JSTMU Journal of Shifa Tameer-e-Millat University

https://j.stmu.edu.pk

Open Access

ORIGINAL ARTICLE

Evaluation of BI-RAD characteristics and data increment of cancer data with computer-aided diagnosis of breast cancer

Imran Majeed Khan[1]*, Hafiz Rafique[2], Abdul Waheed Anwar[3], Basit Attique[4], Muhammad Jahanzab[5]

[1] Consultant Radiation Oncology, Allama Iqbal Medical College, Jinnah Hospital, Lahore, Pakistan

[2] Professor, Department of Physics, Punjab University, Lahore, Pakistan

[3] Associate Professor, Department of Physics, University of Engineering and Technology, Lahore, Pakistan

[4,5] Researcher, Department of Physics, Punjab University, Lahore, Pakistan

Author`s Contribution

[1-5] Main idea, Study design, Data collection, Literature review, Manuscript writing, final approval, and Proofreading

Article Info.

Conflict of interest: Nil

Funding Sources: Nil

Correspondence

Imran Majeed Khan

bisimran@gmail.com

Article information

Submission date: 11-03-2024

Acceptance date: 28-11-2024

Publication date: 31-12-2024

Cite this article as: *Khan IM, Rafique H, Anwar AW, Attique B, Jahanzab M. Evaluation of BI-RAD characteristics and data increment of cancer data with computer-aided diagnosis of breast cancer. JSTMU. 2024; 7(2):128-135.*

A B S T R A C T

Introduction: Malignant growth is one of the main sources of death and dismalness everywhere, with 14.1 million new cases and 8.2 million passings because of disease. Early breast malignant growth location is significant for the treatment and endurance of patients. Computer-aided design is a valuable device for prior malignant growth locations.

Methodology: There are 1863 threatening and harmless cases. The 09 highlights are separated from the DDMS information base and relegated the qualities by utilizing BI-RAD mammography vocabulary. The examination is led at Radiation Oncology, AIMC/Jinnah Medical Clinic, Lahore from October 2021 to November 2023. Case-based Reasoning (CBR) was applied at numerous information augmentation to explore its effect on the discovery of breast malignant growth. Three main distance techniques Euclidean, Manhattan, and Malik approach algorithms are used to evaluate the BI-RAD characteristics.

Results: For the Malik approach, the maximum number of correctly classified malignant cases was found by using the feature set of groups III and IV. The Manhattan distance approach provided maximum correctly classified malignant cases using feature set V and for benign cases, the group III feature set provided better results. Euclidean distance approach correctly classified the malignant cases using group V and correctly classified benign cases using groups III and II

Conclusion: It has been observed that the malignant cases are less often misclassified than the benign cases. For the malignant cases, the Malik approach produces better results and for benign cases, Manhattan distance and Euclidean distance classify better. The CBR represents a useful diagnostic tool for the classification of mammographic lesions.

Keywords: *Malignant growth; Case-based thinking; Accuracy; Head part investigation review*

Introduction

Malignant growth is one of the main sources of death and dreariness from one side of the planet to the other, 19 292 789 new cases and 8.2 million passings because of disease. There are 32.6 million individuals who are living with Malignant growth during five years of identification. The world has accounted for 1590000 demise because of cellular breakdown in the lungs, 745000 passing because of the liver, 723000 disease passing because of the stomach, 694000 malignant growth demise because of colorectal, 521000 disease passing because of breast and 400000 disease passing due to esophageal.[1] The five diseases seen in men were lung, prostate, colorectal, stomach, and liver malignant growth, and in ladies breast, colorectal, lung, cervix, and stomach disease. It is assessed that yearly malignant growth cases will increase from 14 million to 22 in the next twenty years.[2] Early breast malignant growth identification is significant for the treatment and endurance of patients. Computer-aided design is a valuable apparatus for prior disease location. This part contains a survey of the exhibition of computer-aided design execution for breast disease location for various clinical imaging modalities like mammography, X-ray, and ultrasound.[3,4]

