A Framework for Identifying the Factors Impacting Breast Cancer Detection Using CNN

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Abstract

This study aims to determine how socioeconomic status and various treatment modalities affect cancer patients. This study focuses on machine learning methods that researchers have suggested to utilize in the diagnosis of female breast cancer. One of the main obstacles facing women globally is breast cancer. In order to analyze the state of the art in computer-assisted breast cancer diagnoses, this paper covers the execution and outcomes of a systematic investigation. Additionally, a straightforward, novel and effective method was suggested. The suggested study investigates several screening methods for identifying breast cancer's intrinsic stage. Here, the usual Mammography imaging is employed to diagnose breast cancer. Organizations that use image-based classification make the assumption that all patient photos include the same tags as the patient, however, categorizing the data is expensive and is seldom found in the sample. CNN is a complex and scary sort of deep system that has attracted interest from the environment and production to achieve experimental success.

Keywords: Artificial Intelligence, Breast Cancer, CNN, Mammography images.

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1. Introduction

Research has indicated that a number of variables contribute to the chance of developing breast cancer. Age and female gender are two major risk-influencing variables. Breast cancer mostly affects women over 50. Some women get breast cancer without being aware of the risk factors. Neither one risk factor nor all risk factors have the same potential consequences on health. Even though the majority of women have very low risk factors and very few develop breast cancer, [2]

Unchangeable, immutable factors		**Immutable variables can migrate.**	
Age.	The likelihood of developing breast cancer rises with age. It is typically diagnosed when a person is over 50.	Failing to stay active.	Physically inactive women are more likely to develop breast cancer.
Gene change.	Breast cancer risk is higher for women who have altered gene mutations, such as those in the BRCA1 and BRCA2 genes [3].	Postmenopausal obesity or overweight.	Compared to women of healthy weight, older women who are overweight or obese have an increased chance of developing breast cancer [4].
History of reproduction [4].	Breast cancer risk factors include menstruating before the age of 12 and menopause after the age of 55.	using hormones	Breast cancer risk may be increased if estrogen and progesterone replacement medication is used for more than five years after menopause.
The breasts are heavy.	In addition to containing malignancies on mammograms, fatty tissues have more connective tissue than non-fatty tissues. Breast cancer is more likely to strike those with full breasts.	Biological History.	Breast cancer risk factors include not breastfeeding, having a full-term pregnancy, and being pregnant for the first time after the age of 30.
A detailed biography of the deceased	Women who previously had infertility may experience it again. Breast cancer risk is elevated in several noncancerous breast conditions such as intraepithelial lobular carcinoma and atypical hyperplasia.	Ingest alcohol.	According to studies, a woman's risk of breast cancer increases with the amount of alcohol she consumes.
Family relationships and the deceased's family members' history	A woman's risk of getting breast cancer increases if she has a mother, sister, daughter, or another first-degree relative with breast or ovarian cancer on either her mother's or father's side. If a male first-degree relative has breast cancer, the risk is likewise increased for women.	Smoking	According to studies, women who smoke have a higher risk of developing breast cancer.
prior radiation treatment.	Women who have received chest or breast radiation therapy are more likely to develop breast cancer before the age of 30.	Food Customs	According to studies, eating habits are a major cause of death. Low consumption of hygienic meals may contribute to the disease.
Getting high on diethylstilbestrol (DES).	Between 1940 and 1971, some pregnant women in the US received DES as a miscarriage preventative. Breast cancer risk was elevated in those who used DES or whose mothers did so while pregnant.	Living life	The way of life of women, According to research, breast cancer risk may also be increased by other variables like smoking, exposure to carcinogens, and changes in other hormones brought on by night shift work.
Left/Right side occurrence of tumors	The left breast experiences breast cancer more commonly than the right. The risk of breast cancer is 5%–10% higher in the left breast than the right.		
Blood Group	Blood group "A" has a high incidence of breast cancer (45.88%), followed by blood group "O" (31.69%), blood group "B" (16.16%), and blood type "AB" (6.27%). Blood groups "A" and "AB" are most and least associated with breast cancer, respectively.		

