ORIGINAL ARTICLE

OPTIMAL USE OF BIRAD DESCRIPTORS FOR BREAST CANCER DETECTION BY EMPLOYING DATA MINING WITH CORRELATION OF BIOPSY OUTCOME

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ABSTRACT

Background: Breast cancer (BC) is commonest among cancer patients, required early detection to be cured. Multiple techniques are used for the diagnosis of BC but mammography is a commonly available and effective tool around the world due to its ability to diagnose BC before it becomes palpable, in reward treatment cost also decreases. Computer-aided diagnosis (CAD) is advanced research to support medical practitioners in cancer diagnosis.

Objective: To evaluate optimal use of descriptors for early detection of breast cancer by employing data mining with correlation of biopsy outcome

Methods: In comparison to the segmentation technique our research has used "extracted BIRAD characteristics information" from the mammograms. A novel data mining approach for the BIRAD lexicon has been researched in connection with the interactive medical experience. A globally recognized dataset (DDSM) has been used. The characteristics extracted from the mammograms are processed by the data mining method to achieve critical ranges for cancer detection. Multiple classification models with peculiar characteristics have developed to detect BC at the curable stage.

Results: A total of 1863 patients with an average age of 61 years were evaluated, 48% indicated with malignancies, and 52% with benign lesions, proved with truth biopsy. Critical ranges, by the development of multiple CAD tools, showed remarkable improvement in the recall (NB; 26.9%) and precision (CART; 17.6%) along with reduced FP rate (CART; 16.7%).

Conclusion: The proposed method is profitable because of the individuality of CAD with four classification models along with the practitioner's experience and radiologist's opinion in the early detection of BC. For avoiding unnecessary biopsies and differentiating benign and malignant tumor the BIRAD features extraction was benevolent.

keywords: Breast cancer, CAD, BIRAD descriptors, Recall, mammograms:

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INTRODUCTION

Cancer is the uncontrolled growth of abnormal cells. Pakistan is ranked 9th in the world with 27.8 breast cancer deaths per 100,000 population. Early detection is the possibility to decrease the mortality rate by curable treatment well in time.[1-3] Mammography is widely used globally in the early detection of breast cancer. The early detection of cancer can cure cancer and supports the reduction of costs..[4-7]

The American College of Radiology introduced this mammography lexicon for the mammography lesions. The BIRAD lexicon consists of different features such as margin, shape, size and density of mass, calcification number, distribution and morphology, associated findings, special cases and age.

For the indication of these features, the Computer Aided Diagnosis (CAD) systems have been developed. Computers provide aid in the process of characteristics classification of cancer. Computer-aided medical diagnosis is a worldwide addressed research problem among medical scientists. Computers are used in the medical imaging process as a double reader to increase the accuracy of cancer detection.[4,5]

CAD is an automatically analyzer of medical images and gives the opinion in lesion differentiation as malignancy or benign lesions. It has shown efficiency and reliability for the breast carcinomas. CAD system consists of four steps image enhancement, segmentation, feature extraction and classification. While, in the proposed method we added the mammographer's and radiologist's opinion that reduces the need of these four steps, which lead to the reduction of risk of misclassification because of high impact of previous step on the next one.

The new proposed approach used the BIRAD features to meet the CAD common problem of semantic gap, occurs due to low quality features. In this research, we proposed a new method of "data mining" for the classification of lesions as malignant or benign. Data mining is an intelligent technique that explore data for meaningful information to detect and cure cancer in the early stage. Multiple CAD models have developed to improve the recall of malignant and benign lesions. We achieved these models by using the knowledge based and the statistical based approaches. This approach has increased recall by application of multiple computer algorithms with optimal critical ranges to a large dataset. The objective of this study is to evaluate optimal use of descriptors for early detection of breast cancer by employing data mining with correlation of biopsy outcome. The early detection of breast cancer is the purpose of this research which enables the curable treatment of breast cancer. The computer aided early detection can increase the survival, quality of life and can improve treatment costs and social factors.

METHODS

The study was approved by the Ethical Review Board, Allama Iqbal Medical College, Lahore, Pakistan, vide reference No. 194/23/12/2021/52 ERB Dated 17.02.2022. The proposed method is performed in five phases from acquiring data to classification into benign and malignant cases.