A mammogram is the most predictable and successful way for breast malignant growth analyzed in the beginning phase. The PC use is critical to help radiologists in mammography in light of muddled breast engineering, low breast malignant growth likelihood, and nuances that are available among discoveries. Computer-aided design frameworks can be executed for both FFDM and Screen-Film mammography.[5] Joshua J. Fenton et al. showed the viability of a computer-aided design framework executed from 1998 to 2006 on screen-film mammograms on 684 956 ladies that had gotten above 1.6 million screen-film mammograms at Breast Disease Observation Consortium. Computer-aided design framework was applied to 27.8% of screen-film mammograms and results showed a decline in explicitness (0.5%) and with not better identification rate for obtrusive breast disease.[6]

Arifa Sadaf et al. assessed the exhibition of computer-aided design with FFDM in the identification of breast tumors applied on 127 mammographic cases that demonstrated breast diseases with biopsy-determined to have FFDM. Computer-aided design framework mounted to FFDM uncovered 100 percent responsiveness in tracking down microcalcifications and 86% awareness for other malignant growth. The distinction in responsiveness is fundamental because of sore size. They presumed that a computer-aided design framework with FFDM was useful in helping radiologists in early breast tumor identification.[7]

Robert M. Nishikawa et al. showed that radiologist responsiveness expanded by 10% and equivalent expanded in review rate by the utilization of computer-aided design framework on mammograms over 256 cases. Computer-aided design framework effectively perceived 71% of disease cases that were missed by radiologists at screening.[8] Mohamed Meselhy Eltoukhy et al. proposed a factual t-test strategy for highlight extraction and applied breast disease identification and characterization in mammograms. They utilized a Help Vector Machine (SVM) to group (5-crease) by utilizing 70% of the dataset and 30% was utilized for the estimation of the arrangement rate.[9] The exactness rate by the proposed technique is 95.84% to order typical and unusual tissues and 96.56% to distinguish harmless and dangerous cancer utilizing wavelet coefficients. The precision rate by the proposed strategy is 95.98% to group typical and strange tissues and 97.30% to recognize harmless and dangerous cancer through curvelet coefficients.

J. Dheeba et al. examined a new order strategy for breast malignant growth recognition by utilization of Molecule Multitude Improved Wavelet Brain Organization on 216 computerized mammograms given removing Regulations Surface Energy Measures by use of an example classifier.[10] The responsiveness and particularity of the new characterization strategy were 94.167% and 92.105% respectively. Yu-Dong Zhang et al. proposed a clever computer-aided design framework for identifying irregularities in breasts on 200 mammogram pictures. The awareness, explicitness, and precision of their proposed strategy in light of Weighted Kind fragmentary Fourier Change with Head Part Examination notwithstanding SVM was, and separately.[11]

Zhiqiong Wang et al. proposed a computer-aided design recognition framework laid out on an outrageous learning machine by the execution of an ideal combined highlight for breast disease location. They affirmed the viability of their proposed technique on 222 mammograms.[12,13] The primary goals of this study were to explore the effect of information increase on early recognition of breast malignant growth by the use of mechanized calculations on the mammogram data set.

Methodology

This study was completed at Jinnah Clinic, Lahore, and was supported by the clinic's moral panel. The rules of the Helsinki Announcement were continued in leading this exploration work. Members. The information included for which assent was accessible. The examination was led during the 2 years 2021-2023. Those mammographic pictures of ladies who met the accompanying rules were remembered for the exploration: analyzed instances of biopsy-demonstrated breast disease, harmless cases, and complete records were accessible for them. Ethical approval was obtained from the Institutional Review Committee of AIMC/Jinnah Hospital, Lahore (Ref. letter No. 194/23/12/2021/52 ERB). Written informed consent was taken from the participants.

Complete populace testing permitted profound knowledge to concentrate on the elements engaged with delay for the therapy and conclusion of malignant growth. This is a technique through which we incorporated every one of the patients satisfying our measures and rejected the individuals who didn't meet the rules. The means that are utilized by computer-aided design for disease discovery are displayed in Figure 1. As a matter of some importance, take the clinical picture from imaging procedures and after that, the accompanying advances are performed like pre-handling division, and up-and-comer identification, including extraction and characterization by computer-aided design. Radiologists came to the last conclusion about the dangerous region.[14]

