ORIGINAL ARTICLE

Case-Based Approach to Detect Cancer in Women with Curative Intent at Beginning

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Abstract

Background: Breast malignant growth is among the most widely recognized ladies' diseases and a significant reason for disease-delivered ladies' deaths all over the planet. Mammograms have a high pace of missed growths, or "misleading negatives." Over 10% of threatening cancers in mammograms cannot be identified in ladies more than 50 years.

Objective: To Increase the detection rate of mammography for detection of early breast cancer.

Methods: The research work was conducted during 2022-2023 at Radiation Oncology, Allama Iqbal Medical College/Jinnah Hospital, Lahore with data of thousands of cases. Case-based reasoning (CBR) is a strategy to apply problem solution data of currently tackled issues by the arrangement of coming issues.

Results: CBR characterizes benign cases with precision and recall of equivalent to 0.87 and 0.7 and for malignant cases are 0.9 and precision of 0.75 respectively. Our objective is to improve the detection of cancer with principal component analysis of characteristics, precision enhanced by 20% and recall by 11% for malignant cases and by 15% and 28.5% for benign cases respectively. The outcomes acquired by CBR are compared with multiple Knowledge-based algorithms.

Conclusion: The CBR-based approach delivered improved results when contrasted with the wide range of various strategies regarding precision, recall, misleading negative rate, genuine positive rate and F-measure for dangerous cases.

Keywords: *Mammography, malignant growth, case-based approach, similitude measure.*

INTRODUCTION

Breast malignant growth is liable for a greater part of disease-related deaths among ladies all over the planet. A total of 16% of disease-related deaths in the advanced nations are brought about by Breast malignant growths and 12% of all related deaths are credited to it in non-industrial nations. Developed nations revealed up to two percent expansion in Breast disease risk annually [1-4]. Restricted information is accessible from emerging nations. Data from malignant growth vaults demonstrate that age-normalized occurrence rates are expanding at an increasing rate in remote regions of emerging nations. The monetary and way of life variations are creating increasing frequency of Breast cancer in developing nations. It is expected that in the future number of breast cancer cases will surge at a high rate. It is critical to detect breast malignant growth in the beginning phase for curative treatment and a high survival rate. For a country like Pakistan which is restricted in facilities, by and large, the cancer is diagnosed at a later stage. This research has the objective to detect breast changes with the use of computer algorithms to treat breast cancer with curative intent [3-7].

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Mammography has been found useful in increasing the survival of breast cancer patients with the detection of abnormalities. Mammography is a compelling technique to recognize Breast disease in the beginning phases throughout the previous decades. A mammogram presents an X-ray beam picture of the breast. Mammograms are performed for screening or diagnostic purposes and expertise is required to evaluate these images. The computer-aided research helps the radiologists to interpret the medical images.

The modern advances in research lead towards modernized frameworks which are used as information sources for numerous boundaries including thick unpredictable regions, toughness regions and bunches of little calcifications. Radiologists in general cases can't unquestionably report disease based on mammograms just because the malignant and benign developments can resemble the other the same.

The current research involves knowledge base classification for grouping life-threatening and benign cases for a neighbourhood data set of cancer-affected people gathered from Jinnah Clinic Lahore. The data set comprised of thousands breast cancer-diagnosed women. This research has used multiple artificial intelligence classification algorithms to detect the early presentation of malignancy in breasts. The paper investigates the

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correlation of exhibition of the previously mentioned procedures for crude information against pre-handled information utilizing head part investigation.

Related Work

Lodwick *et al.* [8] started an electronic examination of chest radiographs. Suhail *et al*. [9] concentrated on anomalies in mammograms. Qin *et al.* [10] have evaluated numerous procedures applied in the discovery of Breast disease utilizing a multi-methodology approach. Loizidou [11] dealt with the PC-supported location of miniature calcification in mammography. Sharaf-El-Deen *et al*. [12] dealt with CBR and rule-based thinking mix for the identification of malignant growth. In medication, CBR applications are developing due to its case-based methodology of issue-taking care. Zia *et al*. [13] investigated the case recovery period of CBR for Breast disease information. Resmini *et al*. [14] explored the computer-aided diagnosis using breast thermography. The reason for CBR was set somewhere near the Powerful memory hypothesis (Riesbeck [15]) and made sense of the intuitive job of figuring out, learning, and memory, which can further develop an understanding of the arrangement of an issue. CBR is a portrayal [16] of a choice emotionally supportive network. Viveros-Melo *et al.* [17] concentrated on the job of CBR in pursuing choices between medication. Bentaiba-Lagrid *et al.* [18] involved a CBR way to deal with supervised classification in the medical field.