- Mammograms Data
- Characteristics Extraction
- Data Minning
- Pre processing
- Classification Model Development

The proposed method is checked by using a local and globally available database of DDSM. [10]

Every case is biopsy-proven for its ground truth. The data base consisted of 1863 cases with patients of all ages. The average age of the patients was 61 years. The cases with suspected masses without calcification were 708 (38%) and with calcification without masses were 998 (53%). 142 (8%) cases had both mases and calcification and 15 (1%) cases had neither masses nor calcification. Overall 899 (48%) cases after biopsy were presented with malignancies and 964 (52%) cases had benign lesion. So, we may say that 964 patients could escaped from biopsy.

Figure 1: CC and MLO views of both breasts.

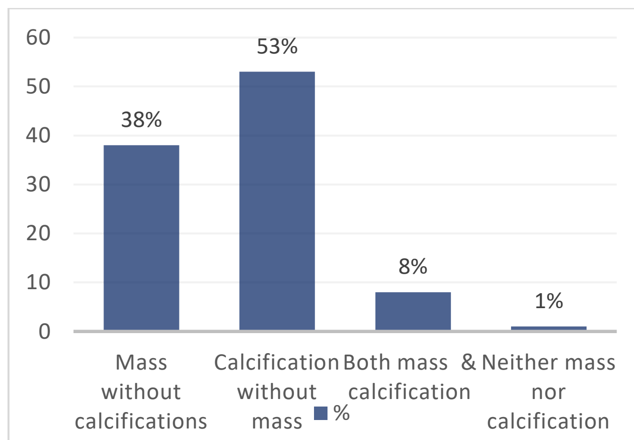

Figure 2: Masses and calcifications distribution.

Characteristics Extraction: Around the globe, medical imaging experts use guidelines of the American college of radiology (ACR) to describe the medical diagnosis. Calcification characteristics including distribution, calcification number, and morphology are obtained from mammograms. Four mass characteristics are included in this research, which are mass size, mass margin, mass shape, and density. The other two features extracted from images are associated with findings and special cases. One characteristic is age obtained from patient details.[11-12]

The analysis of the database establishes the existing association rules, which can be discovered with multiple measures of interest. Let there is a set of binary attributes called items $C=\{c_1,c_2,\ldots.c_n\}$ and transactions are assembled in set $D=\{t_1,t_2,\ldots t_n\}$. Each transaction has a subset of items in C and identified by its own ID. Some rules can be defined as.

$X \implies Y$ where $X, Y \subseteq C$, and $X \cap Y = \Theta$;

The proportion of transactions contain an itemset is called the support of respective itemset. The confidence of a rule is defined as conf $(X \implies Y) = \text{supp}(X \cup Y)/\text{supp}(X)$.

Table: Characteristics are extracted from mammograms.

Features	Findings	Value	Features	Findings	Value
1.Calcification Distribution	No calcification	0	6.Mass Shape	No Mass	0
	Diffuse	1		Round	1
	Regional	2		Oval	2
	Segmental	3		Lobulated	3
	Linear	4		Irregular	4
	Clustered	5	7.Mass density	No Mass	0
2.Calcification number	No calcification	0		Fat-containing	1
	<5	1		Low density	2
	5 to 10	2		Isodense	3
	>10	3		High density	4
3.Calcification Morphology	No calcification	0	8.Associated Findings	None	0
	Milk/ Calcium like	1		Skin lesion	1
	Egg Shell /Rim	2		Hematoma	2
	Skin	3		Post-surgical scar	3
	Vascular	4		Trabecular Thickening	4
	Spherical	5			
	Suture	6		Skin thickening	5
	Coarse	7		Skin retraction	6
	Large Rod-like	8		Nipple retraction	7
	Round	9		Axillaries Adenopathy	8
	Dystrophic	10			
	Punctate	11		Architectural Distortion	9
	Indistinct	12			
	Pleomorphic	13	9.Special Cases	None	0
	Fine Branching	14		Intramammary lymph node	1
4. Mass Margin	No mass	0			
	Well circumscribed	1		Asymmetric breast tissue	2
	Microlobulated	2			
	Obscured	3		Focal asymmetric density	3
	Ill-defined	4			
	Speculated	5		Tubular density	4
5.Mass Size		Mm	10.Age		Years

Pre-Processing: The pre-processing of data is performed by modification of characteristics using data mining:

- Discritize Characteristics Data
- Partitition Benign & Malignant Data
- Generate Critical ranges
- Find Focused Critical Ranges
- Modification of Data
- combine partitions

Our proposed methodology will assist clinician to decide about a new case to recommend for FNAC immediately or after a few periods of time. The output of the models by ensemble provides the decision regarding the class of case under discussion.

Classification Models: We applied four classifiers to unprocessed data and post-processed data to achieve the early detection of breast cancer.