Only around half of breast cancers are caused by all known risk factors, and re-searchers and doctors are unsure of what causes the other cases.
The recognized risk factors included in this briefing are as follows:

high-risk variables for the disease have been identified [5]	**Known risk factors for the survival from breast cancer** [6]
their family's history and genetic propensity. Natural hormone supplements, weight gain, inappropriate physical activity, alcohol use, and smoking are some examples of risk factors.	Early menstrual cycles, missing or delayed menopause, not having children, the value of primarily nursing for a brief length of time, frequent use of oral contraceptives, hormone replacement treatment, Obesity, regular alcohol consumption

Along with the above mentioned risks, having thick breasts, standing taller than the typical person, and undergoing radiation for Hodgkin lymphoma in conjunction with specific benign breast disorders are additional risk factors for breast cancer. In addition, it has been demonstrated that exposure to ionizing radiation, such as X-rays, raises the chance of developing cancer. The potential advantages of early breast tumor detection exceed the danger of subjecting the woman to low amounts of X-rays [7] during the scan, thus the lady still gets a mammography despite this. It is seen as Alternative approaches to early detection might, however, be created in the future, which would be ideal. Additionally, studies indicate that night shift workers are more likely to get breast cancer. This might be as a result of "night lights" suppressing melatonin synthesis, which is considered to stop the growth of cancer cells and boost estrogen release from the ovaries. For complete confirmation, more study is required.

All of these established breast cancer risk factors raise estrogen intake in forgery-focused women. Produces the type of topic data that is beneficial for statistics. Deep knowledge may be non-discriminatory and formalised in a way that avoids the need for field experts to plan feature extractors from data by foreseeing this in advance. Convolutional Neural Networks (CNNs) [8] are a complex variety of deep neural networks that may be utilized to create applications. They combine data from neighborhood and production studies. Experience success in your regular work. By identifying breast cancer histopathology pictures from his IDC regular dataset (breast cancer tissue image dataset) starting with Kaggle [9], this technique seeks to develop behavioral studies using deep learning.

Typically, histological microscopic imaging is used to make the diagnosis. Doctors use imaging tests to perform extra, efficient analysis. Handkerchiefs are extremely variable in appearance, which helps to better capture characteristics. Finding breast cancer augmentation in the early stages is essential to lowering the death rate since it has not been possible to identify them due to immobility. (more than 40%) (Cheng, Shan, Ju,Guo, Zhang, 2010).

Detected previous cancers your situation is enhanced. However, precise and trustworthy studies that can tell benign from malignant tumors are required prior to the start of the discovery process. In order to achieve low false optimism (FP) and false negative (FN) rates, quality discovery must be advanced. The most efficient approach of detection and diagnosis is mammography [10]. (Cheng et al., 2006). However, mammography is not always successful in identifying breast development. The use of ultrasonic imaging (US) to identify breast cancer is becoming more popular and is now a significant alternative to mammography. According to statistics, ultrasonic imaging is used in more than 25% of research, and that percentage is rapidly growing. Images of the United States may be utilised, according to research, to accurately discern between bags that are favorable and those that are repulsive.

2. Literature Review

In this manuscript, four information distance models are applied. Supports Vector Machines [11], Artificial Neural Networks [12], Naive Bayes Classifiers [13] , and Ada Boosted Trees [14]. Not only that, but the manuscript also excellently discusses the characteristic spaces that go far beyond terrestrial forces on the capacity and efficiency of cognitive processes. To test the performance of feature space reduction, a hybrid of adjacent principal part inspection (PCA) and related information elimination models that apply code component analysis measures to reduce the feature space is underway.

Using Machine Learning Tools to Classification [15]
This mechanism examines the Feed Forward Back Broadcast Network-FFBPN to classify decease cases as either hateful or benign. By increasing the number of hidden layers, neurons and its function, Artificial Neural Networks can get sufficient accuracy. ANN's instructions and approval template are taken from the Wisconsin Breast Cancer Catalog (WBCD) Unlocking Credentials.
Analytical Accuracy of Various Machine Learning Algorithms for Calculating Breast Cancer Risk. Based on the use of four major algorithms for the Wisconsin breast cancer dataset (original). We evaluated the proficiency and proficiency of these algorithms in terms of accuracy, precision, compassion, and perspective. Evaluating the efficiency to discover the best classification of specificity, veracity. SVM achieves 97.13% correctness, outperforming the others.