SUBJECTS AND METHODS

Case-Based Approach

Case-based Approach is a strategy where prior encounters give thinking to arrangement development [19-22]. In this type of critical thinking, the similitude of the current issue is determined with the current data set and arrangements of comparative issues clear the path for new arrangement [23, 24]. Issue arrangement matches contribute to their involvement with the information base as cases. On the appearance of an original issue, its correlation is presented with each defence on the off chance that base and when significant likeness is acknowledged between new issues and cases on the off chance that base after matching computations, the cases are considered for conceiving an answer. Different comparability measurements are utilized for this reason, and their choice relies fair and square of precision required and space related to the issue. CBR frameworks cycle in stages **(Fig. 1)**.

Recover

Case recovery is a course of recovering most comparative cases included in the arranged database. It incorporated the ID of applicable mammogram

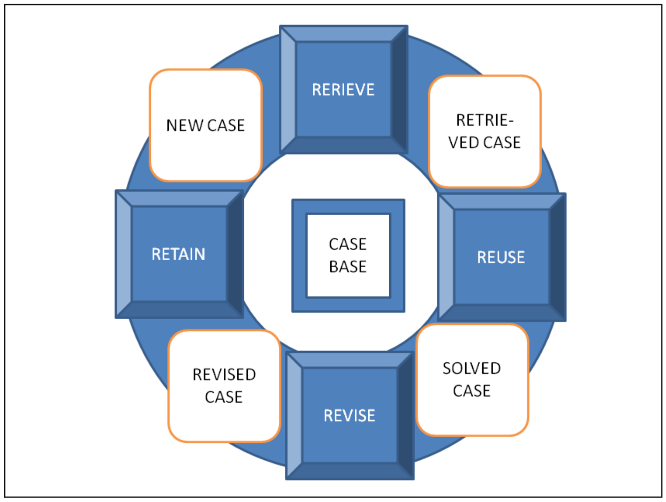

Fig. (1): Case Base Approach.

highlights. Framework sifted through the immaterial highlights of the issue. Matching recovers the most sensible arrangement of comparable instances of Breast disease by utilizing pertinent and powerful elements separated from breast images. For this reason, three strategies including Manhattan distance, I/O similitude measure and Euclidean distance were utilized.

Reuse

Arrangement related to closest neighbours is used to recover the arrangement of the experiment. Numerous arrangement calculations (weighted normal or number juggling normal, and so on) can be utilized for computing the arrangement of new cases.

Modify

To devise a better solution, modifications can be made to the arrangement of the ongoing case. Transformation interaction ought to be restricted and precise to get benefits from a case-based thinking philosophy.

Hold

Extension of the database can be done by retaining the breast new problem-solution pair. The recent issue arrangement must be utilized as a wellspring of knowledge. The arrangement is listed and coordinated to bestow recent information to the dataset.

List of Capabilities

We utilized the experienced imaging subject matter experts and chose the highlights given BI-RAD dictionary universally acknowledged for the order of Breast malignant growth. Eight highlights were extricated. Calcification Morphology (CM), Calcification Distribution (D), Age, Calcification Number (CN), Mass Size, Mass Margin, Mass Density and Mass Shapeare utilized as highlights. The elements were dissected regarding standard deviation and change, normal, least and most extreme (**Tables 1** and **2**).

Table 1: Standard deviation and fluctuation of elements separated for harmless cases.

Features	STDDEV	Max	Variance	Min	Average
CD	2.28	5	5.21	0	1.92
MS	1.606	4	2.581	0	1.5
MM	1.534	5	2.354	0	1.18
CM	5.976	13	35.724	0	5.1
MD	1.387	4	1.924	0	1.44
MSz	5.192	26	26.958	3	9.02
CN	0.543	2	0.295	0	0.48
Age	14.667	86	215.136	24	54.08

Table 2: The statistical analysis of cancer-diagnosed cases.