Case-Based Reasoning: CBR provides an analogy to medical practice. When a cancer case is presented with unusual characteristics, an oncologist remembers old cases from his experience and proposed a solution from similar cases. Doctors validate for characteristics provided in a new case. Time consumption reduces in designing of the new solution with the help of previous experience. [13]

Naive Bays: Naïve Bays a probabilistic, effective, and simple machine learning classifier. It uses maximum posterior rule and is applied successfully in text classification and spam detection. Naïve bayes use easy to write and efficiently run algorithms.[14]

CART: Leo Breiman et al introduced Classification and Regression Tree approach an eminent statistical classifier. The following procedure is observed,

a) How the selection of splitting characteristic is made?

b) Derivation of stopping rules.

c) Allocation of classes to nodes.[16]

Voted perceptron: The voted perceptron classifier classifies a single input into multi outputs. It has an effective property that it replies to errors only if they exist otherwise, it does not change its parameters. So, it is very easier and faster classifier.[17]

Performance Evaluation: The following measures are employed to evaluate the performance of the proposed method

$$Recall = \frac{TP}{TP + FN} \qquad Precision = \frac{TP}{TP + FP}$$

$$False\ positive\ rate = \frac{FP}{FP + TN} \qquad F\ measure = 2 \times \frac{precision \times recall}{precision + recall}$$

Classification of malignant and benign cases done under these four models by calculating the performance metrices, true positive rate, true negative rate, false negative rate, true negative rate, precision, recall, F-measure, ROC Area and the PRC Area that is a precision-recall curve.

RESULTS

The data extracted from mammograms is pre-processed by the application of the proposed data mining method. The discretized data produced four principal components including mass shape(-inf-0.125), mass size(-inf-0.091), age (0.505-0.604), and calcification number with two critical ranges CN1 (0.3-0.4) and CN2 (inf-0). These values of characteristics are used in the preprocessing of data. The classification methods are developed with unprocessed data and preprocessed data. The results are given below:

For Naïve bayes classifier: By using the naïve bayes classifier, for malignant cases, the maximum improvement in TP rate, precision, recall, F-measure and ROC area achieved were 26.9%, 6.8%, 26.9%, 17.6% and 8.2% respectively with preprocessing on critical ranges of calcification number (0.3-0.4). And the maximum reduction in FP rate achieved was 3.1% with preprocessing on critical range of classification number (inf-0).

Table 1: Classification of malignant and benign cases with NB model.

Naïve Bays: Performance Measure Naïve Bays	Unprocessed data		Preprocessing on the critical range of mass shape (-inf-0.125)		Preprocessing on the critical range of calcification number (0.3-0.4)		Preprocessing on critical ranges of calcification number (inf-0)		Preprocessing on critical ranges of Mass Size (-inf-0.091)		Preprocessing on critical ranges of age (0.505-0.604)	
Measure	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign
TP Rate	0.673	0.866	0.939	0.884	0.942	0.894	0.674	0.897	0.835	0.754	0.774	0.893
FP Rate	0.134	0.327	0.116	0.061	0.106	0.058	0.103	0.326	0.246	0.165	0.107	0.058
Precision	0.825	0.738	0.884	0.939	0.893	0.943	0.861	0.745	0.762	0.83	0.872	0.943
Recall	0.673	0.866	0.939	0.844	0.942	0.894	0.674	0.897	0.835	0.754	0.774	0.894
F measure	0.741	0.797	0.91	0.911	0.917	0.918	0.756	0.814	0.797	0.79	0.82	0.918
ROC Area	0.892	0.892	0.97	0.97	0.974	0.974	0.889	0.889	0.878	0.878	0.974	0.974
PRC Area	0.899	0.899	0.977	0.961	0.979	0.969	0.905	0.889	0.885	0.852	0.979	0.969

For voted perceptron classifier: By using the voted perceptron classifier, the maximum enhancement in TP rate, recall, F-measure and ROC area were 11.5%, 11.5%, 13.4% and 12.3% respectively with preprocessing on critical range of classification number (0.3-0.4). In precision the maximum improvement observed was 14.9% and in FP rate the maximum reduction was 15.9%, achieved with preprocessing on critical range of mass shape (-inf-0.125).

Table 2: Classification of malignant and benign cases with VP model.