There are 1863 harmful and harmless cases. The eight elements are removed from the DDMS information base and appointed the qualities by utilizing BI-RAD mammography vocabulary. The accompanying mammogram highlights are removed from the information,

a) Mass Shape (Oval, Round, Sporadic)

b) Mass Edge (Encircled, Clouded, Microlobulated, Ill-defined, Spiculated)

c) Mass Thickness (High thickness, Equivalent thickness, Low thickness, Fat-containing)

d) Calcifications Number (Skin, Vascular, Coarse or "Popcorn-Like", Enormous Pole Like, Round Edge, Dystrophic, Milk of Calcium, Stitch, Dubious)

e) Calcifications Morphology (Nebulous, Coarse Heterogeneous, Fine Pleomorphic, Fine Direct or Fine-Straight Spreading)

f) Calcifications Appropriation (Diffuse, Provincial, Assembled, Direct, Segmental, Engineering Contortion)

g) Related Discoveries

h) Unique cases

The elements removed from mammograms are given mathematical weightage. At the point when the highlights change over into the mathematical qualities, the qualities are standardized into the scope of (0-1) for the use of calculations. The CBR framework is determined into various frameworks relying on the number of cases for the situation base named as 100- - 1,300- -1,500- - 1, 700- - 1, and, 900- - 1. Mammography is a significant clinical imaging methodology utilized for the early finding and location of breast illnesses. Mammography is the low portion X-beam of the breast. X-beams are much of the time utilized for imaging a body part.[15] The picture of mammography is called a mammogram. The mammogram of six unusual breasts is displayed in Figure 1.

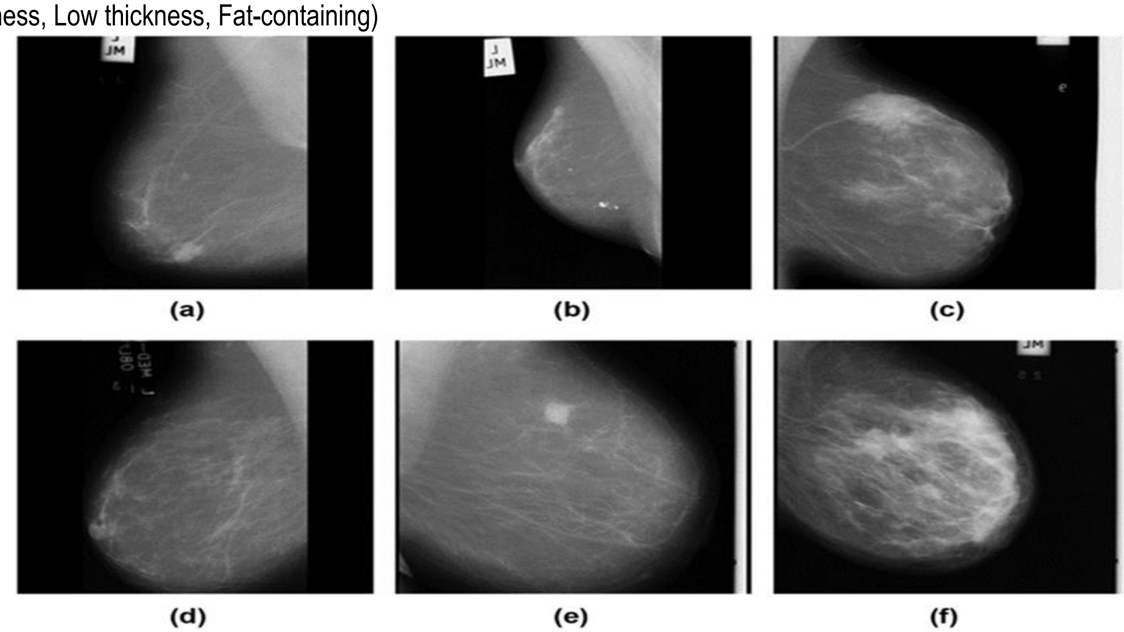

Figure 1: Picture of six strange sorts: (a) outlined mass, (b) imbalance, (c) structural mutilation, (d) calcification, (e) poorly characterized masses, and (f) spiculated masses

Three present high-level mammographies are computerized mammography, computer-aided design, and 3D mammography. In computerized mammography, likewise named FFDM, x-beam film is changed by an electronic framework that changes X-beams into mammographic breast pictures that make better pictures even with a low portion radiation. The electronic frameworks utilized in X-beams are like the computerized cameras' electronic frameworks. Breast Imaging Reporting and Data System (BI-RAD) were laid out by the American College of Radiology (ACR) for normalization of mammographic revealing, and for further developing correspondence.[16] The BI-RAD characteristics are divided into multiple groups to investigate the significant characteristics. The following groups are formed