Features	Max	STDDEV	Min	variance	Average
CM	14	5.776	0	33.364	4.32
MS	5	1.503	0	2.261	2.94
MD	4	1.426	0	2.034	2.92
MM	5	1.837	0	3.375	3.18
CN	2	0.571	0	0.326	0.4
MSz	40	7.413	7	54.966	17.82
CD	5	1.998	0	3.995	1.38
Age	80	12.372	34	153.079	59.32

Case Planning

The computerized information base of breast images from the College of Florida gave the base to this exploration work. Cases are arranged for the recognition of harmful lesions from X-ray images of the Breast. We utilized eight boundaries to depict the issue. These boundaries were separated from the portrayal of mammography data of cancer patients for demonstrative reasons to Jinnah Medical Clinic. We chose boundaries which incorporate Mass Density (MD), Calcification Number (CN), Age (A), Mass Shape (MS), Mass Edge (MM), Calcification Morphology (CM), Mass Size (MSe) and Calcification Distribution (CD). Case portrayal was finished as follows:

$$C = (CD, CN, CM, MM, MS, MD, MSe, A) \quad (1)$$

The separated elements changed over completely mathematical qualities in the range from (0-10) by utilizing expertise and information. All info boundaries were standardized in the reach [0-1] for estimations. We dissected the information boundaries. We determined the normal, mean, change and standard deviation of the highlights separated from the database. There were absolute thousand dangerous and harmless cases on the off chance that base applied from DDSM of College of South Florida. At the point when we accompanied another case we anticipated a choice for the coming problem.

Case Recovery

The recommended methods were applied to establish a likeness between the experiment and all cases putting forth a defence base. Closeness estimations were performed for each case in the information base and existing case [25]. The heaviness of every case is determined by weighted procedure.

Manhattan Distance

Manhattan distance with expertise weightage was utilized to recover comparable cancer cases from the dataset. The weight was set by the experience of the scientist. The estimations for weighted aggregate between new case contrasts to different instances of information base were noticed.

$$d_{ij} = \sum_k w_k \left| X_{ik} - C_{jk} \right| \quad (2)$$

Where d_{ij} addresses distance among I and j cases while thinking about all the mammography highlights. We determined the load for each case.

Euclidean Distance

The Euclidean distance estimated is the distance between each mammographic highlight upsides of the coming case to each case in the information dataset. All characteristics and values were standardized. Euclidean distances were determined for every one of the cases in the data set to the ongoing case.

The distance measure utilized for this reason is,

$$D_{Eucl}(t, r) = \sqrt{\sum_{t=1}^{m} \left| \phi_{test} - \phi_{ref} \right|^2} \quad (3)$$

Where addressed for the particular standardized case and component worth and m addressed the quantity of mammogram separated highlights included, and We found the heaviness of every case utilizing the suggested weighted procedure.

Inward Item/External Item Likeness Measure

Khan *et al*. [26] proposed to address the cases as a vector of boundaries *i.e*., we determined, the external and internal results of C_k and C_p vectors individually.

Considering most cases like one another and, the heaviness of each closest neighbour was determined utilizing comparability values. Numerous limit values were applied to establish the most extreme result in weight estimations. Weight was determined as follows:

$$w_j = \frac{sim_i(C_p, C_k)}{\sum_{keCaseBase} sim_i(C_p, C_k)} \quad (4)$$

This addressed the heaviness of case j present for the situation base. We utilized experience-based weighted normal calculation in the wake of working out the closeness between the coming case and all cancer problem solution cases in the information base for concocting the best arrangement. Cases having greater likeness were given more weightage.

Solution

We utilized three comparability measures to ascertain the best arrangement. Experience-based weighted normal calculation developed to show up at ideal arrangement [27].

$$Sol = \frac{\sum_{jeCaseBase} w_j P_{ij}}{\sum_{ieCaseBase} w_j} \quad (5)$$

The above condition was utilized to devise an arrangement, where, P_{ij} shows the i component of j instance of the information base.

