same as previous
7	Cross channel normalization	Same as previous
8	Max pooling layer	Same as previous
9	Conv3	384, 3x3 convolution filter, with Stride=1, and Padding=1
10	ReLu	Same as previous
11	Conv4	Same as Conv3
12	ReLu	Same as previous
13	Conv5	256, 3x3 convolution filter, with Stride=1, and Padding=1
14	ReLu	Same as previous
15	Max pooling layer	Same as previous
16	FC1	Fully connected layer with 4096 neurons
17	ReLu	Same as previous
18	Dropout	Dropout layer of 50%

19	FC2	Fully connected layer with 4096 neurons
20	ReLu	Same as previous
21	Dropout	Dropout layer of 50%
22	FC3	Fully connected layer of 2 neurons
23	Softmax	Softmax
24	Classification layer	Output layer into two classes (Benign vs Malignant)

Results was obtained during this study was: tumor grades without increasing and tumor grades with increasing MIAS DB. In both cases, performance had been evaluated with evaluation criteria. Part of the agenda was implemented within the second scheduled. First, images in the MIAS DB were resized till been 64 × 64 dimensions to match the CNN entry size to reduce computational complexity. The original copy of the DB. A defensive learning rate was 0.1 and 100 was used as a maximum. The SGD (Enhanced) training function which used with a Workstation with specification measured as RAM up to 18GB, Core i7, and 3 GHz.[5]

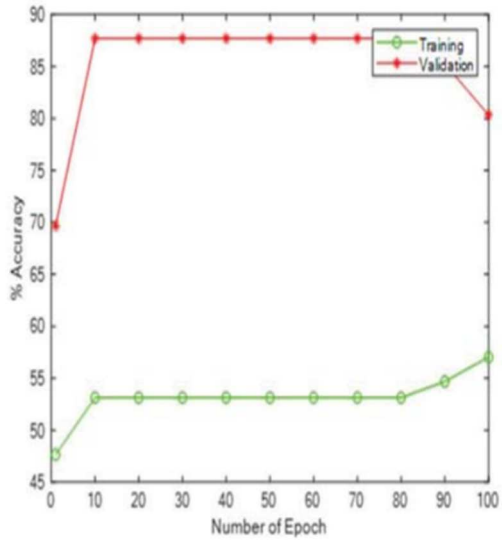

Figure 5. Percentage Accuracy for Training And Validation

Table 6. Convolution Matrix for Proposed System

Actual / Calssified as	Benign	Malignant
Benign	0.95	0.05
Malignant	0.054	0.946

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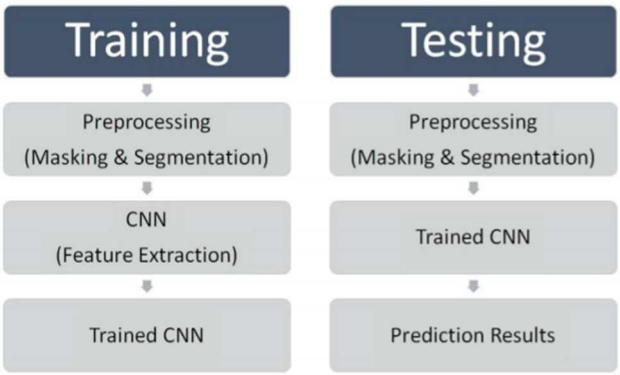


Figure 6. Summary of Process

The preperation of the work needs using different sizes of 5 × 5 and 3 × 3 convolutional filters for the initial layer and three after, respectively. To remove the noise and reduce computational time, a preprocessing methods was used. Results showed that the fully connected layers used as a classifier in modified AlexNet gives classification accuracy of 95.70%, which is a noticable improvement over other traditional ways used for mammogram analysis. By making use of augmentation techniques that involve both reflection and rotation.

2.3 ELM with Feature Fusion using Convolution Neural Network Deep Features

Basically, every CAD system for diagnosing breast cancer follows some steps to achieve detection and classification of breast tumors.