- **Group 1:** Features used Age, Associated Findings, Mass Margin, Calcification Morphology, Mass Shape, Calcification Number
- **Group 2:** Features used Age, Associated Findings, Mass Margin, Calcification Morphology, Mass Size, Calcification distribution
- **Group 3:** Features used Age, Associated Findings, Mass Margin, Calcification Morphology, Mass Size, Mass Shape, Calcification Number, Calcification Distribution
- **Group 4:** Features used Age, Associated Findings, Mass Margin, Calcification Morphology, Mass Shape, Calcificat5ion Number, Calcification Distribution
- **Group 5:** Features used Age, Mass Margin, Calcification Morphology, Mass Shape, Calcification Number

Case-based Reasoning (CBR) is a laid out research in the Man-made reasoning field. It is the review to plan the framework on hypothetical establishments and its viable application to take care of the issue through previous experience. The fundamental of every CBR is the case base, which comprises previously ready and put-away insight, known as cases. A case-based solver settles new issues with the assistance of a comparative past tackled issue present for the situation base.[17] CBR framework chooses one or various comparable cases. The arrangements of chosen comparable cases are adjusted to foster an ongoing issue arrangement. At last, another arrangement of the new issue is put away if base to expand its ability.

CBR can be partitioned into three sorts depending on their case portrayal and thinking procedure name literary CBR, underlying CBR, and conversational CBR.[18] In primary CBR the cases are portrayed as per normally organized jargon (metaphysics). In text-based CBR, the cases are portrayed as free text (strings). In conversational CBR, cases are addressed by the rundown of shifted inquiries in cases. Notwithstanding various methodologies of the CBR frameworks, the essentials of all CBR are a basic and uniform cycle as displayed in Figure 2. The following three main distance techniques are used to apply the CBR algorithm to this data. A) Euclidean distance, B) Manhattan distance, and C) Malik Approach

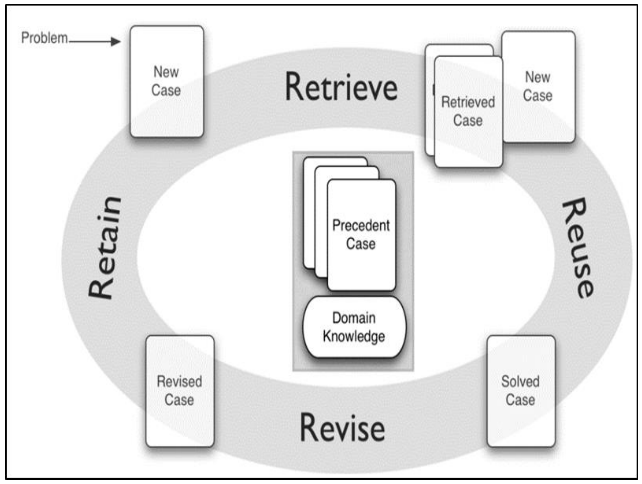

Figure 2: Case-based Reasoning (CBR) Cycle

Principal Component Analysis (PCA) utilizes the standards of science to change various corresponding factors into fewer factors called principal components. PCA is utilized to investigate the multivariate information. The Mathlab is utilized played out this examination. PCA lessens the aspects of multivariate information utilizing vector space change.[19] The informational collection is deciphered in barely any central parts by utilizing numerical projections. In this way, it assists the client by diminishing information with dimensioning to track down patterns, exceptions, and examples in the information.

A more tasteful predicts the outcome as certain or negative in the event of paired choice issues. The result is addressed by the disarray network which is classified into four classes: TP (True positive), FP (False positive), TN (True negatives), and FN (False negatives). TP address accurately sorted as positives. FP relates to negative models inaccurately sorted as certain. TN alludes to negatives accurately classified as negative. FN relates to positive models mistakenly classified as negative.

Results

In the proposed framework, numerous perceptions are made by making the test and preparing cases out of 1863 cases, the two distinct calculations are utilized and set the limit esteem of 0.62.

A) Malik Approach: In the feature set of group 1, there are 36% true negative cases and 80% true positive cases, in group 2, there are 28% true negative cases and 84% true positive cases, in group 3, there are 12% true negative cases and 96% true positive cases, in group 4, there are 44% true negative cases and 64% true positive cases, and in group 5, there are 12% true negative cases and 96% true positive cases.