RESULTS

The proposed philosophy of dangerous and harmless cases was tried on an example informational index. The dataset had equivalent harmless and dangerous cases. The dataset was changed over to a case base as portrayed in past areas. Different trial runs were performed by changing the quantity of the experiment base from 40% to 20% concerning the first case base. Most suitable outcomes were acquired with a split of 70% to 30% between preparing the case base and experiment base individually. The disarrayed framework given this trial split of the case base is displayed in Table **3**.

The general precision emerged to be 83.33% with a moderately little bogus positive pace of 6.66 for the harmless class. Anyway, the misleading positive rate for harmful was recorded as equivalent to 26.66%.

Table 3: Disarray framework for location of dangerous and harmless cases with 30 test and 70 preparation cases. Accuracy = 0.93, Review = 0.78.

		Predicted	
		Malignant	**Benign**
Actual	Malignant	93.33%	6.66%
	Benign	26.66%	73.33%

To build the Review and Accuracy of CBR Approach we chose to apply the info highlights investigation and to apply the CBR at pre-handled information separated from mammograms.

Information Space Reduction

To decrease the bogus order of harmful and harmless classes, the informational collection was correspondingly diminished by applying the Head Part Examination. The size of the diminished information was constrained by shifting the least division (min_frac) boundary. The base part boundary gave a limit that permits a most extreme similitude suitable inside the Head Part Investigation. PCA was executed utilizing Matlab with least division boundary shifting somewhere in the range of 0.04 and 0.1. For every base division, a disarray framework was developed and dissected. The separate disarray networks for three unique least divisions are displayed in Table **4**.

The investigation of the pre-process information execution of CBR delivered positive outcomes. It was found that with the worth of least part of 0.1, the bogus positive rate for harmless (**Table 5**) and dangerous cases decreased to 10% and 0% individually with accuracy and review of 1 and 0.9 (**Table 6**).

Table 4: Disarray grid at least portion 0.04. Accuracy = 0.90, Review = 0.69.

		Predicted	
		Malignant	**Benign**
Actual	Malignant	90%	10%
	Benign	40%	60%

Table 5: Disarray grid at least portion 0.05. Accuracy = 0.90, Review = 0.90.

		Predicted	
		Malignant	**Benign**
Actual	Malignant	90%	10%
	Benign	10%	90%

Table 6: Disarray grid at least portion 0.1. Precision = 1, Recall = 0.90.

		Predicted	
		Malignant	**Benign**
Actual	Malignant	100%	0%
	Benign	10%	90%

Comparison of CBR with Different Strategies

To additionally test the CBR approach a correlation of nine distinct grouping procedures with the CBR classifier was led (**Table 7**). The correlation included BaysNet, RBFNetwork, AdaboostM1, VotedPerception, Bagging, NaiveBayes, ADTree, J48 and Conjunctive Rule procedures (**Tables 8** and **9**). The outcomes from every classifier were tried for the best evident positive rate, F-measure, accuracy, review and misleading positive rate (**Table 10**).

Tables **11** and **12** comparisons for benign cases and malignant cases for CBR that utilized natural information *i.e.*, without PCA. It tends to be found in Table **12** that the CBR-based grouping out played out all others as far as F-measure, genuine positive rate, review and accuracy yet comes up short for bogus positive rate.

A comparative correlation was led for the case base produced after applying the Head Part Investigation (**Fig. 2**).

Table 7: Comparison of results for benign cases.

Classifier	Bayes Net	Naive Bayes	RBF Network	Voted Perceptron	Bagging	Ada Boost M1	AD Tree	J48	Conjunctive Rule	CBR
TP Rate	0.64	0.56	0.66	0.66	0.62	0.62	0.66	0.66	0.62	0.7
FP Rate	0.2	0.14	0.2	0.3	0.3	0.26	0.36	0.3	0.36	0.3
Precision	0.762	0.8	0.767	0.688	0.674	0.705	0.647	0.688	0.633	0.87
Recall	0.64	0.56	0.66	0.66	0.62	0.62	0.66	0.66	0.62	0.7
F-Measure	0.696	0.659	0.71	0.673	0.642	0.66	0.653	0.673	0.626	0.77

Table 8: Examination of results for cancer cases.