Risk prediction analysis of Breast Cancer decease using Machine Learning Algorithms [16]
The main goal is to measure accuracy in classifying information, respecting the power and efficiency of each algorithm under conditions of accuracy, accuracy,

compassion, and specificity. Preliminary scores show that SVM provides the highest accuracy (97.13%) with the lowest error rate. All experiments are conducted in a simulated environment and run on the WEKA Information Mining Instrument.

Breast cancer decease analysis and prognosis by Machine Learning methods[17]
It is one of the major common cancers. Manufacturing is an important issue for the physical condition of communities in today's civilization. Early diagnosis of Breast Cancer can greatly improve prognosis and continued survival because of its ability to support appropriate scientific treatment of patients. Because of this method the choice in classifying Breast Cancer prototypes and predictive models due to its unique compensation for significant discoveries in large numbers of BC datasets.

- Jiyo S. Athertya et al. developed automatic segmentation of contours from his CT images using fuzzy corners. In this method, automatic contour initialization was demonstrated using the active contour method. Fuzzy corners achieved 80% accuracy with high Dice factor and low Hausdorff distance. This algorithm is also suitable for noisy images. For soft tissue imaging, this can be a difficult task, and finding the corners of the image is complicated.

- Elise Ilungam Mbuyamba et al. proposed an alternative He Active Contour Model (ACM) that utilizes multi-population cuckoo hunting algorithms. This strategy supports convergence of the control points to the global minimum of the energy function. This is in contrast to ACM, which is often confined to local minima. This algorithm has been tested and implemented on MRI images. Three metrics were used to evaluate the results: the Jacquard exponent, the Cube coefficient, and the Hausdorff distance. This method requires fewer iterations, is more robust, and is more effective. Computing iterations requires more computing time.

- Agus Platondo et al. provided an improved and robust edge stop function (ESF) for edge-based active contour models. Robust edge-stop functions use gradient information that cannot stop contour development when the image boundaries are poor. The method used a new ESF that contains both gradient information and probability values for classifying masses. The method was evaluated using two quantitative measures, the Jaccard index and the Dice coefficient. This method converges faster and provides global contours, but is a more complicated method.

- Radha M et al. proposed an image enhancement technique for breast cancer detection. Mean, median, Wiener, and linear filters are used for preprocessing. Among these filters, the median filter gives the best results. Image segmentation is performed by thresholding techniques and k-means algorithms. Tumor edges are detected using the canny edge detection technique. This algorithm improves accuracy. A limitation of this method is the difficulty in finding edges in blurred images.

3. Methodology

One of the most prevalent malignancies is it. In today's culture, manufacturing has a significant impact on the physical health of populations. Because early detection of breast cancer can let patients receive the most effective scientific therapy, it can significantly improve prognosis and overall survival. This technique is preferred for categorizing Breast Cancer prediction models and prototypes because to its distinctive compensation for important findings in several BC datasets.

The standard for the diagnosis of breast cancer is Mammogram imaging [18]. You are permitted to use as many cards as you like at once during the trial period. Conservative image-based classifiers use the assumption that every image of a patient has the same tags as the patient, but because categorising the data is expensive, they are seldom found in the sample. The creation of meaningful types using prior statistical domain knowledge is a hard and time-consuming procedure, yet it is essential to the representation of mainly conservative categorization systems. Committed to creating.

Uniqueness can be collected and formalised without taking into account prior in-depth information [19], making feature extraction from data unnecessary. In order to create applications for language trust, signal distribution, object trust, natural language processing, and motion knowledge, convolutional neural networks (CNNs), a complex sort of deep neural network, employ data from neighbourhood and production research. Embrace success in your regular employment. This method uses Kaggle's extensive expertise in categorising pictures of Mammography breast cancer from MIAS dataset [20] to support behavioral experiments. (Dataset of images of breast cancer tissue). Breast cancer diagnosis frames may be seen in Figure 1.