B) Manhattan Distance Approach: In the feature set of group 1, there are 72% true negative cases and 84% true positive cases, in group 2, there are 92% true negative cases and 88% true positive cases, in group 3, there are 92% true negative cases and 92% true positive cases, in group 4, there are 80% true negative cases and 88% true positive cases and, in group 5, there are 72% true negative cases and 94% true positive cases.

C) Euclidean Distance Approach: In the feature set of group 1, there are 72% true negative cases and 84% true positive cases, in group 2, there are 92% true negative cases and 88% true positive cases, in group 3, there are 92% true negative cases and 92% true positive cases, in group 4, there are 80% true negative cases and 88% true positive cases and, in group 5, there are 72% true negative cases and 94% true positive cases.

The experiments both dangerous and harmless are chosen to check the exhibition of the proposed framework to determine the accuracy (P1, P2) and review (R1, R2). The typical accuracy (P) and normal review (R) are likewise determined and the outcomes are summed up in Table 1 for dangerous and harmless.

Table 1: Precision and recall of malignant test cases and benign test cases

Malignant	Precision			Recall		
Cases	P1	P2	P	R1	R2	R
1-100	1	1	1	0.8	.75	0.78
1-300	0.84	0.94	0.89	0.8	0.8	0.8
1-500	0.85	0.89	0.87	0.85	0.85	0.85
1-700	0.81	0.89	0.85	0.85	0.85	0.85
1-900	1	1	1	0.0	0.85	0.88
Benign	**Precision**			**Recall**		
Cases	P1	P2	P	R1	R2	R
1-100	0.83	0.8	0.82	1	1	1
1-300	0.8	0.83	0.82	0.8	0.8	0.8
1-500	0.85	0.86	0.85	0.85	0.85	0.85
1-700	0.84	0.86	0.85	0.8	0.89	0.85
1-900	0.91	0.87	0.89	1	1	1

The BI-RAD characteristics are grouped into multiple groups to evaluate their significance in the detection of breast cancer. The accuracy of threatening experiments in the middle of somewhere in the range of 0.85 and 1. The review of harmful experiments lies in the reach 0.78 and 0.88. The accuracy and review for harmless experiments change between 0.82-0.89 and 0.85-1 individually. The accuracy and review of the proposed computer-aided design framework determined for harmful and harmless experiments are likewise displayed as reference diagrams in Figure 3 (a), (b), (c), and (d) separately.

The accuracy and review of experiments executed on around eighteen hundred case bases and the consequences of accuracy and review of the experiments after the PCA execution are also summed up in Table 2.

Table 2: Result for forty test cases on 1863 case base and after PCA implementation

Forty test cases on 1863 case base						
Malignant						
Precision			**Recall**			
CASES	**P1**	**P2**	**P**	**R1**	**R2**	**R**
1863	0.76	0.66	0.71	0.95	0.95	0.95
Benign						
1863	0.93	0.9	0.92	0.7	0.5	0.6
Forty test cases on 1863 case base after PCA implementation						
Malignant						
1863	0.74	0.81	0.77	0.85	0.85	0.85
Benign						
1863	0.82	0.84	0.83	0.8	0.7	0.75

The outcome showed that the accuracy of malignancy experiments expanded and the review diminished. The accuracy for benign experiments diminished and the review expanded.