Classifier	Bayes Net	Naive Bayes	RBF Network	Voted Perceptron	Bagging	Ada Boost M1	AD Tree	J48	Conjunctive Rule	CBR
TP Rate	0.8	0.86	0.8	0.7	0.7	0.74	0.64	0.7	0.64	0.9
FP Rate	0.36	0.44	0.34	0.34	0.38	0.38	0.34	0.34	0.38	0.1
Precision	0.69	0.662	0.702	0.688	0.648	0.661	0.653	0.673	0.627	0.75
Recall	0.8	0.86	0.8	0.7	0.7	0.74	0.64	0.7	0.64	0.9
F-Measure	0.741	0.748	0.748	0.686	0.673	0.689	0.646	0.686	0.634	0.81

Table 9: Comparison of results for benign cases after use of PCA.

Classifier	Bayes Net	Naive Bayes	RBF Network	Voted Perceptron	Bagging	Ada Boost M1	AD Tree	J48	Conjunctive Rule	CBR
TP Rate	0.96	0.56	0.66	0.7	0.84	0.84	0.78	0.88	0.96	0.9
FP Rate	0.36	0.44	0.34	0.34	0.38	0.38	0.34	0.34	0.38	0.1
Precision	0.69	0.662	0.702	0.688	0.648	0.661	0.653	0.673	0.627	0.75
Recall	0.8	0.86	0.8	0.7	0.7	0.74	0.64	0.7	0.64	0.9
F-Measure	0.741	0.748	0.748	0.686	0.673	0.689	0.646	0.686	0.634	0.81

Table 10: Comparison of Results for cancer cases after use of PCA.

Classifier	Bayes Net	Naive Bayes	RBF Network	Voted Perceptron	Bagging	Ada Boost M1	AD Tree	J48	Conjunctive Rule	CBR
TP Rate	0.6	0.94	0.88	0.74	0.72	0.66	0.78	0.6	0.54	1
FP Rate	0.36	0.44	0.34	0.34	0.38	0.38	0.34	0.34	0.38	0.1
Precision	0.69	0.662	0.702	0.688	0.648	0.661	0.653	0.673	0.627	0.75
Recall	0.8	0.86	0.8	0.7	0.7	0.74	0.64	0.7	0.64	0.9
F-Measure	0.741	0.748	0.748	0.686	0.673	0.689	0.646	0.686	0.634	0.81

Table 11: Examination of results without pre-processing.

Classifier	Bayes Net	Naive Bayes	RBF Network	Voted Perceptron	Bagging	Ada Boost M1	AD Tree	J48	Conjunctive Rule	CBR
TP Rate	0.72	0.71	0.73	0.68	0.66	0.68	0.65	0.68	0.63	0.8
FP Rate	0.36	0.44	0.34	0.34	0.38	0.38	0.34	0.34	0.38	0.1
Precision	0.69	0.662	0.702	0.688	0.648	0.661	0.653	0.673	0.627	0.75
Recall	0.8	0.86	0.8	0.7	0.7	0.74	0.64	0.7	0.64	0.9
F-Measure	0.741	0.748	0.748	0.686	0.673	0.689	0.646	0.686	0.634	0.81

Table 12: Comparison of results after use of PCA.

Classifier	Bayes Net	Naive Bayes	RBF Network	Voted Perceptron	Bagging	Ada Boost M1	AD Tree	J48	Conjunctive Rule	CBR
TP Rate	0.78	0.75	0.77	0.72	0.78	0.75	0.78	0.74	0.75	0.95
FP Rate	0.22	0.25	0.23	0.28	0.22	0.25	0.22	0.26	0.25	0.05
Precision	0.822	0.792	0.7835	0.7205	0.784	0.7585	0.78	0.7605	0.8035	0.95
Recall	0.78	0.75	0.77	0.72	0.78	0.75	0.78	0.74	0.75	0.95
F-measure	0.801	0.771	0.77675	0.72025	0.782	0.75425	0.78	0.75025	0.77675	0.95