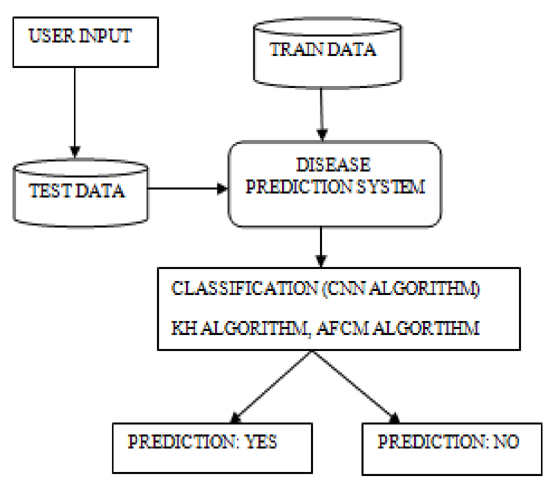


Fig. 1. Framework design for Breast Cancer Identification

The handkerchief is displayed in a highly unpredictable manner that enables it to be viewed at different visual magnifications, emphasizing the prison's selective nature.

In this research, we provide a method for categorising histological breast pictures using an ensemble of classifiers [21] and a common color texture characteristic [20]. This endeavor demonstrates the influence of futuristic structures. This project's main aim is to teach readers how to categories photographs with varying degrees of visual exaggeration. This project uses a cross-fold training test to illustrate apparent class invariance. To obtain understanding, compare and contrast scale-specific versus scale-independent models. The project advises testing the model on photos at various magnifications after training it at a particular magnification. We also contrast this cross-magnification investigation with a model that can be trained and evaluated on pictures at any magnification. In this study, an ensemble of classifiers and the merging of color-texture characteristics are used, followed by majority vote. Because multiple classifiers may perform differently at various scale factors, ensembles are used. The suggested model's schematic is also shown in Figure 1.

The suggested process involves four phases. Pre-processing is the initial phase, which involves removing extraneous components like labels. The photos were optimised for use with other processing techniques in a subsequent stage. To determine the precise impacted sections, he performs his third segmentation process [22]. Segmentation is followed by feature extraction in the fourth stage. Through this extraction, certain unique traits are obtained and made classifiable [23].

3.1 Feature Extraction

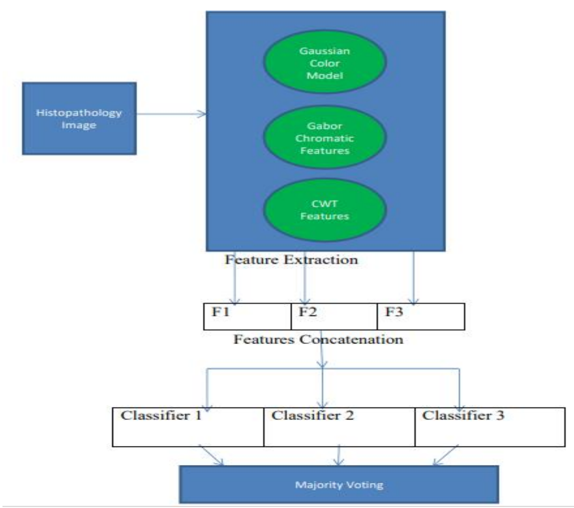


Fig. 2. Proposed Frame work for Breast Cancer identification

The proposed framework for identifying and classifying breast cancer is shown in Fig. 2 below. For measuring texture, feature extraction techniques like the Gabor filter and Gaussian colour model are utilized. The brightness graph is made up of them all. Additionally, we compute each colored route using the Dual Tree Complex Wavelet Transform (DT-CWT) [25]. It offers several benefits over the Discrete Wavelet Transform due to its selectivity and redundancy [26].