Voted Perceptron Classifier: Performance Measure VP	Unprocessed Data		Preprocessing on the critical range of mass shape (-inf-0.125)		Preprocessing on the critical range of calcification number (0.3-0.4)		Preprocessing on critical ranges of calcification number (inf-0)		Preprocessing on critical ranges of Mass Size (-inf-0.091)		Preprocessing on critical ranges of age (0.505-0.604)	
Measure	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign
TP Rate	0.798	0.823	0.905	0.972	0.913	0.967	0.858	0.873	0.798	0.823	0.774	0.948
FP Rate	0.177	0.202	0.028	0.095	0.033	0.087	0.127	0.142	0.177	0.202	0.052	0.226
Precision	0.809	0.812	0.968	0.916	0.962	0.922	0.864	0.867	0.809	0.812	0.933	0.817
Recall	0.798	0.823	0.905	0.972	0.913	0.967	0.858	0.873	0.798	0.823	0.774	0.948
F measure	0.803	0.818	0.936	0.943	0.937	0.944	0.861	0.87	0.803	0.818	0.846	0.877
ROC Area	0.82	0.86	0.939	0.95	0.943	0.955	0.876	0.915	0.82	0.86	0.736	0.875
PRC Area	0.755	0.808	0.923	0.915	0.925	0.924	0.821	0.874	0.755	0.808	0.834	0.814

For Case-based reasoning classifier: By using the case-based reasoning classifier, the maximum increase in TP rate, recall, and ROC area were 15.7%, 15.7%, and 6.4% respectively with preprocessing on critical range of mass size (-inf-0.091). The maximum improvement in precision and F-measure observed were 2.4% and 6.4%, and the maximum reduction in FP rate was 4%, achieved with preprocessing on critical range of calcification number (0.3-0.4).

Table 3: Classification of malignant and benign cases with CBR model.

Case-Based Reasoning	Performance Measure	Unprocessed data		Preprocessing on the critical range of mass shape (-inf-0.125)		Preprocessing on the critical range of calcification number (0.3-0.4)		Preprocessing on critical ranges of calcification number (inf-0)		Preprocessing on critical ranges of Mass Size (-inf-0.091)		Preprocessing on critical ranges of age (0.505-0.604)	
	Measure	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign
	TP Rate	0.809	0.797	0.922	0.795	0.92	0.801	0.881	0.798	0.966	0.682	0.828	0.795
	FP Rate	0.203	0.191	0.205	0.078	0.199	0.08	0.202	0.119	0.318	0.034	0.205	0.172
	Precision	0.789	0.816	0.809	0.916	0.813	0.914	0.804	0.877	0.741	0.955	0.791	0.831
	Recall	0.809	0.797	0.922	0.795	0.92	0.801	0.881	0.798	0.966	0.682	0.828	0.795
	F measure	0.799	0.806	0.862	0.851	0.863	0.854	0.841	0.836	0.838	0.796	0.809	0.812
	ROC Area	0.898	0.898	0.951	0.951	0.956	0.956	0.939	0.939	0.962	0.962	0.92	0.92
	PRC Area	0.896	0.906	0.958	0.945	0.963	0.95	0.939	0.944	0.964	0.955	0.928	0.918

Table 4: Classification of malignant and benign cases with CART model.

Classification and Regression Tree	Performance Measure CART	Unprocessed Data		Preprocessing on the critical range of mass shape (-inf-0.125)		Preprocessing on the critical range of calcification number (0.3-0.4)		Preprocessing on critical ranges of calcification number (inf-0)		Preprocessing on critical ranges of Mass Size (-inf-0.091)		Preprocessing on critical ranges of age (0.505-0.604)	
	Measure	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign	Malignant	Benign
	TP Rate	0.806	0.814	0.913	0.981	0.806	0.814	0.93	0.967	0.857	0.851	0.749	0.953
	FP Rate	0.186	0.194	0.019	0.087	0.186	0.194	0.033	0.07	0.149	0.143	0.047	0.251
	Precision	0.803	0.817	0.979	0.923	0.803	0.817	0.963	0.936	0.844	0.863	0.937	0.801
	Recall	0.806	0.814	0.913	0.981	0.806	0.814	0.93	0.967	0.857	0.851	0.749	0.953
	F measure	0.805	0.816	0.945	0.951	0.805	0.816	0.946	0.951	0.85	0.857	0.832	0.871
	ROC Area	0.911	0.911	0.986	0.986	0.911	0.911	0.985	0.985	0.956	0.956	0.931	0.931
	PRC Area	0.914	0.914	0.988	0.982	0.914	0.914	0.988	0.981	0.956	0.958	0.939	0.925

For classification and regression tree classifier: By using the classification and regression tree classifier, the maximum increase in TP rate, recall, and F-measure were 12.4%, 12.4%, and 14.1% respectively with preprocessing on critical range of calcification number (0.3-0.4). The maximum improvement in precision and ROC area observed were 17.6% and 7.5%, and the maximum reduction in FP rate was 16.7%, achieved with preprocessing on critical range of mass shape(-inf-0.125).