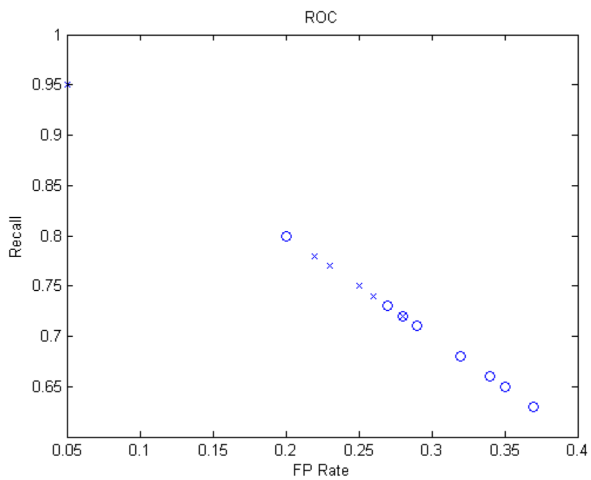

Fig. (2): ROC bend among review and FP rate.

DISCUSSION

Case-based reasoning (CBR) is a form of analogical reasoning in which the solution for a (new) query case is determined using a database of previous known cases with their solutions. Cases similar to the query are retrieved from the database, and then their solutions are adapted to the query. In medicine, a case usually corresponds to a patient and the problem consists of classifying the patient in a class of diagnostic or therapy. Compared to “black box” algorithms such as deep learning, the responses of CBR systems can be justified easily using similar cases as examples. However, this possibility is often under-exploited and the explanations provided by most CBR systems are limited to the display of similar cases.

CBR gave recall and precision for non-cancerous cases equivalent to 0.7 and 0.87 individually. For the detection of cancer cases, CBR revealed a precision of 0.75 and recall of 0.9. To achieve better sensitivity from mammograms by enhancing precision and recall, the head part investigation was applied to the information and cases were arranged utilizing the pre-processed data. At the point when CBR was carried out for the preprocessed data the precision expanded by 20% and recall by 11% for cancer cases. In the CBR order of non-cancerous cases, an increment of 15% in precision and 28.5% in recall was accomplished separately reaching 0.9.

In this paper, we propose a CBR method that can be both executed automatically as an algorithm. After retrieving similar cases, a visual interface displays quantitative and qualitative similarities between the query and similar cases, so that one can easily classify the query through visual reasoning, in a fully explainable manner. It combines a quantitative approach (visualized by a scatter plot based on Multidimensional Scaling in polar coordinates, preserving distances involving the query) and a qualitative approach (set visualization using rainbow boxes). We applied this method to breast cancer management. We showed on three public datasets that our qualitative method has a classification accuracy comparable to *k*-Nearest Neighbors algorithms, but is better explainable. We also tested the proposed interface during a small user study. Finally, we apply the proposed approach to a real dataset in breast cancer. Medical experts found the visual approach interesting as it explains why cases are similar through the visualization of shared patient characteristics.

CONCLUSION

This research proposed creating CBR to accomplish the early detection of breast cancer to achieve better survival and quality of life for women. This paper utilized three comparability measures to track down the case similitude. The outcomes obtained by CBR outperform in comparison to different multiple characterization methods. The CBR-based characterization developed improved results when contrasted with the wide range of various techniques as far as obvious positive rate, misleading negative rate, accuracy review and F-measure for cancer cases. At the point when CBR was carried out for the preprocessed data the precision expanded by 20% and recall by 11% for cancer cases. In the CBR order of non-cancerous cases, an increment of 15% in precision and 28.5% in recall was accomplished separately reaching 0.9.

The limitation of the study is a database, the approach can be evaluated with a large number of multiple databases.

The research in future can be used to accomplish a diagnostic tool for early detection of breast cancer.

ETHICAL APPROVAL

Ethical approval was obtained from the Institutional Review Committee of AIMC/Jinnah Hospital, Lahore (REF letter No. 194/23/12/2021/52 ERB Dated: 17 February 22). The research conducted in this work following the ethical standards of the institutional and/ or national research committee and the Helsinki Declaration.

CONSENT FOR PUBLICATION

All authors consented for this article.

AVAILABILITY OF DATA

Data is available.

FUNDING

Declared none.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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AUTHORS' CONTRIBUTION

All authors have contributed equally for the article.

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