4. Implementation

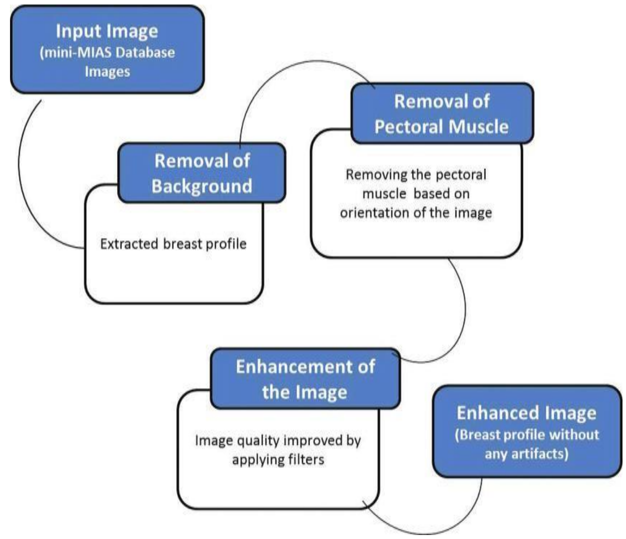


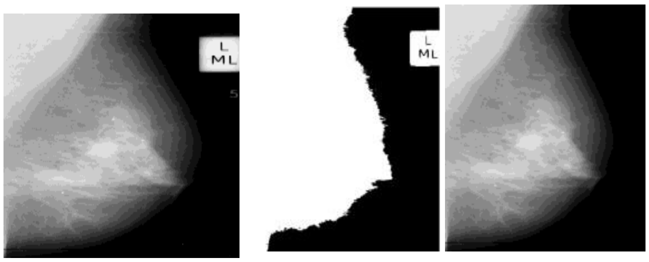
Fig. 3. Flow diagram for Pre-processing

Pre-processing is mostly used to efficiently enhance image quality. The recommended method involves pre-processing stages that, depending on the image orientation, eliminate the pectoral muscles and background image. The image should be enhanced to raise its caliber in a third phase. The preservation of artefacts [27] shouldn't cause them to harden. Figure 3 depicts the flowchart for the pre-processing procedure.

4.1 Labels and other background artefacts have been eliminated. [28]

Follow these steps to identify the breast's tissue borders. After transitioning from the unsigned component of the picture to the doubled decimal, obtain the image energy of the decimal image equal to her square. The graphic displays the energy model from the modified picture [29]. Reset the threshold to return to the initial binary image [30].

The chest is not covered by background regions, which predominately appear on the left and right sides of the picture. Because the background is dark and has consistently low grey level values, these grey levels do not differ from one another. Set the intensity value accordingly to discover a new function. In other words, the parameter is set here to the desired value, and the maximum intensity value is applied to the region covered by this setting. Zero refers to the space between the fixed value and all other values. This will eliminate the additional components. Figure 5 displays the result of the image without the label.

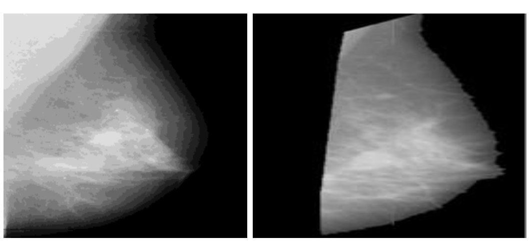


(a) input image (b) binarized image (c) label removed image

Fig. 4. Mdb209 image: Removal of labels and other artefacts,

4.2 Take the pectoral muscles out. [31]

The muscles behind the border of the chest are known as the pectoral muscles. Removing this area will aid in the subsequent segmentation procedure because it is essentially an undesirable portion of the mammography picture. This region can be removed in a number of ways. We will locate the proper edge of the chest piece in this work and cut off this undesirable region. By establishing sound boundaries, any remaining undesirable regions may be quickly removed. Figure 5 illustrates the output of the pectoral muscle removal. The first image is the input image, which was acquired from the small MIAS database.



(a) **(b)**

Fig. 5. Mdb209 image: Removal of labels and other artefacts, (a) input image, (b) binarized image, (c) label removed image

4.3 Image Enhancement [32]

The last stage of preprocessing methods is enhance ment.The image quality is raised during this process. This is more crucial for what will happen afterwards. The two basic classification methods for picture enhancement are frequency domain and spatial domain [33]. The proposed technique enhances picture consistency by means of median filtering [34].To do median filtering and enhancement, the image's pixel values' median is determined. The algorithm used to calculate the median is described below.