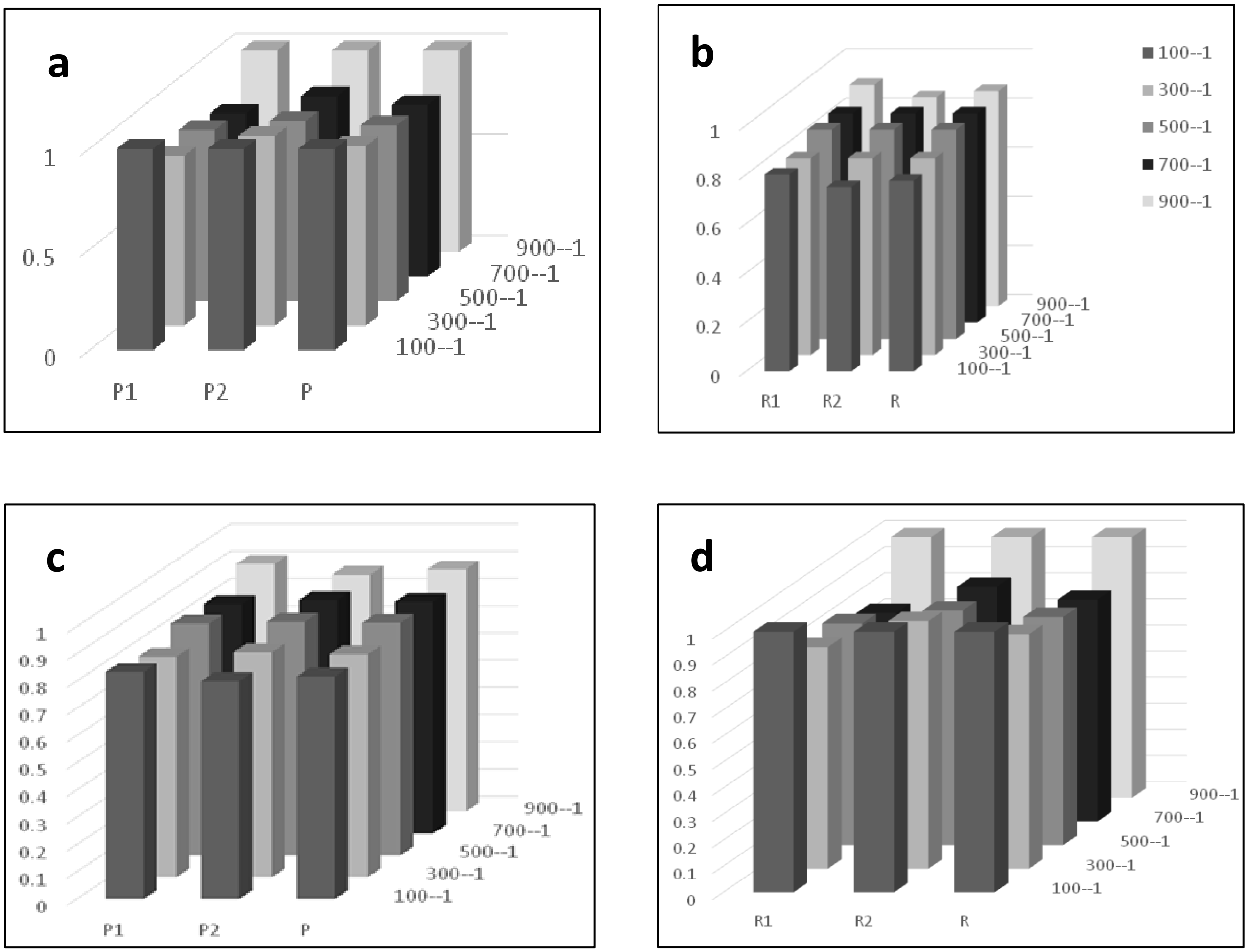

Figure 3: (a) Precision for malignant cases (b) Recall for malignant cases (c) Precision for benign cases (d) Recall for benign cases

Discussion

Numerous Analysts introduced different computer-aided design frameworks in light of various strategies to distinguish different sorts of malignant growth on the visual data gathered from clinical pictures and demonstrated that their computer-aided design framework had clinical applications.[20] The precision of computer-aided design framework carried out on breast mammograms changes somewhere in the range of 92% and 97.3%. The precision of computer-aided design framework mounted on breast X-ray is in the scope of 88.42% and 91.67%. The precision of computer-aided design framework carried out on breast ultrasound is in the middle of somewhere in the range of 90% and 100 %. The proposed computer-aided design framework responsiveness for the cellular breakdown in the lungs is between 90% with 0.05 bogus up-sides and 98.2% with 9.1 misleading up-sides. The exactness of various computer-aided design frameworks for mind growth is more than almost 100%. Yet, the majority of computer-aided design frameworks are simply used to recognize specific malignant growth types on specific data sets. The specialists/oncologists demonstrated the way that joining various strategies could work on the precision and adequacy of computer-aided design framework to distinguish disease.