The above results are showing the very modified outcomes after processing, not only by increasing the TP rate but also by decreasing the FP rate. For the unprocessed data, the TP rate was high for all the classifiers and the FP rate was low but a remarkable increase was observed in the TP rate and the FP rate also decrease with processing on a critical range of mass shape.

The most improved results were obtained for the NB classifier, that had very low TP rate before processing of 67.3%, which increased and reached a value of 93.9%. The processing with mass size also improved the results with TP and also reduced the FP rate.

There is highest value of the TP rate for the NB classifier and the lowest FP rate for the VPC classifier. The processing with classification no. CN1 showed no change in the TP rate and FP rate from the unprocessed data.

The processing with classification no. CN2 also indicated the demanded high TP rate and reduced FP rate. The processing with age showed improved results but not as remarkable as with mass shape and mass size processing.

DISCUSSIONS

The new research to apply computer artificial intelligence in the process of detection of cancer is a feasible way to help doctors in improvement of diagnosis. This method provides the reasoning in the process of detection and classification tools provide the justification for its efficacy. This approach utilized BI Rad descriptors which can be easily understand and applied by radiologist and mammographers. This approach can be deployed in developing countries, with lack of experienced doctors and resources. This approach has increased recall by application of multiple computer algorithms with optimal critical ranges to a large dataset.

We successfully optimized the classification of malignancy and benign lesions by using BI RAD lexicon, with the help of CAD classification models CART, CBR, VPC and NB systems.

The actual proficiency achieved by using the data mining technique that thoroughly evaluated the characteristics and extricate the knowledge hidden in the features. The focus of the medical practitioner's is to increase and improve the recall for the accurate and early diagnosis of cancer rather than performance of the classification model.

This research has utilized the most prime set of features. In a very recent study by Sutong Wang et al.[20] an improvement random forest (RF)-based rule extraction (IRFRE) method was used on three type of data base and found the maximum sensitivity of 96% and precision of 96.7%. Ning Mao et al.[21] extracted the radiomic features and utilized the four types of classification algorithms named as SVM, NB, KNN and LR classifier. The highest sensitivity of 86.7% and precision of 92.4% was achieved by LR and SVM classifiers, respectively. A. C. Phadke et al.[04] proposed the SVM algorithm and obtained the sensitivity of 92.71%. M. Shibusawa et al.[05] designed the KNN classifying model and got 87.8% sensitivity. In another recent study Q. Huang et al.[06] extracted the BIRAD features by using biclustering mining. The Fuzzy interference model was used to improve the TP rate and precision. The evaluated sensitivity and precision were 97.7% and 95.45% respectively. However, the increase in TP rate was remarkable but the reduction in FP rate was not indicated. While, in our work the deduction in FP rate was also incredible. Another author W. K. Moon et al.[07] used the LR model for the classification of benign and malignant tumors and found 84% positive instances as positive at output. A new classification model QDA was used by P. Casti et al.[08] and 83% sensitivity was observed. Support Vector Machine-Recursive Feature Elimination (SVM-RFE) and One-Dimensional Naïve Bayes Classifier (1-DBC) were utilized by A. Bustamam et al.[9] for the feature extraction and classification. These both models indicated the recall of 93.61%. W. Sun et al.[10] proposed the DL classification model and TP rate of 81% was achieved by using this algorithm. In another study W. Sun et al.[11], for the improvement of TP rate, developed the ANN classifier and this time the TP rate of 81.6% was observed. G Santamaría et al.[12] indicated 88.5% recall for PCR.

CONCLUSION

This research is highly beneficial in the early detection of breast cancer, improving the diagnostic efficiency and for aiding the radiologist in making the decision of either biopsy or follow up by accurate detection and classification of malignancy and benign lesions. A number of superfluous biopsies can be avoided in this way. The proposed work used data mining technique to evaluate the useful knowledge from the ACR's presented BIRAD features. While pre-processing the partition of benign and malignant cases was done, 48% cases were malignant and 52% cases were benign. Then the critical ranges were generated and applied on both malignant and benign cases. The involvement of the practitioner or experienced radiologist improved the efficiency of developed algorithm. In the developing countries, where the radiologists are not as much experienced, the proposed CAD setup is capable of giving the best opinion. The comparison of four classifiers NB, VP, CBR and CART help to improve the recall and precision. The distinction of this work is the remarkable reduction in false positive rate. The highest recall of 96.6% is achieved by using CBR classification model and generating the critical range of calcification number.

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