Algorithm

1. With the pectoral muscle removed, images can be taken.
2. If the resulting pixels are noisy, the median value ought to be applied before further processing.
3. Adjust the window
4. For each pixel value, repeat step 2
5. Get a better image

4.4 PSNR and MSE value measurements

Peak Signal to Noise Ratio (PSNR) and MSE Values are used to determine the effectiveness of these median filters.

$$\text{MES} = 1/n \sum_{i=1}^{n} (yi - \hat{y}i)2 \qquad (1)$$

$$PSNR = 10 \, \log_{10} 255^2/MSE \qquad (2)$$

Peak signal-to-noise ratio (PSNR) [35] is a measure of how well a signal is presented relative to the greatest amount of signal (power) that is feasible. Because many signals have a very wide dynamic range, PSNR is typically given in logarithmic dB. (ratio between maximum and minimum transformable quantities). Image enhancement, or enhancing the visual quality of digital photos, is a personal choice. The resulting PSNR value in this case is 35.28, suggesting that the final augmented image has good quality. The MSE score is 2.9861, which shows that the final image has extremely few mistakes and excellent image quality. The proposed strategy yields more accurate findings than Farhan et al. These findings imply that contrast enhancement in our present study significantly increased image quality and that different people have different perceptions of what constitutes high-quality photographs.

As a result, in order to compare how various image enhancing methods affect image quality, quantitative and empirical measurements must be created. Comparable test images may be used to rigorously analyze different picture enhancing techniques. See if a particular strategy results in better results. The statistic we take into account is the peak-to-signal-to-noise ratio. If we can show how an algorithm or guide like the original can improve the widely recognized representation of degeneracy, we may be able to conclude that this is the best approach.

4.5 Optimization and Segmentation

Compared to other digital photographs, medical images are generally blurry, noisy, and of very poor quality. As a result, straight segmentation of these pictures produces subpar segmentation and makes it more difficult to identify cancer cells. The obtained medical pictures are initially optimized in order to lessen these difficulties.

The optimization problem is solved in this paper using the superb method Krill Herde (KH) [36]. According on the simulated behaviour of krill members, the KH algorithm operates. Krill members work to keep densities that automatically shift due to contact at greater levels. The local group density (local effect), target group density (target effect), and repulsive group density can all be used to determine the initial direction of movement I. (repulsive effect). The most accurate description of this krill migration is:

$$N_i^{new} = N^{max}\alpha_i + \omega_n N_i^{old} \tag{3}$$

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \tag{4}$$

N^{max}- stands for maximum speed, n for the weight of motion supplied up to the range [0, 1], N old for neighbouring motion, and I for the optimal direction to affect individual krill. The highest induced speed recorded values are taken as 0.01 (ms). The neighbours' effects are said to have an enticing or repellent propensity among those looking for a neighbourhood. The following list of members of the neighbourhood krill movement is

$$\alpha_i^{local} = \sum_{j=1}^{NN} K\hat{}_{i,j}\, X\hat{}_{i,j} \tag{5}$$

$$X\hat{}_{i,j} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \tag{6}$$

The neighbor's vector can be gorgeous or scary because the standardised esteem might be either positive or negative. There are numerous methods for calculating the separation between each krill. Here, it is resolved by running each cycle through the corresponding equation:

$$d_{s,i} = 1/5N \sum_{j=1}^{N} \|X_i - X_j\| \tag{7}$$

The Advanced FCM (AFCM) methodology for producing partitioning is a new advanced FCM clustering technique [37] that is introduced in this article. The Neighborhood EM (NEM) technique was used to create the penalty time, which was then modified depending on FCM references. By varying the penalty rate, this algorithm has the benefit of being able to handle any noise levels. Additionally, although the membership is altered by this method, the computation of the core object is identical to that of the conventional FCM algorithm. Only after realizing that this adaptive FCM takes both spatial and feature information into account during segmentation, is it offered. Thus, implementation is simple. Experimental findings and comparisons of several versions of this method in various photos demonstrate the effectiveness and power of the suggested algorithm.