Joshua J. Fenton et al. have executed a computer-aided design on an enormous data set of film screen mammograms however explicitness was diminished in contrast with our exploration the particularity and responsiveness were expanded.[6] Arifa Sadaf et al. assessed the exhibition of computer-aided design with FFDM in the discovery of breast tumors applied on 127 mammographic cases and uncovered 100 percent awareness in tracking down microcalcifications and 86% responsiveness for another disease.[7] Our exploration was executed on huge information of 1863 cases and accomplished better computer-aided design execution. Robert M. Nishikawa et al. showed that radiologist awareness expanded by 10% and confirmed our exploration that information size increases help in determination by computer-aided design calculations.[8] Mohamed Meselhy Eltoukhy et al. proposed a factual t-test strategy for highlight extraction and applied breast malignant growth location and grouping in mammograms. They utilized the Help Vector Machine and the exactness rate gave 95.84% to group ordinary and strange tissues in correlation we have shown improved results by expanding the data set.[9]

J. Dheeba et al. explored a new order technique for breast malignant growth location by utilization of Molecule Multitude Streamlined Wavelet Brain Organization on 216 advanced mammograms uncovering awareness and explicitness of strategy was 94.167% and 92.105% individually Case Based Thinking approach shows improved results and addresses purposes for their reaction.[10] Yu-Dong Zhang et al. proposed an SVM and PCA computer-aided design framework for distinguishing irregularities in breasts on 200 mammogram pictures. Our CBR and PCA-based model created improved results with rationales utilizing more information.[11] Zhiqiong Wang et al. proposed an AI computer-aided design location framework for 222 mammograms. Our outcomes show with an enormous information base including more harmless and threatening cases the exactness can be moved along.[12]

Conclusion

The best feature subset found for malignant cases differed from the benign cases. It has been found, that different subsets are best for different techniques. For the Malik approach, the maximum number of correctly classified malignant cases was found by using the feature set of groups III and IV. Both feature sets have IV common features and feature set III has three additional features than set V. For Malik's approach the maximum benign cases are correctly classified based on feature set IV. The Manhattan distance approach provided maximum correctly classified malignant cases using feature set V and for benign cases, the group III feature set provided better results. Euclidean distance approach correctly classified the malignant cases using group V and correctly classified benign cases using groups III and II. It has been observed that the malignant cases are less often misclassified than the benign cases. For the malignant cases, the Malik approach produces better results and for benign cases, Manhattan distance and Euclidean distance classify better. The CBR represents a useful diagnostic tool for the classification of mammographic lesions.

References

1. International Agency for Research on Cancer. Agents classified by the IARC monographs, volumes 1–129. [Homepage on the internet] Lyon: IARC; [cited 2021 May 19; updated 2021 Mar 26]. https://monographs.iarc.who.int/agents-classified-by-the-iarc/
2. Majeed I; Ammanuallah R; Anwar A; Rafique H; Imran F. Diagnostic and treatment delays in breast cancer in association with multiple factors in Pakistan. East Mediterr Health J. 2021;27(1):23-32.
DOI: https://doi.org/10.26719/emhj.20.051
3. Ikram A, Pervez S, Khadim M H, Sohaib M, Uddin H, Badar F et al, National Cancer Registry of Pakistan: First Comprehensive Report of Cancer Statistics 2015-2019, JCPSP, Volume 34, 12 Issues, 2024
DOI : https://doi.org/10.29271/jcpsp.2023.06.625.
4. Majeed I , Amanuallah R, Rafique H (2018). Time delay barriers in diagnosis and treatment of cancer, World Cancer Research Journal: 5(3): e118.
DOI: https://doi.org/10.32113/wcrj_20189_1118
5. Majeed I, Imran F, Nadeem A, Ashiq R, Nasir B, Early detection of Cancer using Mammograms with Advanced Artificial Intelligence (AI) Algorithms for Breast lesions, Journal of Liaqat National Hospital, vol 1, no 2, 2023
DOI: https://doi.org/10.37184/jlnh.2959-1805.1.15
6. Fenton J. J. , Abraham L, Taplin S. H., B. M. Geller, P. A. Carney, C. D'Orsi, et al, B. C. S. Consortium, Journal of the National Cancer institute 103, 1152 (2011).
DOI: https://doi.org/10.1088/0031-9155/59/15/4357
7. A. Sadaf, P. Crystal, A. Scaranelo, and T. Helbich, Performance of computer-aided detection applied to full-field digital mammography in detection of breast cancers, European journal of radiology 77, 457 (2011).
DOI:https://doi.org/1 https://doi.org/10.1016/j.ejrad.2009.08.024
8. Nishikawa R. M. , de Cea M.V.S., & Yang, Y. (2018). Locally adaptive decision in detection of clustered microcalcifications in mammograms. PHYSICS IN MEDICINE AND BIOLOGY, 63(4), 045014.IOP Publishing.
DOI: https://doi.org/10.1088/1361-6560/aaaa4c