1. First we found the ROI on pre-made mammograms, then defining the tumor region
2. Extract feature based on knowledge, as texture and shape and density, to generate feature vector manually
3. Diagnosis of malignant and benign by classification of this trait vector

As an earlier history of this method, the author relied on the result of another method mentioned earlier: An adaptive ambiguous C algorithm is used for segmentation on each mammogram itself. A supervised ANN were used as classification tool for judgement of region Pixels were employed as a surrogate feature and the area growth method was used for segmentation of the tumor on that mammogram [3]. An improved was the watershed algorithm. As first perform a coarse segmentation for the breast tumor, followed by images edges detection using combining of regions with gray-scale has similar values for mean. They proposed a new algorithm for detecting suspicious masses in mammography, where they used a segmentation method which are globally and locally adapted to original mammography [3]. Differentiating between the two type (benign and malignant) tumors, a Bayesian network has been established that uses two features were physical and manual defined probabilistic properties to perform computer aided diagnosis for cancer of breast. The ELM used is designed for classification of those features and compare between the results with the Support Vector Machine [4]. CNN was applied to breast cancer risk prediction after training on a huge amount of tries.[4] Deep neural networks were also used for prediction as near-term for risk breast cancer based on 420 time series of mammographic records. Another woman has designed deep feature based tool for classifying mass, in which Convolution Neural Network and decision tree were used. CNN was used to strip presentation of a tumor and then classify it to benign or malignant. Introduce retrieval image system using ZMs for feature extraction since it can affect of a breast CAD system. Another CAD method, used genetic algorithms for extracting significant and informative features, after so a rotation forest were used to take the decision.

This method used five basic steps in detecting and grading breast cancer:

1. *Breast image processing*. In mammogram preprocessing, noise reduction and contrast-enhancing processes were used on the mammogram for the increasing of contrast of masses and its surroundings.
2. *Comprehensive detection.* Return on investment is localized.
3. *Feature extraction.* Features with depth, along with features which can be called as morphological, and finally the texture and density properties are extracted from region of interest
4. *Training data generation.* Classifier were trained on each image data set using extracted features vectors and its labels.
5. *Workbook training*. Underdiagnosed mammography can be identified using well-trained classifiers [4].

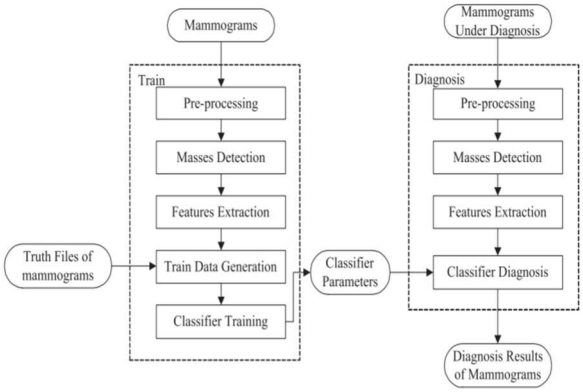
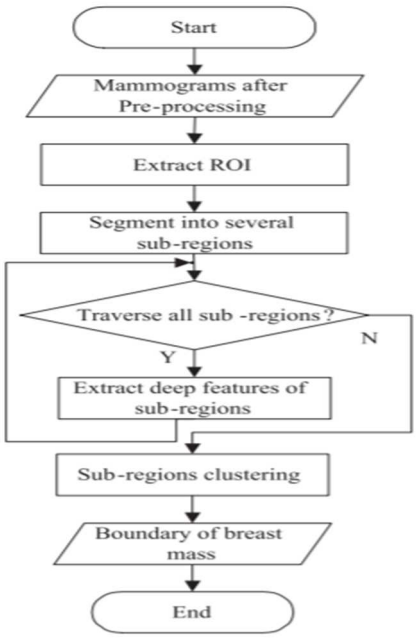


Figure 7. Flowchart for The Training and Validation



Algorithm 1 Self-Adaptive Mass Region Detection Algorithm

1 Input: Mammography I
2 Output: Mass area M
3 for $i = 1$ to L **do**
4 find the first and the last nonzero pixel x_s, x_d.
5 end for
6 for $i = 1$ to n **do**
7 find the first and the last nonzero pixel y_s, y_d.
8 end for
9 Cut off a rectangle M by the coordinates (x_s, x_d) and (y_s, y_d).
10 Return M.

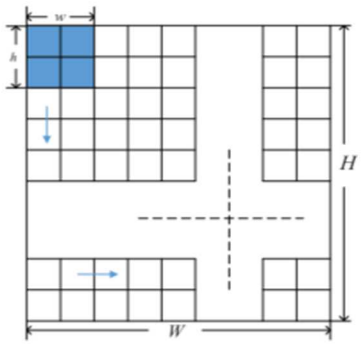


Figure 8. Mass Detection Process Flowchart and Algorithm

Table 7. Type and Feature Mass Detection Process Flowchart and Algorithm

Type	Features
Deep features	20 deep features extracted from CNN
Morphological features	Roundness, normalized radius entropy, normalized radius variance, acreage ratio, roughness
Texture features	Inverse difference moment, entropy, energy, correlation and contrast coefficient
Density feature	Density mean, density variance, density skew, density peak gray density variance, gray density skew, gray density peak