Algorithm

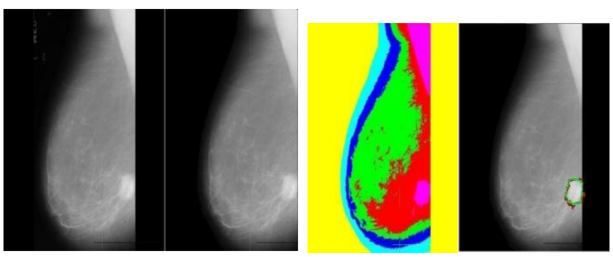
1. Start the cluster values at C
2. Apply the objective function to the adaptive FCM values.
3. Determine the cluster mean.
4. Next, group the object values. Give no assignments to the designated function.
5. If the requirement is satisfied, stop; if not, calculate the population entropy function and recalculate the centroid value.
6. Re-examine the fitted value and determine that the resulting value is higher, replacing the current value.
7. To ascertain the raw value, use the Gold Selection technique.
8. Upload the actual results determined by a qualified radiologist.
9. The output of step (6) should be compared to the ground truth of the anomalous region from step (8).
10. He performs the FCM iteration once more to update the new cluster center values if the criteria are met. If not, repeat step 7 one more.
11. Complete Defuzzification.

The fuzzy matrix [38] function is defuzzified to create a crisp partition. The maximum membership algorithm is one of the key types among the many techniques created to defuzz the partition matrix U. j = 1, 2,..., x, and xi = argi max (vij) The aforementioned approach is defuzzed and helpful for segmentation with the aforementioned equation.

5. Results and Discussion

You require feature extraction if you need distinct information. As a result, it is regarded as one of the most significant ways of image processing processes since it enables us to exclude the data that is most crucial for classification. There are several algorithms, including DWT, PCA, histogram matching, template matching, and more. The entire characteristics that can be helpful for the classification process are extracted using the DWT with Adaptive FCM approach that is being offered. One of the most effective feature extraction techniques, the Discrete Wavelet Transform (DWT), gathers both time and frequency information. Two 1D functions can be multiplied to provide a DWT 2D signal.

$$\alpha \ (i, \ j) = \alpha(i\ )\ \alpha(j\ )$$



(i) (ii) (iii) (iv)

Fig. 6. Results: (i) mdb271 Original image, (ii)Optimized image, (iii) FCM segmented image, (iv) Ground truth image compared with resultant image

Through the use of a pair of low pass and high pass filters, this distorts the input picture into subbands. Here, we divide the picture into subbands using the Haar transform. The input picture is split into 4 bands (HH, LH, HL, and LL) following the first phase decomposition, and three different types of detail maps are produced for each resolution. Each resolution includes three distinct detailed pictures in the HL, LH, and HH directions. With the aid of a second stage of a homogeneous filter bank
the activity can be repeated in the low-low (LL) band.
In medical imaging, classification is a technique for separating benign from malignant tumour cells. Breast cancer is categorised using various programme criteria for a variety of reasons. Histopathological type, tumour quality, tumour status, and protein and gene expression are the primary classifications. In this study, we employ a gray-level co-occurrence matrix to separate cancerous cells from healthy cells.
The many subtypes found at various cancer stages are depicted in Figure 7, along with the current approaches to treating cancer cells. BCL stands for B-cell lymphoma, ERBB2 stands for erythroblastic leukaemia tumour gene homolog, AR stands for androgen receptor, CK stands for cytokeratin, EGRF is for oestrogen receptor, PARP stands for polymerase (ADB-ribose), and PR represents for progesterone receptor. Mammography has a sensitivity and specificity range of percentage 75-90% and 90- 95%, respectively. Mammographic (+ve) predictive estimates of malignant breast development range from 20% to 80% in women between the ages of 50 and 69. Furthermore, unfavourable future projections for women over 40 might be between 90% and 95%.