9. Eltoukhy M M, Faye I, Samir B B ,"A statistical based feature extraction method for breast cancer diagnosis in digital mammogram using multiresolution representation", Computers in Biology and Medicine , vol. 42, 2012, pp. 123–128. DOI:https://doi.org/10.1016/j.compbiomed.2011.10.016
10. J. Dheeba, S Shamy , A research on detection and classification of breast cancer using k-means GMM & CNN algorithms International Journal of Engineering and Advanced Technology 8 (6S), 501-505, 2019.
DOI:https://doi.org/10.35940/ijeat.F1102.0886S19.
11. Zhang Y-D, Wang S-H, Liu G, Yang J. Computer-aided diagnosis of abnormal breasts in mammogram images by weighted-type fractional Fourier transform. Advances in Mechanical Engineering. 2016;8(2).
DOI: https://doi.org/10.1177/1687814016634243
12. J.M. Górriz, I. Álvarez-Illán, A. Álvarez-Marquina, J.E. Arco, M. Atzmueller, F. Ballarini, et al, Computational approaches to Explainable Artificial Intelligence: Advances in theory, applications and trends, Information Fusion, Volume 100,2023,101945,
DOI: https://doi.org/10.1016/j.inffus.2023.101945
13. Rosenberg SM, Zheng Y, Ruddy K, Poorvu PD, Snow C, Kirkner GJ, Meyer ME, Tamimi RM, Schapira L, Peppercorn J, Come S, Borges VF, Warner E, Gelber S, Collins L, Winer EP, Partridge AH. Helping ourselves, helping others: the Young Women's Breast Cancer Study (YWS) - a multisite prospective cohort study to advance the understanding of breast cancer diagnosed in women aged 40 years and younger. BMJ Open. 2024 Jul 1;14(6):e081157.
DOI: https://doi.org/10.1136/bmjopen-2023-081157.
14. Rose, C., Turi, D., Williams, A., Wolstencroft, K., Taylor, C. (2006). Web Services for the DDSM and Digital Mammography Research. In: Astley, S.M., Brady, M., Rose, C., Zwiggelaar, R. (eds) Digital Mammography. IWDM 2006. Lecture Notes in Computer Science, vol 4046. Springer, Berlin, Heidelberg.
DOI: https://doi.org/10.1007/11783237_51
15. Siu A L; U.S. Preventive Services Task Force. Screening for breast cancer: U.S. Preventive Services Task Force recommendation statement. Annals of Internal Medicine 2016; 164(4):279-96.
DOI: https://doi.org/10.7326/M15-2886
16. Radswiki T, Elfeky M, Ashraf A, et al. Breast calcifications. Radiopaedia.org (Accessed on 13 Jul 2024) .
DOI: https://doi.org/10.53347/rID-13952
17. Paruchuri V A, Granville B C, A Case-Based Reasoning System for Aiding Physicians in Decision Making, published by Intelligent Information Management, Vol.12 No.2, 2020. DOI:https://doi.org/10.4236/iim.2020.122005
18. Rawat D, Sharma S and Bhadula S, "Case based Reasoning Technique in Digital Diagnostic System for Lung Cancer Detection," 2023 8th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2023, pp. 1355-1361,
DOI: https://doi.org/10.1109/ICCES57224.2023.10192863
19. Greenacre, M., Groenen, P.J.F., Hastie, T. et al. Principal component analysis. Nat Rev Methods Primers 2, 100 (2022).
DOI: https://doi.org/10.1038/s43586-022-00184-w
20. Zicheng G, Jiping X, Yi W, Min Z, Liang Q, Jiaxuan Y, et al A review of the current state of the computer-aided diagnosis (CAD) systems for breast cancer diagnosis , Open Life Sci 2022; 17(1): 1600-11.
DOI: https://doi.org/10.1515/biol-2022-0517