Algorithm 2 US-ELM Algorithm

1 Input: Deep feature matrix $\mathbf{X} \in \mathbb{R}^{N \times n_0}$
2 Output: Embedding matrix $\mathbf{E} \in \mathbb{R}^{N \times n_0}$
3 Output: Clustering index vector $\mathbf{y} \in \mathbb{R}^{N \times 1}$
4 Construct the Laplacian operator $\mathbf{L}$ from the training set $\mathbf{X}$
5 Randomly generate hidden layer neuron output matrix $\mathbf{H} \in \mathbb{R}^{N \times n_h}$
6 if $n_h \leq N$ **then**
7 Use equation $\min_{\beta \in \mathbb{R}^{n_h \times n_o}} \| \beta \|^2 + \lambda Tr\left(\beta^T \mathbf{H}^T L \mathbf{H} \beta\right)$ to calculate output weights
8 else
9 Use equation $\left(I_0 + l\mathbf{H}^T L \mathbf{H}\right) v = \gamma \mathbf{H}^T \mathbf{H} v$ to calculate output weights
10 end if
11 Calculate the embedding matrix: $\mathbf{E} = \mathbf{H}\beta$
12 Use k-means algorithm clustering N points into K categories
13 Denote $\mathbf{y}$ as the dimension vector for all point classification indexes
14 return $\mathbf{y}$

Algorithm 3 ELM Training Algorithm

1 Input: $N = \{(\mathbf{x}_j, \mathbf{t}_j) | \mathbf{x}_j \in \mathbb{R}^n, \mathbf{t}_j \in \mathbb{R}^m, j = 1, 2, \cdots, N\}$
L: number of hidden neurons; N: labeled dataset size
2 Output: Three parameters of ELM: $\mathbf{w}, b, \beta$
3 for $i = 1$ to L **do**
4 randomly generate weights $\mathbf{w}_i$ and bias b_i of the hidden layer
5 end for
6 Calculate the single hidden layer output matrix $\mathbf{H}$
7 Calculate the output weight vector $\beta = \mathbf{H}^T\mathbf{T}$
8 Return $\mathbf{w}, b, \beta$

2.4 Noise Reduction DWT, PNN-RBF

Scientific (ANNs) are the most widely used as models when classifying cancer cells, as we talked about earlier [2]. Using fuzzy and probabilistic network, feature extraction from images was used to understand retrospective mammos to the detection process of a mass malignant for early breast cancer detection. One of best practices found was the HMLP network that gave the best and highest accuracy For more specific details, feature extraction was performed by DWT and classification by PNN. For the detection and the classification each patient's tumor type, specialists refer to images and report on patient's images analysis. The way which proposed helps the doctors in the diagnoses of breast tumors [5]. With it, the doctor can do the network trainings on the system with some known data first and after that they can use it for generating a patient picture report after testing the data they had [5].

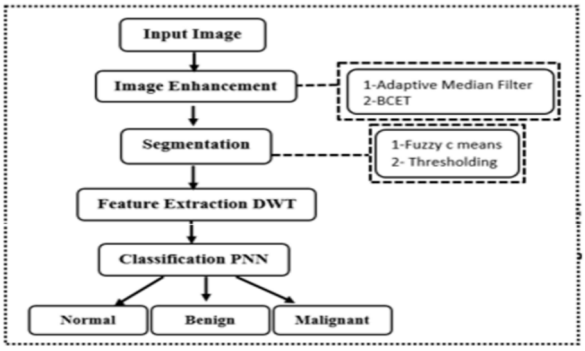


Figure 9. Simple ANN Classifier Flowcahrt

The images were obtained will be converted to the grayscale form. After that plenty of computations will be performed:

• Image processing enhancement (which include masking an adaptive mean filter for removing noise and improving balance and contrast with BCET filter).

• The application of segmentation threshold and fuzzy FCM methodology.

• Feature extraction process using DWT.

• Classification and Tumor detection using PNN.

Some of the techniques used were this way

• Enhance the image with the adaptive median filter

• Segmentation using Fuzzy segmentation

• Extracting Features using DWT

Classification using a probabilistic neural network

3. Conclusion

With the evident requirement of regular tests and importance of medical check ups, The search brings to the lime light the challenges which will arise with the update of CAD systems an medical image analysis and diagnosis. In the midst of other possible solutions, the paper expounds the use of the medical image analysis, image diagnosis and classifications of these images. We proposed many approaches to reduce time and increase accuracy and make the operations more easy for the early detection and diagnosis of the breast cancer tumors.

4. Future Work

How to implement a CAD System and include the tumor medical image analysis techniques on it, with more accuracy and less time and simple hardware structure.

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