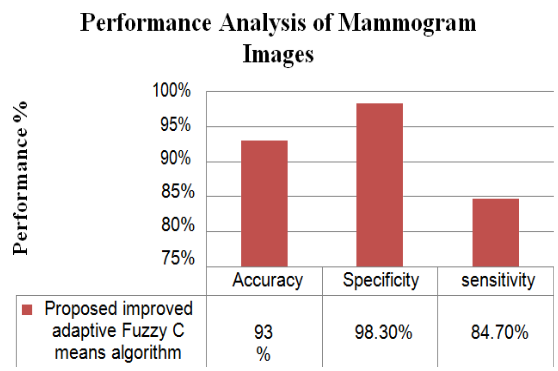


Fig. 7. Analyzing the effectiveness of mammogram images

Table1. The ratio of reliability ratio figures for the diagnostic process

Reliability	**Diagnosticprocedures**
	Mammography
Percentage of Sensitivity	**52.400%**
Percentage of Specificity	**66.700%**
Percentage of Positive Predictive value	**40.700%**
Percentage of Negative Predictive value	**76.200%**

We came to the conclusion that the observation and opinion are generated by the cancer patients attitude to treatment based on the observations from the field research. The conclusions were reached using data that had been categorised and evaluated using the appropriate statistical tools, such as Chi square and factor analysis.

We came to the conclusion that treatment options for cancer patients influence attitudes and observations based on observations from field research. Results were derived from data that had been categorised and examined using chi-squared factor analysis, a suitable statistical method. At the 0.05% level, there is a substantial correlation between age and cancer stage. The value of the chi-square is 35.051. Humans have an age characteristic. Nevertheless, youthful age-related health concerns can be offset by addressing health mechanisms and maintaining
Dietary management.

People in their middle years and older have trouble managing their physical conditions when they experience the signs of cancer. Cancer sufferers, whether young or middle-aged, witnessed strange changes in their bodies when cancer was diagnosed. Most of them are unable to identify cancer in its earliest stages. This table demonstrates how age and stage affect how long cancer symptoms last and how dangerous they are. Only 33% of respondents in the 14 to 20 year old age range believed that the patient's condition worsened within a month after three months and six months, respectively. (1 out of 5).
Likewise, the age range of 21 to 30. The respondents' age group was the same as when they examined the cancer stage three months prior. (2 out of 10). Respondents who had a confirmed cancer site at least three years prior and were 61 years of age or older are included in this age group. (23%, 8 out of 16).

Table2. Age with Duration of Identified

Age	Duration of Identify						Total
	Within this month	Past 03months	Past 06months	01-02 Years	02-04 Years	Above 05 Years	
14-20 Years	1 33.3%	1 33.3%	1 33.3%	0 0%	0 0%	0 0%	3 100%
21-30 Years	1 33.3%	1 33.3%	0 0%	0 0%	0 0%	1 33.3%	3 100%
31-40 Years	1 7.7%	2 15.4%	4 30.8%	2 15.4%	1 7.7%	3 23.1%	13 1000%
41-50 Years	0 0%%	2 16.7%	1 8.3%	4 33.3%	4 33.3%	1 8.3%	12 100%
51-60 Years	2 0%	1 4.5%	9 40.9%	5 22.7%	4 18.2%	3 13.6%	22 100%
Above 61 Years	2 5.9%	3 8.8%	2 5.9%	13 38.2%	6 17.6%	8 23.5%	34 100%
Total	**5** **5.7%**	**10** **11.5%**	**17** **19.5%**	**24** **27.6%**	**15** **17.2%**	**16** **18.4%**	**87** **100%**

6. Conclusion

A thorough investigation and thorough assessment of the literature indicated that the mammography image classification methods for breast cancer that are often utilized lack accuracy. Longer machine learning algorithm training durations were required for techniques with better accuracy. The trade-off between speed and accuracy offered a chance to use the suggested model to handle this problem for optimization. Extensive investigation for this project revealed that a CNN has never before used a mix of three separate feature extraction techniques and classifiers. As a result, this project study develops a reliable approach for mammography image categorization of breast cancer. The proposed system's performance and accuracy were evaluated by performing the necessary computations on a training dataset taken from the IDC breast cancer dataset.

7. Reference

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